# DEVELOPMENT OF A DIGITAL MATURITY MODEL FOR SMALL AND MEDIUM SIZED ENTERPRISES:
# A CASE STUDY IN TURKEY

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# DEVELOPMENT OF A DIGITAL MATURITY MODEL FOR SMALL AND MEDIUM SIZED ENTERPRISES:

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DECLARATION OF ORIGINALITY

I, Sedanur Yıldız, certify that

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# ABSTRACT

Development of a Digital Maturity Model for SMEs:

A Case Study in Turkey

SMEs play an immense role in the value chain and their daily operations are relatively more flexible than larger companies due to their smaller sizes and existence of less bureaucracy in their operations. SMEs are recognized by their high product customization skills. However, there are many obstacles that SMEs have in their DX maturity advancements such as financial and technical insufficiencies, organizational drawbacks, issues with standardizations and lack of alliances with research institutions. Given these distinct characteristics the DX maturity of SMEs should be evaluated accordingly by considering the challenges they face. The aim of this study is to develop a valid and reliable digital maturity model for SMEs and to implement this framework to analyze the factors that affect the digitalization levels of these companies. The DX assessment survey D3A is developed with the special focus on SMEs and the restrictions on their DX journeys. The generated framework is applied on 100 SMEs by face-to-face interviews and the results are analyzed. Valuable contributions are made to the DX literature by showing that D3A is a reliable and valid framework that can be used in assessing the DX maturity of SMEs. Furthermore, insights are generated on the factors that affect the digitalization levels of SMEs. These findings can be effectively used by the SMEs to generate critical improvement directions in developing their DX roadmaps. Nevertheless, D3A framework provides a general understanding of the digital maturity of SMEs in our area.

ÖZET

Kobiler için Dijital Dönüşüm Değerlendirme Aracı Geliştirilmesi:

Türkiye'de Örnek Bir Çalışma

Kobiler değer zincirinde önemli bir rol oynamaktadır ve günlük operasyonları küçük olmaları ve daha az bürokratik süreçlerden geçtikleri için büyük şirketlere göre daha esnektir. Ürün özelleştirmedeki yetkinlikleriyle bilinirler. Öte yandan, dijital dönüşüm yolculuklarında finansal ve teknik yetersizlikler, organizasyonel yapı eksiklikleri, standartlaşma problemleri ve araştırma kuruluşlarıyla iş birliği eksikleri gibi kısıtlamalar bulunmaktadır. Kobiler bu kısıtlamalar göz önünde bulundurularak değerlendirilmelidir. Bu çalışmanın amacı kobiler için kullanılabilecek geçerli ve doğrulanmış bir dijital dönüşüm değerlendirme aracının geliştirilmesi ve dijitallik seviyesini etkileyen faktörlerin analizi için bu modelin uygulanmasıdır. D3A değerlendirme aracı kobiler için özel olarak geliştirilmiş ve bu kısıtlamalara odaklanılmıştır. Geliştirilmiş modelle yüz yüze görüşmelerle 100 kobinin dijital dönüşüm olgunluk seviyeleri ölçülmüş, dijital dönüşüm süreçlerini etkileyen faktörlerin tespit edilebilmesi için sonuçlar analiz edilmiştir. D3A'nın geçerli ve doğrulanmış bir değerlendirme aracı olarak kobilerin mevcut durumlarını analiz etmede kullanılabileceği kanıtlanarak akademiye katkıda bulunulmuştur. Dijitalleşmeyi etkileyen faktörler incelenerek çeşitli bulgular elde edinilmiştir. Bu bulgular kobiler tarafından öncelikli çalışma alanlarını tespit edebilmek için kullanılabilir. Ayrıca D3A bölgemizdeki kobilerin dijitalleşme seviyeleriyle ilgili de bir durum tespiti sağlamaktadır.

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# CHAPTER 1:

# INTRODUCTION

Continuous progress in information and communication technologies create a need for adapting business operations to daily challenges and being in an everlasting change for companies which is called digital transformation (DX). While the advancements in technology are inevitably pushing the companies to change their practices, the frequently changing customer expectations are pulling the companies to improve their flexibility and responsiveness in all services. So, DX can also be considered as aligning the company with technological improvements in order to respond to the rapid changes in competition, demand and regulations. (Teichert, R., 2019).

DX is a process of change that companies need to adapt while running their ongoing life in a rapidly changing environment (Kane, 2017). The current situation must be approached within the limitations of keeping the existing business running while trying to adapt these changes. These limitations are caused by both inner operations as well as external factors such as suppliers and customers.

The value chain is now connected more than ever both vertically among the hierarchical levels of a manufacturing system and horizontally between the functional units of an enterprise, or end-to-end among the supply chain parties. The companies become more vertically integrated among the stages of production with the help of technologies like Internet of Things (IoT), mobile technologies, cloud computing connected with cyber-physical systems. So, the machines, parts, products, resources can be tracked in real time and the operators can control the progress anytime from anywhere. In the last decade, Industry 4.0 (I4.0) has become a common term for vertical integration in manufacturing. It refers to the integration of manufacturing processes for increased automation, improved communication, self-monitoring, and production of smart machines that can analyze and diagnose issues without human intervention (Fiaidhi, J., 2018) Nevertheless, the suppliers, partners, logistics service providers are digitally integrated through end-to-end connectivity, and social media technologies provide real time customer data. The data from all integrated sources can now be transferred at real-time and analyzed with advanced data analytics to help tracking the progress of operational processes and take decisions based on accurate predictions. These digital integrations enable the supply chain to apply more dynamic business models with increased collaboration, faster interaction between the parties and higher agility in actions. The improved levels of effectiveness, efficiency and flexibility achieved in operational processes provide the enterprises with sustainable competitive advantage.

DX is reflected in many studies as a process that emerges in multiple stages such as creating DX awareness, analyzing the current digital maturity level, identifying the digital targets, developing roadmaps and implementing projects (Wang et al., 2016). The later steps highly depend on an accurate assessment of the current situation and DX awareness of the company.

Motivated by these, vast amount of research has been made over the years in developing digital maturity models. Companies are getting more aware that the evaluation of the current digital status of an enterprise plays an important role on the DX journey of companies. However, great majority of these studies focus on the assessment of big enterprises in terms of revenue and number of employees. Afterall, DX is adapted by large companies relatively faster as they have enough resources, and their corporate structure, innovation culture and global knowhow provide a more favorable environment for them to plan improvements in accordance to the changing needs of the organization. However, the value chain consists of various small and medium sized enterprises, SMEs such as electrical parts producers in automotive industry, metal boards producers in white-goods industry or plastics producers in fast moving consumer goods, FMCG industry. It is notably a fact that the DX performance of the value chain is bounded by these weakest players (Akarun et al., 2020a).

SMEs play an immense role in the value chain and their daily operations are relatively more flexible than larger companies due to their smaller sizes and existence of less bureaucracy in their operations in spite of this critical advantage in agile decision making and acting, there are many obstacles that SMEs have in their DX maturity advancements (Mittal et al., 2018). First of all, DX improvements are long-term investments that require the availability of technical and financial resources where SMEs are significantly weak. Organizational structure is another critical aspect of an enterprise. SMEs mostly have more function oriented and informal organizational structure compared to MNEs. Organizational culture is not flexible enough to adapt to changes. Mittal et al. also stated that SME's decisions are mostly made by managers with 'gut-feeling' rather than market research or accurate analyses (2018) which causes uncertainty and lack of confidence. Furthermore, employees lack of high skills in technology or automation and they cannot build expertise in a particular field as they are busy with day-to-day occupations in a variety of different areas. This leads to lack of employee participation that further leads to employee resistance to change. SMEs do not usually make alliances with universities or other research institutions, and this adversely affects their research and development capabilities, so innovation is a challenge in SMEs.

Given these distinct characteristics, the DX maturity of SMEs should be evaluated accordingly by considering the challenges they face. Since existing maturity models fail at reflecting these characteristics of SMEs in DX journey, reliable maturity models for SMEs are needed.

The aim of this study is to develop a valid and reliable digital maturity model for SMEs and to implement this framework to analyze the factors that affect the digitalization levels of these companies. This study is made as part of a funded research project conducted by the I4.0 Platform of Bogazici University, Istanbul, Turkey. The DX assessment survey D3A is developed with a special focus on SMEs and the restrictions on their DX journeys (Akarun et al., 2020b). In this thesis study, the generated framework is applied on 100 SMEs by face-to-face interviews and the results are analyzed. We make valuable contributions to the DX literature by showing that D3A is a reliable and valid framework that can be used in assessing the DX maturity of SMEs. Furthermore, we generate valuable insights on the factors that affect the digitalization levels of SMEs. These can be effectively used by the SMEs to generate critical improvement directions in developing their DX roadmaps. Nevertheless, our framework provides a general understanding of the digital state of SMEs in our area.

The organization of the thesis report is as follows. In Chapter 2, we provide our literature survey where we explore and compare the existing digital maturity models in the literature that consider the special characterizations of SMEs. In Chapter 3, the background of this study is explained with further details of D3A framework and methodology of its implementation. Data pre-processing, reliability and validity analyses of the study are presented in Chapter 4. Detailed analyses of all dimensions of D3A and the overall D3A score analysis are explained in Chapter 5. In Chapter 6, we provide the results of hypothesis tests and our main findings. In Chapter 7, we present the results and the outcomes of this study. Finally, in Chapter 8 we provide an overall summary of the study and our conclusions.

# CHAPTER 2:

# LITERATURE REVIEW

In this section, we explore and compare the existing DX models in the literature that are characterized for SMEs. In Section 2.1, we provide a general overview and focus on the five basic studies that inspired us the most during the development of our framework. Next, we compare these models with two main perspectives that include several attributes. In Section 2.2, we compare these studies with respect to their content and scope. In Section 2.3, we compare them with respect to their development procedures (Akarun et al. 2020a).

## 2.1. Digital maturity models for SMEs

The earliest studies in DX maturity models go back to 1995 and there has been quite a number of studies since then (Denision et al., 1995). However, the models with concerns on SME characteristics appear after 2015 (Ernst et al., 2015). In these studies researchers focus on the several attributes that are worthy of consideration in generating specialized frameworks for the SMEs.

As stated in the previous section, the SME weaknesses that must be considered in DX maturity models are the lack of financial and technical resources availabilities, standardization culture, organization or corporate culture, employee participation, alliances with research institutions, and collaboration with the partners. Nevertheless, SMEs have more improved flexibilities in processes relative to large manufacturers.

In a recent study, Mittal et al. (2018) analyze 15 maturity models. Qin et al. (2016) is focused on the automation of advanced manufacturing systems that might not be available for SMEs. Schumacher et al. (2016) developed a maturity index that can be used to evaluate the readiness level of an SME to adopt digital and smart automation practices and Industry 4.0 technologies. Kannan et al. (2017) performed a gap analysis, between the current Manufacturing Execution Systems (MES) in the automotive industry and industry standards which may not directly reflect SME needs as mostly do not consider standards. Weyer et al. (2015) considers dealing with less involvement of human resources with automated workflows in the production line that does not correspond entirely with the requirements of SMEs as they are not financially secure enough. Jung et al. (2017) proposes a novel Smart Manufacturing Readiness Assessment based on statistical analysis that may help SMSs to demonstrate their readiness levels. Ganzarain and Errasti (2016) covered a tailored DX vision for SMEs that can be used to analyze certain dimensions in a company but does not include the implementation phase of this maturity index. Lichtblau et al. (2015) developed a wide assessment model with an online self-assessment tool, but the levels may be too advanced for SMEs in manufacturing technologies, digital products, and employee awareness topics. Geissbauer et al. (2016) highlighted the requirement of real-time update of product movements for a fully digitalized and automated supply chain which might not be financially available for SMEs. Rong and Automation (2014) also focused on a fully connected enterprise with a formal collaboration with vendors/suppliers which may not be possible to achieve for many manufacturing SMS. Anderl et al. (2015) provide a step-by-step method for SMEs to realize DX goals using low-priced sensors/ actuators and training employees to make use of these sensors to be feasible for SMEs. However, it assumes SMEs to clearly know their present situation and which tools they need which may not be challenging for most of the SMEs. Lee et al. (2017) used Analytic Network

Process (ANP) tool for smart factory based on the study of 20 Korean SMEs. Schuh et al. (2017) assumed technologies and mindset for DX vision that may not be available in SMEs. Gökalp et al (2017) considered employee participation that suits SME characteristics but do not cover other limitations of SMEs. Akdil et al. provided a maturity index to evaluate the readiness level for Industry 4.0 but do not consider SME requirements. Scremin et al. (2018) developed a more MNE oriented maturity model with a focus on advanced manufacturing technologies.

Mittal et al. (2018) identified three research gaps with this comparison of 15 maturity models. Firstly, SMEs and MNEs have different starting conditions for smart manufacturing and Industry 4.0 practices. Many of the reviewed maturity models start from an advanced level assuming the presence of connected machines, sensors, and integration that might be too advanced for SMEs. The financial constraints of SMEs or lack of high skilled employees have not been considered neither. Second research gap is the disconnect between maturity models and self-assessment tools. Accordingly, the transition between self-assessment and maturity model must be easy to use and smooth which is not the case for reviewed models. Finally, third research gap is the support (tailored to SMEs) for next step after maturity and readiness assessed. SMEs mostly do not have dedicated departments working on DX strategy; therefore, they need guidance for building a roadmap after assessing their present situation.

The performance of five studies is highlighted in Mittal et al. (2018) for incorporating SME characteristics. In the rest of our literature review, we focus on these five studies that inspire us during the development of our framework and scrutinize them (Wang et al., 2016, Ganzarain & Errasti, 2016, Jung et al., 2017, Lee et al., 2017, Lichtblau et al., 2015).

### 2.1.1. Generic Procedure Model to Introduce Industrie 4.0 in Small and Medium-sized Enterprises (Wang et al., 2016)

The framework by Wang et al. (2016) conceives I4.0 in terms of a generic procedure model for DX which includes the stages for preparation, analysis, idea generation, valuation, and implementation. Each of these phases is introduced by its procedural aims, the methods to achieve those aims and the output of each phase. Here, the output of each phase constitutes an input for the procedures in the following phase.

Generic Procedure Model I4.0 (GPMI4.0) is designed to be realized in multidisciplinary teams of an enterprise in order to create diverse comprehension of wide range of I4.0 topics. Therefore, in the preparation phase of DX, a mutual understanding of DX concepts must be created among the team members to start analysis. The team can consult external specialists to raise knowledge, change experiences among the team members and can consult literature in preparation phase.

During the analysis phase of DX, GPMI4.0 toolboxes are used to assess each perspective respectively. The first version of GPMI4.0 toolbox includes two sections, i.e., products and production (Wang et al., 2016). Later it is enhanced to include two more perspectives on intralogistics and assembly (Wang et al., 2016). Intralogistics toolbox is focused on flow of information, material, parts and goods within the facility with the aim of optimizing the internal production and distribution processes. Assembly toolbox considers the assembly processes that are not fully covered in production toolbox with a focus on the level of IoT integration and flexibility of the architecture. In its most recent version, three new perspectives for IT security, new business models and engineering in I4.0 are added (Wang et al., 2018a). IT security toolbox focuses on protection measures to threats and vulnerabilities of a systems adapted in DX (Wang et al., 2017). The new business models toolbox is focused on the development of the new business models with DX from product development to production improvement (Wang et al., 2018a). Engineering toolbox is used to measure optimization of new product development processes for higher level of digitalization in the production field (Wang et al., 2018b). With these toolboxes an illustration of I4.0 competence overview of the companies can be reached in the analysis phase of DX process.

The toolboxes are designed in an illustrative way to provide a current state and a target state for each application level. So, during idea generation, the toolboxes are used to set target levels regarding the actual positioning of the company in its sector, the capabilities of its suppliers and the expectations of its customers.

In the valuation phase, the fields of actions described in idea generation phase is reviewed to provide clear action plans. These include the cost analysis of the actions considered in the roadmap. Clustering and prioritizing of the actions are done through methods like growth-share matrix and calculation and simulation tools. After finalizing the roadmap for I4.0 competency development, the implementation phase should be followed consciously for successful results.

In general, the I4.0 toolbox considers a great variety of application levels of I4.0, ranging from the lowest position of no data collection, up to the most advanced level of I4.0 vision related to any perspective. The application levels of a perspective are displayed in the rows, whereas the development stages are shown in the columns of the toolbox. The toolboxes help generating an overview of I4.0 competences by allocating the development stage of each application on a 5-level scale of 0-4.

### 2.1.2. Three stage maturity model in SMEs toward I4.0. (Ganzarain & Errasti, 2016)

Three-stage maturity model aims to develop new value propositions for new business opportunities for SMEs working in collaboration with different companies and increasing the strengths. The focus areas of these collaboration opportunities are digital business, advanced manufacturing, energy, and advanced electronics. The three stages of DX process are developed based on the model of strategic guidance towards I4.0 (Erol, Schumacher & Sihn, 2016) and they are identified as follows; envision as vision, enable as roadmap, and enact as projects. Vision stage includes providing capacity and analysis of resources and creating a common understanding of I4.0 with a company specific strategy. The roadmap stage includes identifying the requirements to achieve the I4.0 strategy defined in the previous stage and analyze the technologic capabilities with the perspectives of market, product, process, and value network. Finally, the projects stage is the realization phase of the activities in the roadmap.

Each stage is evaluated individually with a five-level maturity scale. First level is "Initial" and means that a company specific I4.0 vision is missing for all 3 stages. "Managed" as level 2 represents a structured I4.0 vision, a defined customer segmentation and expectations and having a set of non-prioritized digitalization projects. "Defined" as the level 3 covers the development of a comprehensive I4.0 strategy with capability specification, definition of value propositions and evaluated project proposals. Level 4 is called "Transform" and represents a clear vision turned into actual projects with defined resources and capabilities. Finally, level 5 is "Detailed Business Model", and it shows that the company is ready for the future challenges of I4.0 with managed projects, covered risk factors and adapted new business models.

2.1.3. Smart manufacturing system readiness assessment. (Jung et al., 2017)

Smart Manufacturing System Readiness Level (SMSRL) aims to help manufacturers to assess their current level in smart manufacturing and develop a customized improvement roadmap. The assessment is made in three stages, profiling the current state, assessing the current state, and developing an improvement plan.

In the profiling current state stage, the scope of the study is constructed, then information is collected and reinforced with all stakeholders regarding the operations within the scope. The profiling is made in four dimensions: C1: Organizational Maturity, C2: IT Maturity, C3: Performance Management Maturity, C4: Information Connectivity.

The analysis of the current state is made by comparing the current state stage with comparison to the reference activity model proposed by Jung K, et al. (2017). Computational methods such as counting measure are used for the assessment of C1, C2, C3, activity maturity scoring scheme is used for measuring the dimension C1 which is based on the capability maturity model integration (CMMI), incidence matrix-based similarity measure and incidence scoring scheme are used to quantify the information connectivity dimension's maturity (C4).

All these mathematical methods are applied to each dimension resulting in quantitative measures that can be used for comparison and benchmark. The scores for 4 dimensions are shown in a radar chart. For simplicity a single SMSRL index can be computed by using the average of the scores for C1, C2, C3 and C4. Lastly in the developing an improvement plan stage a k-means clustering analysis on the simulated SMSRL results is performed based on its results, which helps to make high-level recommendations for each SMSRL cluster.

### 2.1.4. A smartness assessment framework for smart factories using analytic network process (Lee et al., 2017)

A smartness assessment framework is developed based on the evaluation of analytic network process (ANP) and SME clusters created with respect to the importance of their value chain. ANP is used to create a network structure that can incorporate correlations among criteria that are influential for evaluating the performance assessment of a smart factory. It is shown that in practice the information on SME clusters and the interdependencies among criteria are the essential characteristics to be considered in developing an assessment framework.

Digital maturity of management activities is assessed in three phases: strategic planning, management control and operational control. Operational requirements can be analyzed with 10 different sub criteria that is grouped under 4 criteria. Leadership criterion includes the leadership and strategy sub-criterion. Process criterion consists of product development, production planning, process control, quality control, facility management, logistics management. System automation criterion includes the information management and facility automation. Performance criterion includes performance assessment sub criterion. Each sub criteria includes 3-6 assessment items. A hierarchical cluster analyses is made to classify SMEs in terms of the importance of sub criteria for process sub criterion which reflects a classification in terms of their value chain. Next, the weights of each sub criterion are determined for each SME cluster in accordance with an analytical network process evaluation. Hence, an evaluation framework is generated for three clusters of SMEs respectively.

Digital maturity level of a smart factory is reflected under five levels. The first level is “Checking”, which represents a factory without an external monitoring system.

“Monitoring” is the second level where the factory can be externally monitored with gathered data. Third level “Control” means the data monitored can be used as meaningful analysis. “Optimization” level is when further improvements can be made based on the analysis. Lastly the “Autonomy” level means the factory can make optimizations of processes with the help of AI technologies.

2.1.5. Industrie 4.0 Readiness framework - IMPULS (Lichtblau et al., 2015)

IMPULS –developed by Lichtblau et al. (2015) provides a digital assessment for mechanical engineering and manufacturing enterprises. The assessment is made in six dimensions including 18 items to indicate readiness using a 5-level Likert scale. Number of employees, economic sector, country of headquarters and industry associations are included as categorical options in the questionnaire to be able to compare groups.

The strategy dimension aims to assess the capabilities to develop new business models based on digital technologies. It assesses the implementation of digitalization strategy and usage of analytics, different technologies, technology investments and management of innovation among different departments of the company. Smart factory dimension is assessing the collaboration of production systems, information systems and people. It focuses on machine-to-machine communication, human-machine interaction, data collection of machines and processes. Smart operations dimension assesses production and production planning activities. The focus areas are the level of vertical and horizontal integration of the company, autonomous production processes, data infrastructure, data security applications and cloud services usage. Flexible, smart and effective products are the outcomes of the smart factory applications and assessed under smart product dimension. Technological functionalities like product memory, identification, localization, and monitoring are measured. Data-driven services is the dimension focuses on data collection through different processes of production that can be used for new business opportunities. The organizational aspect of the I4.0 competences are measured under employees dimension. Technical skills like data analytics, IT infrastructure, data security and automation collaboration software of employees are measured as well as non-technical skills like system thinking and process understanding.

### 2.2. Comparison with respect to content and scope

We now provide a more detailed overall comparison of these models in Table 1 (as cited from Akarun et al. 2020a). Our first set of evaluation criteria includes i) aim of research, ii) dimensions of the framework, iii) SME characteristics considered, iv) type of integration considered (horizontal/vertical/end-to-end), v) application sector, vi) existence of a self-assessment tool, vii) existence of a road map in addition to the assessment framework. The comparison attributes are selected to highlight SME limitations and provide correct requirements in developing a digital maturity model specialized for SMEs.

Overall, the five studies are different from each other in accordance to how they locate their DX assessment models among the stages of a DX process. The toolboxes developed by Wang et al. (2016) are positioned in the Analysis and Ideation stages of DX processes whereas Ganzarain and Errasti (2016) place their DX assessment in the Roadmap stage where more detailed plans are made. Jung et al. (2016) provides their DX maturity assessment in the Profiling the Current Stage of DX process without focusing on the target and roadmap generation. Yet, an overall view of DX is missing in studies of Lee et al. (2017) and Lichtblau et al. (2015) as they focus only on the current assessment of DX competencies.

Table 1. Comparison of Maturity Models (as Cited from Table 1 in Akarun et al.,(2020a))

| Model | Aim | Dimensions of the framework | SME characteristics. | Type of Integration | Sector | Self assessment tool | Includes Roadmap |
|---|---|---|---|---|---|---|---|
| Wang et al., 2016<br>Wang et al., 2017<br>Wang et al., 2018a<br>Wang et al., 2018b | To give SMEs a guidance on how to address Industrie 4.0 in order to identify enterprise-specific technology solutions,<br>to optimize existing processes,<br>to advance existing business models and to exploit new business models. | General DX framework that includes preparation, analysis, idea generation, valuation and implementation.<br>Toolboxes for products, production, intralogistics, assembly, engineering, IT security and business model. Toolbox evaluation in accordance to application levels and their development stages that vary between a zero level and Industry4.0 vision. | Financial constraints and technical resource availability are considered as a step-by-step approach is recommended. However, it doesn't consider employee participation as some questions are too technical and might be misevaluated by SME. | Vertical<br>Horizontal | Manuf | Yes | DX framework includes roadmap developments. |
| Ganzarain et. al, 2016a<br>Ganzarain et. al, 2016b | To develop new value propositions for new business opportunities for SMEs working in collaboration with different companies, exploiting the strengths of each of the companies within Industry 4.0. | Seek collaborative opportunities among companies in the fields of; Digital business, Advanced manufacturing, Energy, Advanced electronics.<br>Stages of this process model towards industry 4.0 are "Envision 4.0 Vision", "Enable 4.0 Roadmap", "Enact 4.0 Projects". Main perspectives are market, product, process, and value network and assessed under maturity scales for: 1: initial, 2: managed, 3: defined, 4: transformed, 5: detailed BPM | As Mittal states, it encourages SMEs to consider their financial constraints, technological infrastructure and employees skills, yet it does not lead them how to decide their status without any consultancy. | End to end . | Manuf | No | Roadmap is mentioned but no directions or explanations are given. |
| Jung et. al, 2017 | This study is focused on first helping manufacturers determine their current level in smart manufacturing and secondly developing a customized improvement plan. | General DX framework includes 3 stages, profiling the current state, assessing the current state and developing an imporovement plan.<br>Profiling stage includes scope determination, information collection and consodalitaion and made among the dimensions of C1: Organizational Maturity, C2: IT Maturity, C3: Performance Management Maturity, C4: Information Connectivity.Assessing the current state stage includes computational methods such as counting measure, activity maturity scoring scheme, incidence matrix-based similartiy measure and incidence scoring scheme. No explicit details were given on developing an imporovement plan stage. | It does not consider the lack of advanced manufacturing technologies in SMEs. The organizational maturity evaluations can also mislead the results as SMEs don't generally have solid strategic base, employee participation and financial constraints. | Vertical<br>Horizontal | Manuf | No | Roadmap is not included, but planned for future studies |
| Lee et. al, 2017 | A smartness assessment framework is developed based on ANP evaluation and clustering of SMEs with respect to the importance of their value chain. | Assessment dimensions include 10 different subcriteria that is grouped under 4 criteria: Leadership (Leadership & Strategy),<br>Process (product development, production planning, process control, quliaty control, facility management, logistics management), System automation( information management, facility automation),<br>Performance (performance assessment) Each subcriteria includes 3-6 assessment items.<br>Scoring the maturity level of a smart factory is reflected under 5 levels: checking, monitoring, control, optimization, autonomy. | It considers the dependence on collaborative network and customer/supplier relations and strategy approaches, however performance and automation aspects can be too advanced for SMEs. | Vertical<br>Horizontal | Manuf | No | Not specified |
| Lichtblau et al, 2015 | Development of an online self-assessment to give companies the ability to check their own Industrie 4.0 readiness and make a comparison. | The assesment is made among dimensions that define Industrie 4.0 competences under strategy and organization, smart factory, smart operations, smart products, data-driven services, and employees and companies are classified into three types: “newcomers,” “learners,” and “leaders.” | Technically the self-assessment is suitable to SMEs as the options of 0-19 employees and a total of less than 1 million euro sales are possible. However, overall specifications are not suitable to SMEs in the aspects of technological resources availability, employee awareness and training, suitable strategies and organizational culture. | Vertical<br>Horizontal | Manuf<br>Mechanical eng. | Yes | Not specified |

*Table 1: Comparison of digital maturity models*

The evaluation dimensions are the aspects that are covered in the frameworks. Product development, manufacturing processes and intralogistics are common in almost all maturity models as they are the main focus areas of DX technologies. Organizational structure features like leadership, strategy and human resources appear in the recent studies as the importance of organizational readiness is noted more commonly for the success of DX. Business models, collaboration culture and value network are known as disruptive effects of DX and included in the recent studies of Wang et al. (2018a), and Ganzarain and Errasti (2016). Jung et al. (2016) and Lichtblau et al. (2015) include information connectivity and data-driven services as more specific dimensions. Finally cyber security appears only in a recent study by Wang et al. (2017) as a critical aspect of a DX journey. This comparison shows us the major dimensions to include in our DX assessment model. It also provides the more contemporary and critical areas like IT security and new business models based on collaboration.

Next, we highlight how SME characteristics are reflected in these frameworks. As stated in (Mittal et al., 2018) none of the existing frameworks include all 15 special characteristics classified above. We further study this issue by addressing the specific SME characteristics to be considered in evaluating any DX dimension. Such an analysis provides us with the causes of performance limitations of SMEs in each DX dimension. Firstly, “financial, and technical limitations” cause obstacles for product design, production, assembly, automation, intralogistics, operations, engineering, as well as IT maturity, connectivity, performance maturity, and data-driven services. “Organizational structure drawbacks” like culture, employee participation and collaboration must be considered in the evaluation of business models, organizational maturity, leadership, strategy, and employees in terms of DX awareness and readiness. “Consideration of industry standards" and "lack of alliances" with research institutions affect improvements in almost all areas including products, production, operations, IT security, performance management, connectivity, and data-driven services. Nevertheless, "improved customization skills" of SMEs may create positive bias by generating high product dimension scores in SMEs.

Manufacturing sector is the focus area common in all frameworks as expected, since I4.0 emerged from the advancements of process automations in manufacturing. Hence, all studies incorporate vertical and horizontal integration abilities of the enterprises. Abilities to create dynamic business models with suppliers and customers through end-to-end integration is considered only in (Wang et al., 2018a) and (Ganzarain and Errasti, 2016). We identify end-to-end integration capability as a critical property to be included in our assessment framework.

Frameworks are quite similar in terms of their scoring methods. Wang et al. (2018a) and Lichtblau et al. (2015) include a 6-level scale, while and Ganzarain and Errasti (2016). And Lee et al. (2017) include a 5-level scale and Jung et al. (2016) evaluates the maturity in a 4-level scale. All frameworks include a 0-level showing that no data are collected.

Two frameworks provide self-assessment tools, while others are assessed with interviews. Self-assessment tools might be easy to perform for SMEs, but it can be misleading in absence of clear instructions. However, hiring a consultant may not be a financially affordable solution for an SME. Therefore, maturity models focused on SMEs must consider these drawbacks in their evaluation method to provide specified digitalization levels and guidance for assessment.

Finally, all SMEs ask for a reasonable roadmap for improvement after the assessment of their current state. Some frameworks further extend their current DX assessment to a more detailed roadmap. This requires setting proper targets and generating detailed action plans probably by considering several other factors like market conditions and competitors. Wang et al. (2016), Ganzarain and Errasti (2016), and Jung et al. (2016) provide improvement directions in their assessment frameworks that further supports a roadmap. Lee et al. (2017) do not specifically mention a roadmap process whereas Lichtblau et al. (2015) mention action items for improvement.

## 2.3. Comparison with respect to the development procedures

In the previous decade over a hundred maturity models have been developed to support IT management. However, the development procedures have hardly been documented properly which introduce several questions on the reliability and the validity of the models. In their well-known study, Becker et al. (2009) present a procedural framework for the development of maturity models as a design artifact. These criteria also serve as a basis for the comparison of digital maturity approaches. Hence, as a second comparison approach, we consider the study by Becker et al. (2009) and compared the selected five maturity models based on the eight requirements of the framework. These eight requirements are as follows: i) comparison with existing maturity models, ii) development with an iterative procedure by proposing, refining, evaluating, and enhancing solutions, iii) evaluation of the usefulness, quality, and effectiveness of the model, iv) use of thoroughly adapted and well-grounded research methods for the development of the model, v) identification of problem relevance to researchers and practitioners, vi) problem definition, vii) targeted presentation of results based on the application conditions and target users, and viii) providing scientific documents for the development process. The complete comparison details can be found in Table 2 as cited from Akarun et al. (2020a).

The GMPI4.0 framework of Wang et al. (2016) is one of the most comprehensive studies that cover almost all eight requirements of Becker et al., (2009). The toolboxes are developed iteratively with the feedback from the industry and experts and published individually by improving the previous version. The development process was published as academic papers and presented in several workshops and conferences which proved scientific methods used in their process. Several projects, workshops and pilot studies were held to validate the models. The GMPI4.0 framework only lacks explicit information on the development motivation and comparison with existing maturity models.

Ganzarain and Errasti (2016) do not explicitly state their development process and their motivation. Moreover, there is no comparison with the existing maturity models. They state that a pilot study which is supported by the government is made for the verification and validation of the model. There is a certain need for documentation and academic publications.

Jung et al. (2017) share their development process with comparison to existing maturity models. The model is developed based on a prior model developed by Jung et al. (2017). It cannot be clearly said that there is an iterative development, but they include very detailed validation of the framework as well as the methodologies used.

Lee et al. (2017) include a detailed comparison of their approach with the existing studies including the IMPULS model (Lichtblau et al., 2015). The model is developed iteratively and stated clearly how the criteria network is constructed and how the criteria weights of the ANP methodology are calculated. A pilot study is made with 20 SMEs to validate the effectiveness of the model. It is presented in conferences and published as an academic paper.

The IMPULS model by Lichtblau et al. (2015) do not include an overall comparison with the existing studies. The model is developed iteratively in several workshops with companies and project partners. A pilot study is made to validate the framework by a survey conducted with 431 companies. The final framework is published as an online self-assessment tool for SMEs.

Overall, these fives studies do not fulfill all eight requirements of Becker et al. (2009). The GMPI4.0 (Wang et al., 2016) and IMPULS (Lichtblau et al., 2015) are more advanced compared to other studies to be evaluated as design science artifacts.

In conclusion to our literature survey, we see that the SME characteristics must be reflected into the DX maturity models in a way to set the limitations to the maximum performance expectations of SMEs. Furthermore, evaluations of the current status of SMEs should accompany practical guidance to the improvement opportunities, preferably by a DX roadmap to overcome these limitations and improve the digital maturity. The assessment method is also an important part of a DX maturity model. The complicated terms and wide scope topics can be overwhelming for SMEs to support a poorly designed self-assessment. The assessment must be done in an explanatory way of the maturity item with the actual life scenarios or must be done with expert evaluations. Finally, the frameworks must be developed with respect to the requirements in (Becker et al., 2009), i.e., they should be developed iteratively, validated, presented, and well documented.

Table 2. Comparison of Maturity Models with Respect to the Procedural Model in (Becker et al., 2009) (as Cited from Table 2 in Akarun et al.,(2020a))

| Model | Comparison with existing maturity models (R1) | Iterative Procedure (R2) | Evaluation (R3) | Multi-methodological Procedure (R4) | Identification of Problem Relevance (R5) | Problem Definition (R6) | Targeted publication of results (R7) | Scientific Documentation (R8) |
|---|---|---|---|---|---|---|---|---|
| Wang et al., 2016<br>Wang et al., 2017<br>Wang et al., 2018a<br>Wang et al., 2018b | Literature review is not provided. | First product and production toolboxes, than intralogistics, engineering and other added. | Validation in 4 project formats | Iterative modeling<br>Workshops | SME needs, self assessment tool and roadmap creation | To give SMEs a guidance on how to address Industrie 4.0 in order to identify enterprise-specific technology solutions | Toolbox<br>Documents,<br>Reports | |
| Ganzarain et. al, 2016a<br>Ganzarain et. al, 2016b | Focused on diversification, it is based on the strategic guidance towards Industry 4.0 (Erol, Schumacher & Sihn, 2016) | The development process is not provided explicitly. | Evaluated in a panel meeting with participants from companies, regional development agencies and the University.<br>No results are provided. | A narrow scope literature review is provided.<br>No explicit explanations are given. | Support of Basque Government to boost competitiveness and industrial innovation in Basque companies.<br>This project aims to seek collaborative opportunities among companies. | There is a need to update and upgrade competences and skills on Industry 4.0 and its opportunities to diversify into new industry sectors, by developing innovation management, operational and strategic capabilities. | Not specified | A journal article exists highlighting only the underlying idea of the MM, i.e., not containing any detail at all about the content and development process. |
| Jung et. al, 2017 | Comparison with Technology Readiness Level (TRL), Manufacturing Readiness Level (MRL), Supply Chain Readiness Level SCRL) , The MESA manufacturing transformation strategy (MTS).<br>The SMSRL is based on the Factory Design and Improvement (FDI) reference-activity model technologies. | First developed a reference model (FDI in 6) 2017.<br>No feedback and update steps are mentioned. | Four hypothesis tests were performed. Statistically significant, positive-correlations with the SMSRL index were found on the operational performance, overall performance, and value- based performance. The financial performance was not found (hence not shown) to have a statistically significant positive-correlation. | Literature research<br>Iterative modeling<br>Statistical validation<br>Activity maturity measures by CMMI are used. | They claim their model is developed for small and large enterprises but they do ignored any SME-MNE differences. | Manufacturers lack a concrete methodology to choose and prioritize emerging technologies that aid in the creation of smart manufacturing systems and factories.<br>Existing models largely ignore the use of information and communication technologies in assessment of smart manufacturing. | Conference presentation in academic environment. | Validation test results, measurements, radar charts |
| Lee et. al, 2017 | A wide literature review has been done.<br>Governmental plans are analyzed.<br>A research project of VDMA, 'Industrie 4.0 Readiness'<br>European Foundation for Quality Management (EFQM) | The criteria are collected from a wide literature review, the initial weightings of these criteria were determined through consultancy and then proposed weightings are determined with analytical network process. | They set the weights for criteria of the framework and performed a case study of 20 SMEs to validate the model. | Hierarchical Cluster Analysis According to the Importance of Value Chain analytic network process methods are used. | To strengthen the overall competitiveness of manufacturing and narrow the gap between SMEs and big companies in productivity, it is necessary to markedly accelerate SME's productivity improvement. Korean government is promoting key aspects of the 'Manufacturing Innovation 3.0' strategy, including the diffusion of smart factories. | Many manufacturing companies make an effort to raise the level of smartness by considering a number of aspects related to smart factories with automated data collection from sensor networks. | Not specified | Not specified |
| Lichtblau et al, 2015 | The model is developed upon an analysis of the literature, workshop results with companies and the expertise of the project partners. However no comparison with existing models are specified. | 232 participants completed online directly and smaller or unaware companies were contacted purposefully to create a homogenous dataset which had result of 431 companies in total. | 289 Industry 4.0 friendly companies were chosen for futher questions and their vision of industry 4.0 were compared. | A mixed methodology of an analysis of the literature, expertise, workshops, and a comprehensive company survey. | The need of assessment where they stand in the digital transformation process and whether they are exploiting the full potential of Industrie 4.0. Comparison of manufacturing and mechanical engineering industry. | The company survey yields some initial findings on the general attitude of Germany's mechanical engineering industry toward Industrie 4.0 and the opportunities and risks it presents. | Online tool | Real company assesment results were used as emprical data to provide insights |

*Table 2: Comparison of digital maturity models with respect to the procedural model in (Becker et al. 2009)*

# CHAPTER 3:

# BACKGROUND & METHODOLOGY

In this section, we introduce a digital assessment framework for the SMEs in manufacturing industry. D3A was developed by the I4.0 Platform of Boğaziçi University in a funded research project by Akarun et al. (2020b). The project includes the development of a DX maturity model for SMEs and its implementation on 100 SMEs in Istanbul, Turkey to assess the general digitalization level of SMEs in the related region. Here, we present the development team, the development procedure, the dimensions and the assessment method of the framework. We also discuss how the generated framework fills the research gaps in the literature as highlighted from two perspectives in the previous section.

## 3.1. The development team

I4.0 Platform of Boğaziçi University consists of a multi-disciplinary team of professors and graduate students in engineering and management sciences, as well as industry experts and consultants. D3A was developed by this multi-disciplinary team and tested by various experts along the development process. The most notable feature of D3A is its application method which includes industry expert evaluation based on a half-structured interview and field trip. This method helps to incorporate SME characteristics into digital maturity evaluation together with the operational details in different dimensions of the companies.

### 3.2. Dimensions of D3A

The final model of D3A includes 65 questions asked to assess the DX maturity of a manufacturing SME in 5 dimensions: organization (12 questions), customer (12 questions), product (10 questions), supply chain (16 questions) and manufacturing (15 questions). The D3A questionnaire is provided in Appendix A.

#### 3.2.1. Organizational Structure

One of the characteristics of SMEs is that organizational capabilities like human resources, employee participation, strategy and decision making are usually not well structured and improved. SMEs lack in management capabilities as they are commonly ruled by the owner and its family (Mittal et al., 2018).

DX is not only a matter of technology adoption; it requires many strategic decisions to adapt the business model to survive or even to create new business opportunities. Therefore, in the organizational structure dimension the focus of assessment is internal capabilities like decision-making processes where leadership and agile working practices are measured, collaboration between departments with information flow, IT infrastructure where flexible working environments and accecibility of data is assessed, skill development of employees and employee participation Organizational structure dimension reflects the readiness of a company for possible DX advancement as well as the outcomes of existing DX implementations. DX improvements can be adapted faster and more effective if the employees are taking active roles and giving valuable feedback along the way. On the other hand, these changes can cause other problems in daily operations if employees react with resistance. Human resources focused questions take employee participation in DX journey as a limitation or facilitator. Likewise, new business models and with DX opportunities that leads to competitive advantage can be applied only if the organizational structure is prepared.

### 3.2.2. Customer

SMEs work as suppliers of manufacturers and have mostly a B2B sales model. Nowadays B2B customers expect their suppliers to understand their business truly and respond promptly to forthcoming needs as well as the actual needs that are expressed in the first place (Blocker et al., 2010). Being proactive for customer needs requires a deep analysis of customer data that is derived from the whole communication with the customer.

In the customer dimension, D3A assesses the sale processes with a holistic point of view starting from the marketing activities and digital visibility of the company, to the processes for pricing quotes, taking orders, managing branches or sales teams, and taking customer feedbacks.

Usage of a CRM software and its horizontal integration with the other software used in the company is also assessed. The more data is shared between different departments like accounting, manufacturing or delivery, the more data can be transformed into customer knowledge that can be used to improve given service and create competitive advantage.

### 3.2.3. Product

DX technologies create a vast opportunity in the advancement of the final product from idea generation processes to packaging and delivery. The companies might adopt different levels of technology depending on the field they work for. In order to create a common level of maturity, both technology usage and creation are measured along with the team communication and product customization. New product development processes are included in product dimension from the perspective of employee participation and usage of technological tools.

### 3.2.4. Supply Chain

In order to provide a continuous delivery in the value chain the companies need non-intrusive communication and collaboration with their suppliers. Supply chain dimension consists of capacity planning, inventory management, daily manufacturing planning and both internal and external communication. Continuous evaluation of suppliers is also important to improve their performance and prevent problems in the delivery.

The inventory management methods vary between companies depending on their model of delivery. In the 100 companies we examined different models like produce to order or produce to stock. Capacity planning, production orders and inventory management are fields that must be coordinated. Therefore, communication between these departments in sharing stock levels and sale orders are also included in this dimension's set of questions.

### 3.2.5. Manufacturing

Manufacturing is the major focus area of I4.0 technologies as the information flow and connectivity between materials, operators and machines create an immense change in value creation. Hence, the digital maturity of manufacturing dimension must be evaluated through the integration of these elements. The production orders scheduling and the flow of the materials for the production are assessed as well as the reporting of operators' daily work and start-stop time of the machines.

Quality control processes and maintenance of the machines were also included under manufacturing dimension along with the energy consumption as indirect inputs to the result of production.

## 3.3. Scoring and Assessment Method

The assessments are made with a scale between 0 and 4 according to the DX maturity in the related question (see Figure 1). Level 0 represents that no data is collected during to process or the improvement in that field did not start. Level 1 means that there are data collection or improvement activities, but it cannot be processed or turned into meaningful information. Level 2 means that the data is used in manual reporting and analyses to support decision making but it is not stored in a continuous system. Level 3 is where the data analyses from level 2 is made with an integrated system that collects the data directly from related processes. Finally, level 4 includes suggestions from the system with AI based suggestions and analyses.

It must be noted that some questions are not directly connected to a digital data usage or a system such as a question that reflects the organizational readiness for any improvement in that field. The scoring is adapted accordingly to represent process improvement.

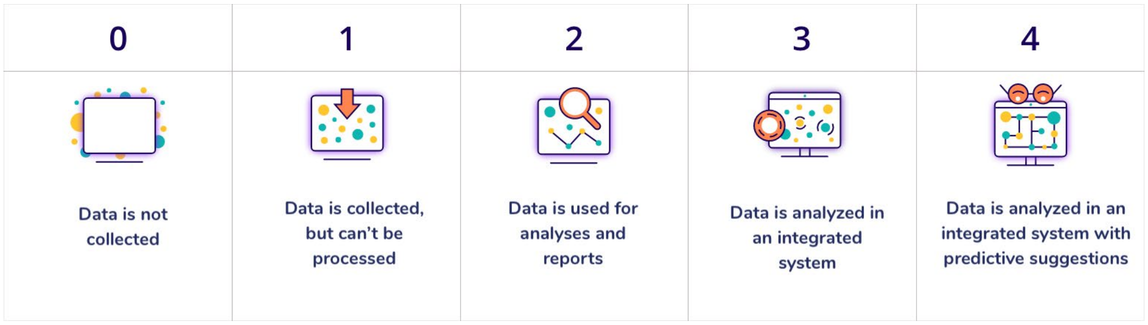



Figure 1. Scoring levels of D3A as cited from Akarun et al., 2020b, p. 22.

D3A's unique feature is the fact that it is designed to be implemented by experts through face-to-face interviews and site visits to assess the maturity of a company. In the literature, some frameworks include digital self-assessment tools which make the evaluation process more practical and faster (Lichtblau et al., 2015, Wang et al., 2016). However, self-assessment tools might not be very appropriate for SMEs since these evaluations might be unreliable due to the low perspective of digital technologies, lack of digital awareness and application knowledge at SMEs (Mittal et al., 2018).

### 3.4. Implementation

The theoretical assessment framework was implemented by company visits to 100 SMEs between January 2019 and March 2020. The main location of the companies was the Dudullu Organized Industrial Zone, (OIZ) as partner of Boğaziçi University in the project. But some companies from other OIZs of Istanbul also took place to increase the variety.

The interviews were made during 300 days with breaks in between. Some days the visits could be completed in up to four companies, some days only one company could be visited due to the problems of scheduling. The appointments were arranged beforehand where during the phone conversation the company was asked to assign the meeting to their DX leader. Having a dedicated responsible employee for DX is an indicator for the evaluation of the maturity in organization dimension. Some interviews were made with different representatives based on the field of interview; some interviews included only the owner of the company.

### 3.4.1. Face-to-face interviews

An average interview would take 2 hours approximately depending on the size or level of advancement in DX of the company. The interviews were conducted in half-structured method as the questions were asked by the DX expert of our team with the flow of the conversation and the answers were noted to the question related to topic. The questions were distributed into multiple groups under one dimension to simplify the transition between different topics.

### 3.4.2. Field trip

After the interview, a field trip was conducted in order to have an understanding of the physical state of the company. The field trip helped the team to compare the answers of the respondent with the actual situation of the company with their daily operations.

### 3.4.3. Maturity Level Evaluation

The questions were modelled under 5 maturity levels that was scored from 0 to 4. The evaluation of the maturity levels was made afterwards by the expert based on the notes from the conversation and the field trip. Some features of the company like number of employees or the field of work that do not take place in the questionnaire as a direct question were also taken into consideration by the experts while evaluating the maturity level. The scores of the maturity levels were provided to each company as customized company reports after the interview.

### 3.5. Design principles of the development process

Development process of D3A complies with the design principles of Becker et al. (2009) introduced in Section 2.2.

D3A was developed based on a detailed comparison with the existing studies in the literature and it was very well documented. A thorough research was made on the existing frameworks and the results were presented in international academic conferences and published as an academic book chapter (Akarun et al, 2020a).

D3A was developed iteratively with several revisions made based on the feedbacks obtained from the preliminary implementations. First version was tested with a pilot study on 20 SMEs and the structure of the questionnaire was reformed accordingly. Then the next interviews were made. The team met regularly to discuss our performance in the interviews and made revisions in the theoretical framework when necessary.

Validation and reliability of D3A were tested by detailed statistical analyses, expert opinions, and comparisons with the existing studies.

D3A was a funded project by the government. The aim of the framework was clearly stated in the project proposal and regular audits were made by the government officials after the project kick-off.

D3A covers almost all SME characteristics under all five dimensions incorporated with questions and maturity levels. Scoring of D3A covers the current status of SMEs under level 0 and 1 with a focus on starting conditions due to financial constraints. The application method where a consultant visits the company for the assessment suppress the gap between self-assessment tools and SMEs considering the drawbacks in the organizational culture and employee capabilities of SMEs (Mittal et al., 2018). These drawbacks are considered in organizational structure dimension together with more advanced concepts of DX like remote data access, IT security or employee education. Standards and alliances are questioned under product and organizational structure dimensions to highlight innovation opportunities of companies. A general DX perspective is provided with a focus on assessment of the current DX status of SMEs.

The current version of D3A do not include a self-assessment tool and roadmap generation processes as the evaluation made by industry experts to support accuracy of the model, future versions will be developed based on this validated study.

Findings from the implementations generated several academic contributions and were published as a graduate thesis research. The project report was published in I4.0 platform of Boğaziçi University and was launched to the Ministry of Technology and Development by an online meeting. Furthermore, specialized company reports were given to all 100 SMEs that participated in the development process.

Overall, it can be stated that D3A is a scientifically well-grounded framework that can be evaluated as a design science artifact.

## 3.6. Thesis Contribution

The main contribution of this thesis is the implementation of D3A in 100 companies from different industries and sizes to create the dataset and the statistical analyses of this dataset. First of all, reliability and validity tests are conducted with all five dimensions and 65 maturity questions. Next the statistical analysis of each dimension is made along with a clustering analysis to discover the discriminating items within a dimension. Next, several hypotheses were tested in order to gain managerial insights.

# CHAPTER 4:

# DATA PRE-PROCESSING, RELIABILITY & VALIDITY

## 4.1. Data pre-processing

D3A framework was implemented on 100 SMEs by professional experts via face-to-face interviews. In the original dataset there are 65 maturity items of D3A which are evaluated as numeric values between 0 and 4 and there are two categorical variables: the company size and the industry groups. The categorical variables are labeled accordingly with numerical values for statistical comparisons.

Some datasheets had missing values for certain items, so missing value identification controls had been conducted and these fields are re-evaluated afterwards by the visitor experts for subsequent companies. Hence, in the final version there is no missing data.

## 4.2. Descriptive statistics

In total there are 100 companies that have scores under five dimensions and 65 maturity items. There are 4 different groups under company size giving the number of employees. First group is the micro size with one to nine employees, second group is small size with 10-49 employees, third group is middle size with 50-249 employees and the last group is big companies with more than 250 employees. The SME definition varies between different countries. In some countries the upper limit is considered as 250 employees, in some countries like the United States 500 employees is counted as the upper limit for SMEs (OECD, 2005). In our dataset there are 10 big sized companies and nine micro sized companies. We wanted to include these two extremes to be able to compare these groups and test if our model fits all. 50 of the companies are medium sized, and 31 of companies are small sized.

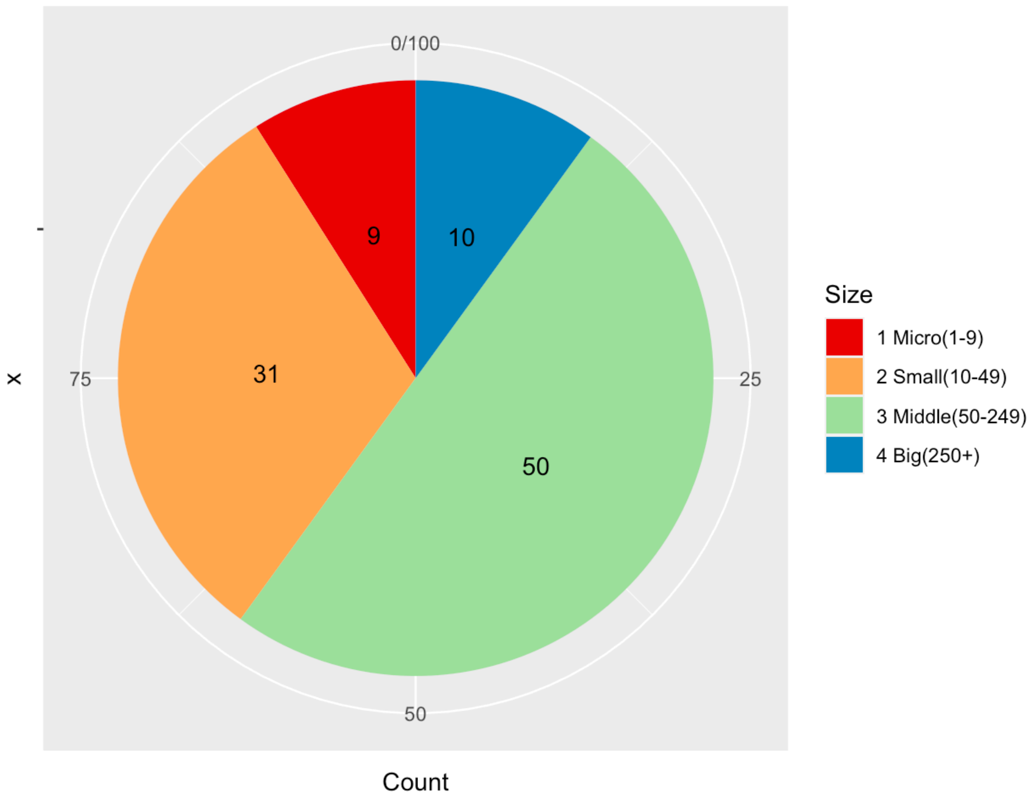



Figure 2. Distribution of 100 companies by company sizes

All the companies are from manufacturing industry, however smaller industry groups are formed with expert reviews based on the industrial groups of Standard Industrial Classification (SIC) for deeper comparisons (SIC, 2007). Accordingly, 100 companies are grouped under nine industrial groups by adapting SIC groups. Some groups with less than 3 companies are combined together based on their working areas and practices to decrease the number groups for comparison. Industrial groups are shown in Figure 3 which are metal, electric/electronic, plastic, machinery, automation, food, textile, medical and furniture with descending order of company counts under each group. The industrial groups which have less than 10 companies in our data set are shown with white bars whereas the bigger groups are shown as blue bars in industry comparison charts.

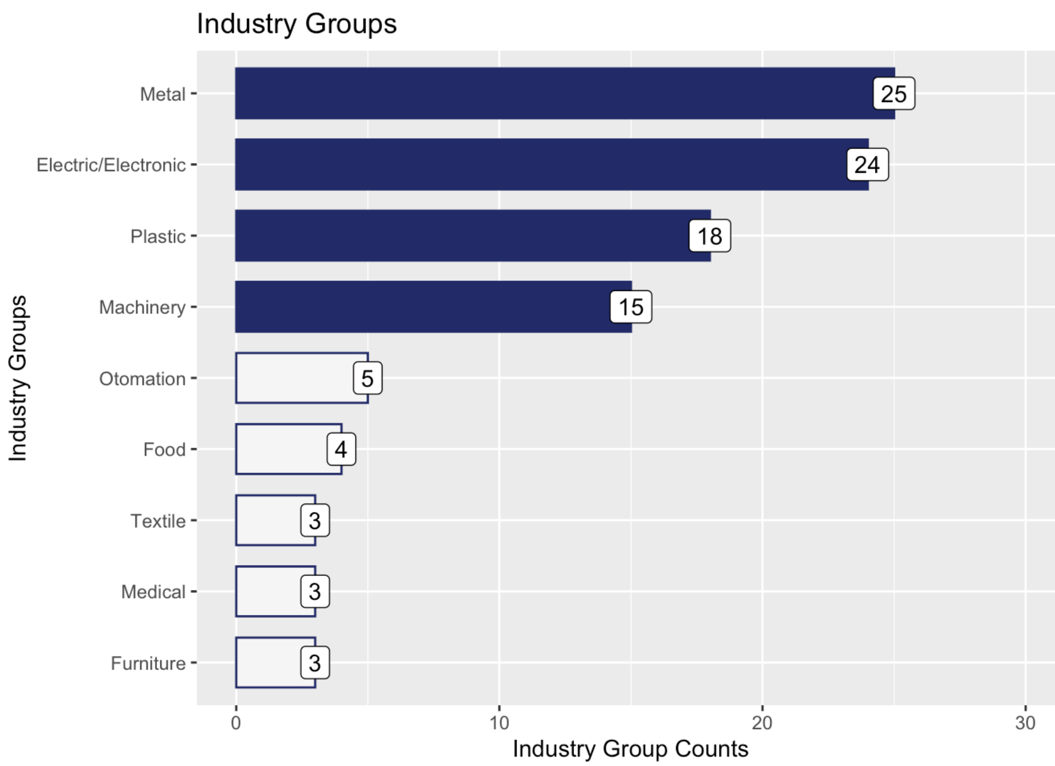
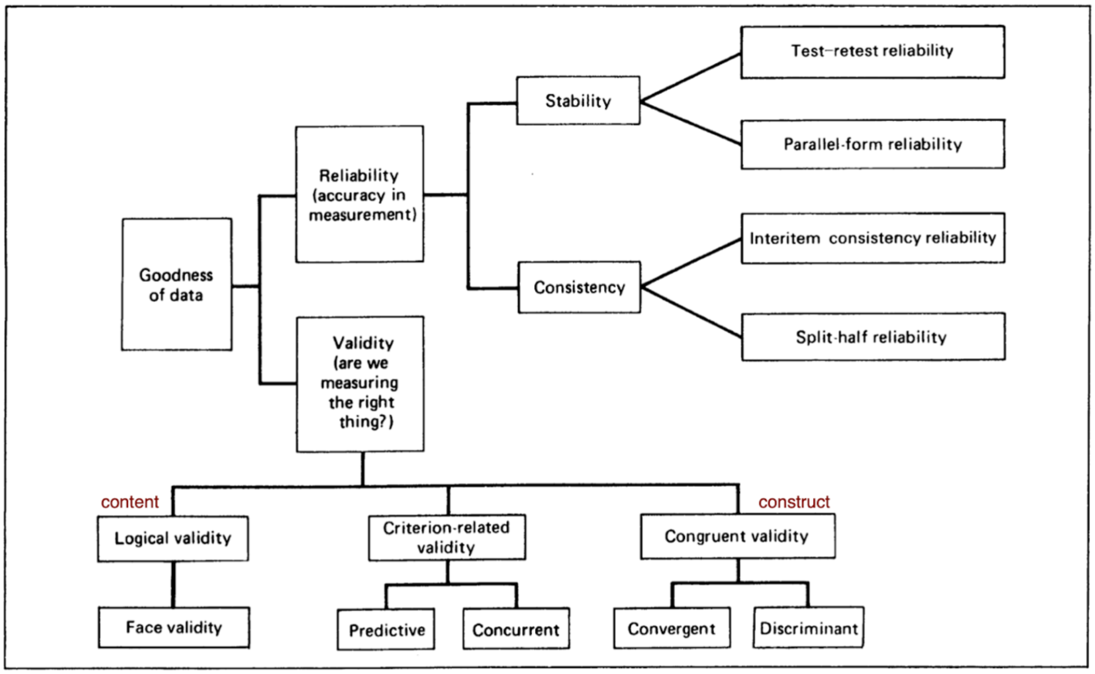



Figure 3. Distribution of 100 companies by industries

## 4.3. Reliability and validity analysis

The development process of most of the existing studies are vague and undocumented. So as indicated in principles 4 and 8 in Becker et al. (2009), a DX index should be tested with respect to its reliability and validity before generalizing its usage. Here, we present analyses concerning the content validity (including face validity), construct validity and reliability for stability and consistency of the five digital maturity measures (Figure 4).




Sekaran, U., Research Methods for Business, John Wiley and Sons Inc., 2010, p.158.

Figure 4. Goodness of data measures as cited from Sekaran et al., 2010, p.158

Sekaran and Bougie (2010) define construct validity as ensuring that all measurement items are related to research concept and what they mean to measure. The dimensions for digital maturity of D3A is formed with an extensive literature survey, reviewing existing DX frameworks for common and discriminative aspects. SME characteristics were also taken into consideration with academic perspective. In the development process, D3A was validated by a panel of judges consists of senior academicians and professional experts for construct (face) validity.

D3A consists of five different dimensions to assess digital maturity among different aspects of a company. The scores obtained under the same dimension must correlate with each other to establish convergent validity. On the other hand, the items that are designed not to correlate must not be correlated eventually in the results to prove discriminant validity. D3A is designed to evaluate digital maturity from a bottom-up perspective, therefore there are no items to cover discriminant validity. However, convergent validity must be established under the items of digital maturity dimensions. Convergent validity under each dimension was analyzed using bivariate correlations with Pearson coefficient (Figure 62). Ideally correlations between the items of a measure must be between 0.3 and 0.7 to indicate convergent validity. Almost all bivariate correlations are between 0.3 and 0.7 for five dimensions. There are some exceptions with negative correlations which can be explained with distributions of the scores that are explained in the next Chapter 5 in detail.

Criterion-related validity can be established with predictive and concurrent areas. Concurrent validity tests if the measurement instrument matches another validated result in a similar field. In our case some companies that were score above 2.0 for D3A has been researched for other digital maturity validations. We saw that these companies had several prizes in their field such as innovation or supplier competency tests which shows an accuracy of D3A measurement for concurrent validity. We did not yet got the chance to re-test some of the companies for predictive validity, but it is planned for further development of D3A.

Establishing a valid base is not sufficient alone for a model to be accepted, it should also be proved as reliable based on sample data. Test-retest reliability is obtained by delivering the same test twice over a period of time to the same group of respondents. During the implementation, first a selection of companies is visited multiple times for test-retest reliability to confirm the stability of the measure. These visits are realized with one week difference.

Parallel-form reliability is a method where two or more equivalent forms of assessment are used with same participants to analyze the correlation between results. Some companies are also assessed multiple times with different versions of questions that helped verifying parallel-form reliability.

The final version of the scale is later tested for internal consistency with the dataset of 100 companies. The Cronbach's Alpha scores were calculated which ideally should be above 0.70 is to accept the scales as reliable. The Cronbach's Alpha scores are high above 0.85 for all 5 dimensions (0.85 > 0.70) which confirms the consistency of the items under same dimension indicating high correlations within the constructs, and that they are all highly relevant in determining the constructs. (Appendix B).

Multicollinearity occurs when two or more independent variables are highly correlated. Some of the Cronbach's alphas were even greater than 0.9 which can cause multicollinearity in certain cases. Multicollinearity is checked with Variable Inflation Factors (VIF) method and all VIF values are below 5 (Appendix C). Hence there is no multicollinearity between the items of all five dimensions.

# CHAPTER 5:

# ANALYSIS OF THE DIMENSION SCORES AND THE OVERALL D3A SCORES

We analyze our evaluation results in two sections. In Section 5.1, we analyze the digital performances of the companies in each DX dimension respectively. In Section 5.2 we analyze the companies with respect to their overall digital performances, i.e., D3A scores.

## 5.1. Analyses of D3A dimension scores

A series of analyses is made for each of the five dimensions respectively to understand the performances of companies in that dimension. We start by interpreting the means of the questions to identify the most improved and the weakest areas in each DX dimension. Then we explore the distributions of the scores in each question. We see that some questions have higher dispersion of scores whereas some have very low. The questions with higher dispersions help us in differentiating companies with respect to their digitalization levels in any dimension. On the other hand, questions with low variability help us in generating an understanding of the overall state of all SMEs in that question area. Hence, both information is valuable for us.

Next, the dimension scores for each company are calculated by taking the arithmetic mean of all question scores of a company in that dimension. The distribution of the dimension scores for all companies and the overall means of the dimension scores are analyzed and interpreted.

Later, the companies are clustered in each dimension with respect to their question scores in that dimension. Dimensional clustering enables us to see which questions are more important in differentiating the companies' digital maturity level in any dimension. It also helps us to understand how the DX performances of companies differ in that DX dimension. We use the two-step clustering algorithm with log-likelihood distance measure method and normalized scores since we have both categorical and continuous data for dimension scores and overall D3A scores.

We further improve our analyses to explore the impacts of company size and industry on the dimensional scores. The changes in the dimension scores of companies with respect to the company sizes and industries are analyzed by ANOVA tests to see if these factors significantly affect the digitalization levels in any dimension.

### 5.1.1. Organizational structure

There are 12 questions under the organizational structure dimension as seen in Appendix A. As seen in Figure 5, the highest mean score is recognized in Q6[1] as 2.21 which is about the digitalization level in keeping financial records of the company. The legal obligations lead the companies to keep their financial records in digital environment. So, although most of the processes are not automated, many companies have a financial tool for tax declarations and invoice generation. Hence, there are only seven companies that have 0 scores from this question. However, more than half of the companies are still scored between 1-2 in this question, providing a poor performance even in the most successful area in this dimension.

[1] Question i is abbreviated as Qi throughout the text.

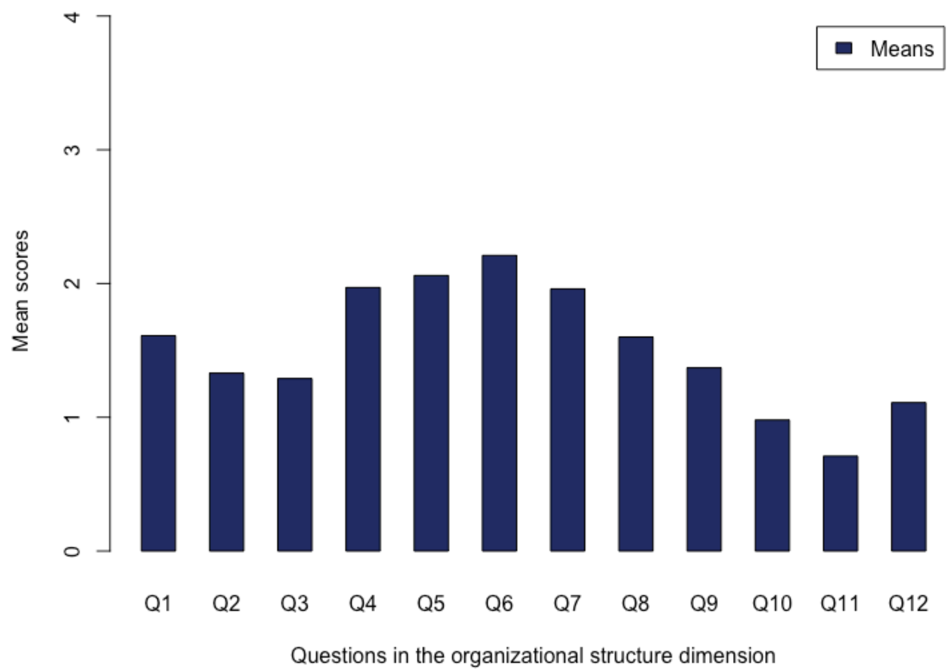



Figure 5. Mean scores of the questions in the organizational structure dimension

The questions about education (Q10) and self-improvement of the employees (Q11) have the lowest mean scores. It is not surprising to see that companies with weaker corporate structure do not have enough support for the education of their employees as they are more focused on the daily tasks. Q11 has a mean of 0.71 where more than 90% of the companies are scored between 0-1. Only four companies are scored more than 3 for this question.

In Figure 6, we provide the distribution of scores in each question. Accordingly, companies are mostly scored between 0 and 2. Q7 has the highest dispersion of scores among 5 scoring levels. So, having an IT infrastructure responsible is an important factor in differentiating the companies in the organizational structure dimension. Some companies have a dedicated employee for IT management whereas some have outsourced technicians. Companies have low scores in Q2 and Q3 and most of the companies scored 0. Hence, companies lack strategic plan adapted to everyday life of the company and they do not have clear objectives for DX. Low scores in Q9 shows that most of the companies do not have access to data outside the office.

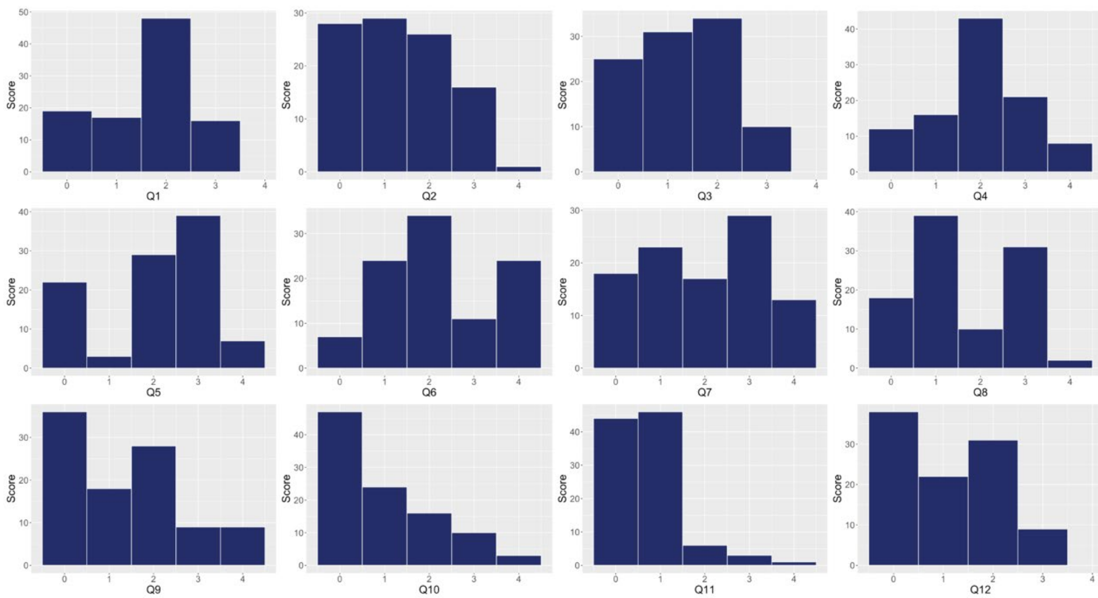



Figure 6. Distribution of question scores in the organizational structure dimension

The overall score for the organizational structure of a company is the arithmetic mean of the scores of this company from 12 questions in this dimension. The distribution of the organizational structure scores of all companies is quite symmetric with a skewness value of 0.038 as it can be seen in Figure 7. The overall mean score of all companies for the organizational structure dimension is 1.52 which is very low. The highest score for organizational structure is 3.25 and the lowest score is 0. There are three companies that scored 0 for this dimension. 29 companies are scored between 1.5 and 2.0. 52 companies have an organizational structure score more than the mean and five companies are scored more than 3.

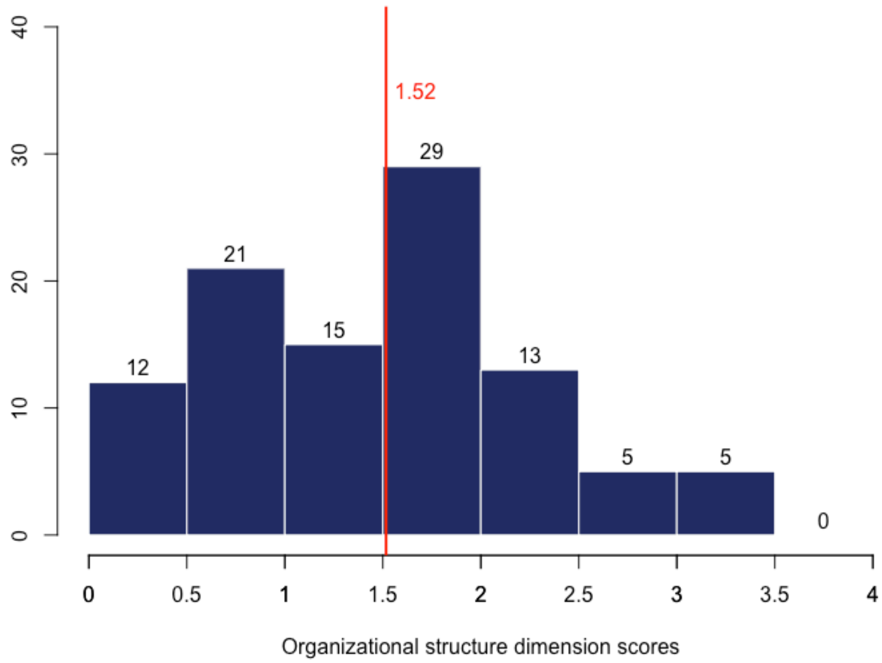



Figure 7. Distribution of the scores in the organizational structure dimension

Next, the companies are grouped under 3 clusters with sizes of 21%, 35% and 44% based on their scores in 12 questions in the organizational structure dimension. We can see in Figure 8 that in the first cluster the organizational structure scores are mostly between 0-1, whereas in the second cluster they vary between 1-2, and the third cluster's scores are between 2-3. Therefore, we can call these three clusters as beginner, intermediate and advanced in terms of their DX maturity in organizational structure dimension.

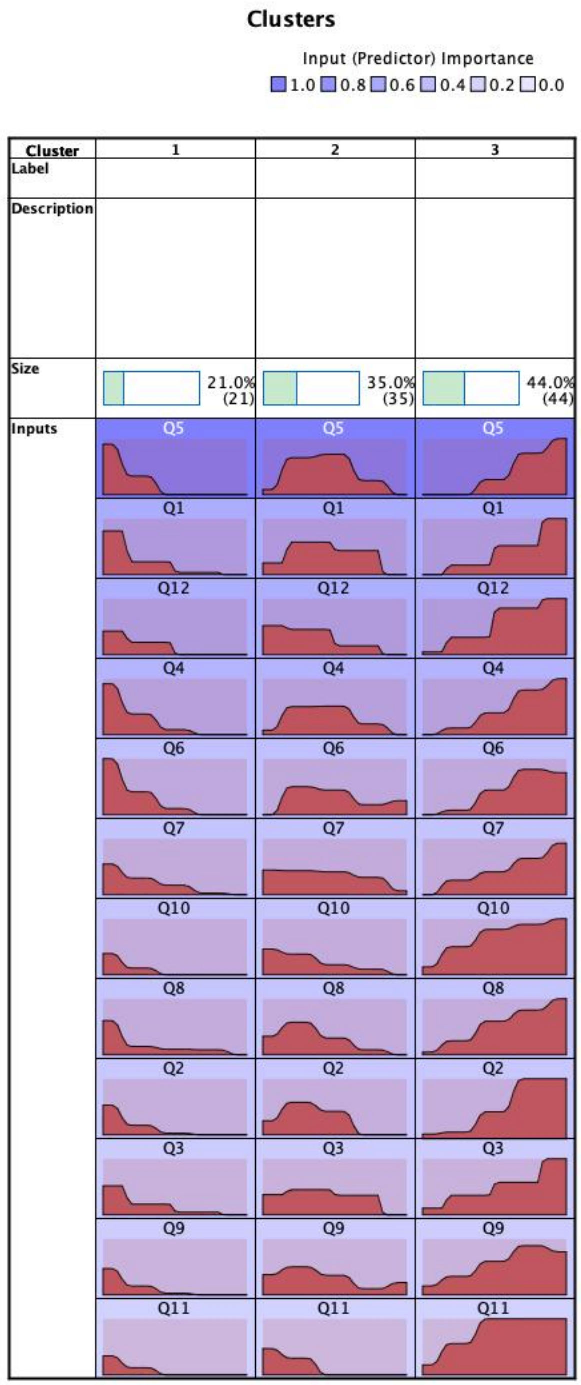



Figure 8. Question score distributions in the clusters for organizational structure dimension

The most essential reason of doing a clustering analysis with 12 question scores is to see which questions are more important to discriminate the companies in terms of their DX performances in organizational structure. To analyze this, we consider the predictor importance of the questions for clustering in Figure 9.

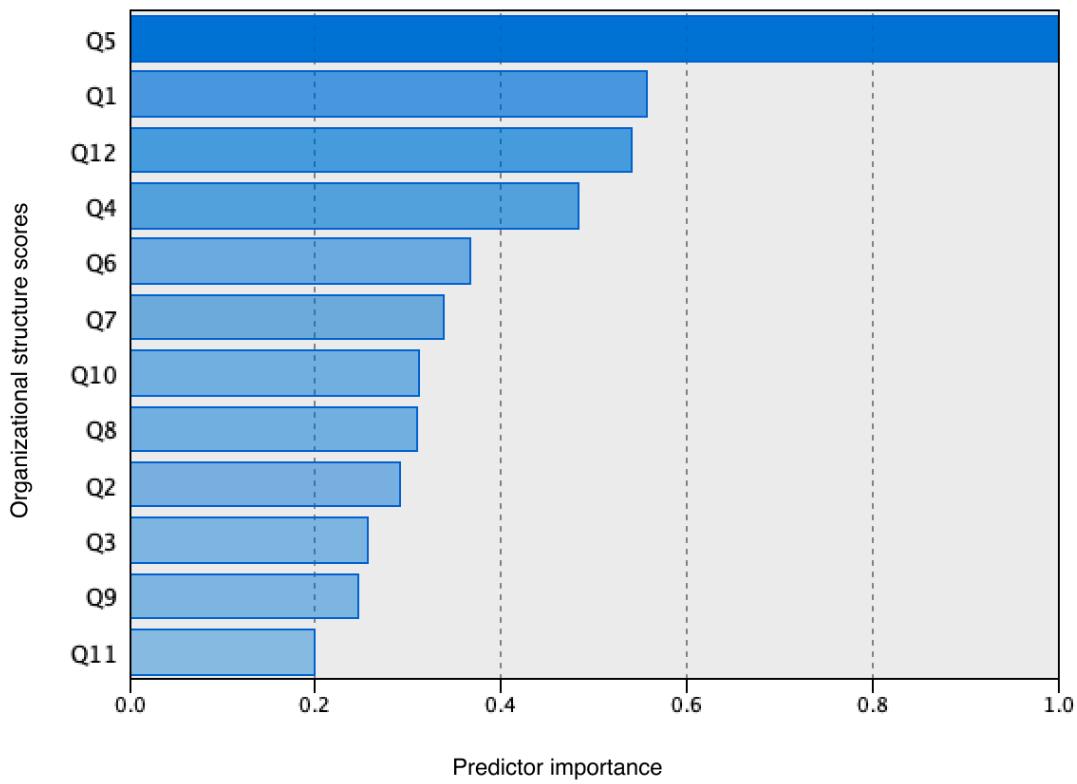



Figure 9. Predictor importance of questions for clustering in the organizational structure dimension

Accordingly, Q5 which is about the level of collaboration between the departments has the highest impact on clustering the companies in accordance with their organizational structure scores. The collaboration level is determined between two extremes where the departments are working as functional silos and where there is cross-team cohesion. Accordingly, the companies with higher level of collaboration between departments have higher organizational structure scores. This fact can also be followed in Figure 9, where the average scores for Q5 significantly increase among the clusters of the organizational structure dimension. Hence, the companies in the advanced cluster of the organizational structure dimension are very improved in collaboration with a mean score of 3.2, whereas the ones in the beginner cluster have very poor performances of collaboration with a mean score of 0.8. The intermediate cluster companies have moderate collaboration scores with mean score of 2.5. Collaboration increases with digital information sharing since the information exchange gets faster and easier between parties (Mittal et al., 2018). Hence, beginner and intermediate cluster companies should improve their digital systems in order to fulfill the needs of collaboration between departments.

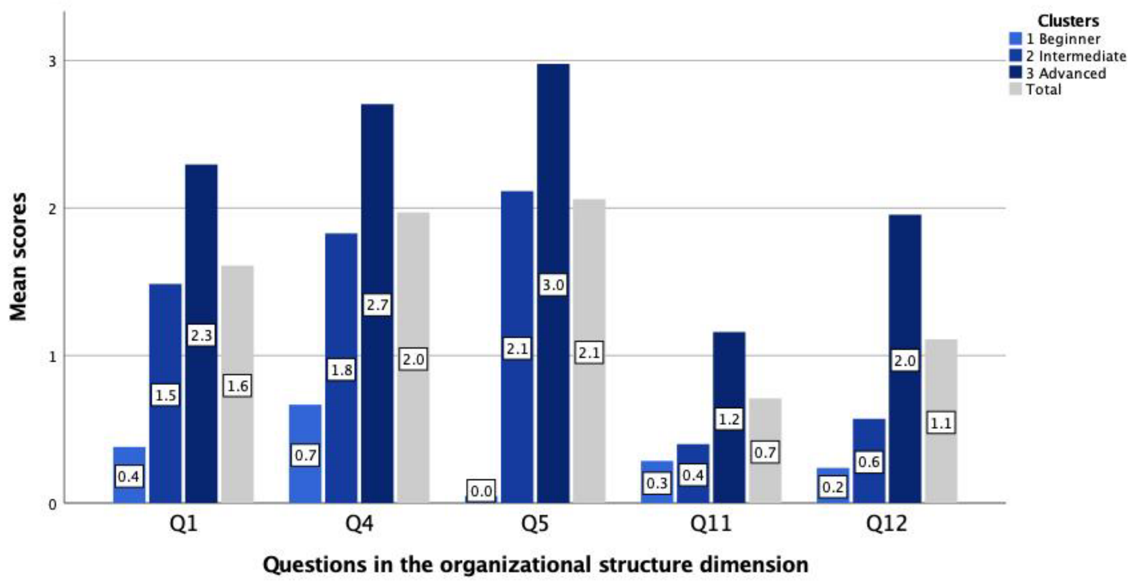



Figure 9. Mean scores of Q1, Q5, Q12, Q4 and Q11 based on clusters

In Figure 8, Q1 has the second highest predictor importance. Here, the level of rational decision-making in the companies are evaluated between two extremes where the decisions are made without data insights or decisions are made rationally based on data analyses of the past operations and future predictions. As seen in Figure 9, the average scores for Q1 significantly increase as 0.6, 1.9 and 2.6 among the three clusters of organizational structure dimension. Accordingly, decision making structure affect a company's DX performance in organizational structure dimension. So, companies with more rational decision-making environments have higher DX performances in the organizational structure dimension.

The subsequent two questions with a relatively high impact on the organizational structure score are Q12 and Q4 in Figure 9. These reflect the level of quality standardizations implemented in the company. Companies with certain quality certificates such as ISO/CE have employee evaluation systems and well-defined business processes. As seen in Figure 9, the average scores for Q12 improve as 0.4, 1.1, and 2.2 among the more advanced clusters in the operational structure dimension.

On the other hand, Q11 has a very low predictor importance of 0.2 in Figure 8 showing that the improvement of digital skills of the employees has almost no significant impact on the DX performance of the companies in organizational structure dimension. As a matter of fact, more than 80% of the companies have very low Q11 scores between 0-1 as seen in Figure 6. Moreover, in Figure 9, the average scores for Q11 among the organizational structure clusters are 0.3, 0.7 and 1.3, showing that this score is very low even in the most advanced cluster in this dimension. Therefore, this question is not critical in the organizational clustering of the companies. Nevertheless, Q8 for cyber security and Q9 for remote data access abilities are also not significant in differentiating the companies with respect to their organizational scores as seen in Figure 8. We consider these areas as the general improvement directions for all SMEs in the operational structure dimension.

The organizational structure scores are further analyzed in relation to company sizes. As seen in Figure 10, the mean organizational structure scores increase with company sizes. Micro-sized companies have a mean organizational structure score of 0.87, small-sized companies have a mean score of 1.1, middle-sized companies have a mean score of 1.76 and finally big-sized companies have a mean score of 2.18. We conduct ANOVA tests in Figure 11 to see if the mean organizational structure scores are significantly different among different company sizes. The analysis result shows that company size is a highly significant factor (p-value $< .01$) in the organizational structure score of a company. This is indeed a quite intuitive result. The first step of DX is creating a DX awareness (Lee et al., 2010). Larger companies have improved corporate structures leading to better collaboration abilities, improved rational decision-making environments and more standardized processes compared to smaller companies. Hence, they are positioned in higher DX levels in the organizational structure dimension.

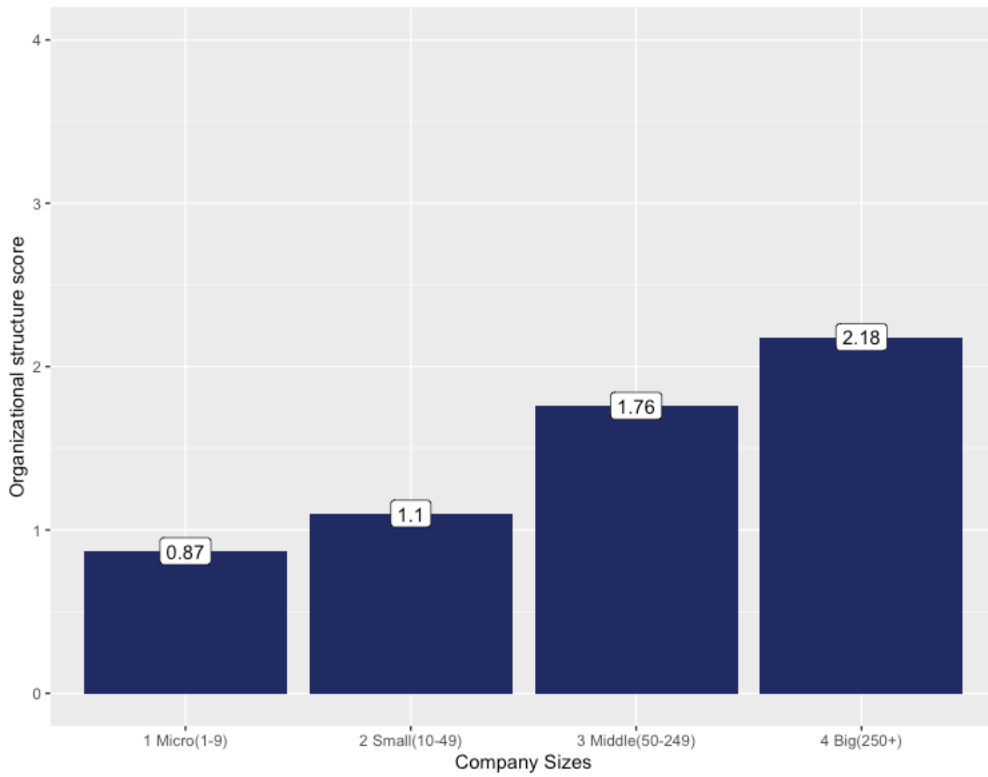



Figure 10. The mean organizational structure scores by company sizes

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Organisation_score * Size | Between Groups | (Combined) | 16.520 | 3 | 5.507 | 10.898 | .000 |
| | Within Groups | | 48.508 | 96 | .505 | | |
| | Total | | 65.028 | 99 | | | |

Figure 11. ANOVA results for the effect of company sizes on the organizational structure scores

Finally, we analyze the organizational structure scores in different industries. As seen in Figure 12, metal and plastic industries have the highest organizational structure scores of 1.86 and 1.81, whereas furniture and textile industries have the lowest mean scores of 0.81. Let us note that the top industries include more than 10 companies in our sample thus providing more reliable results.

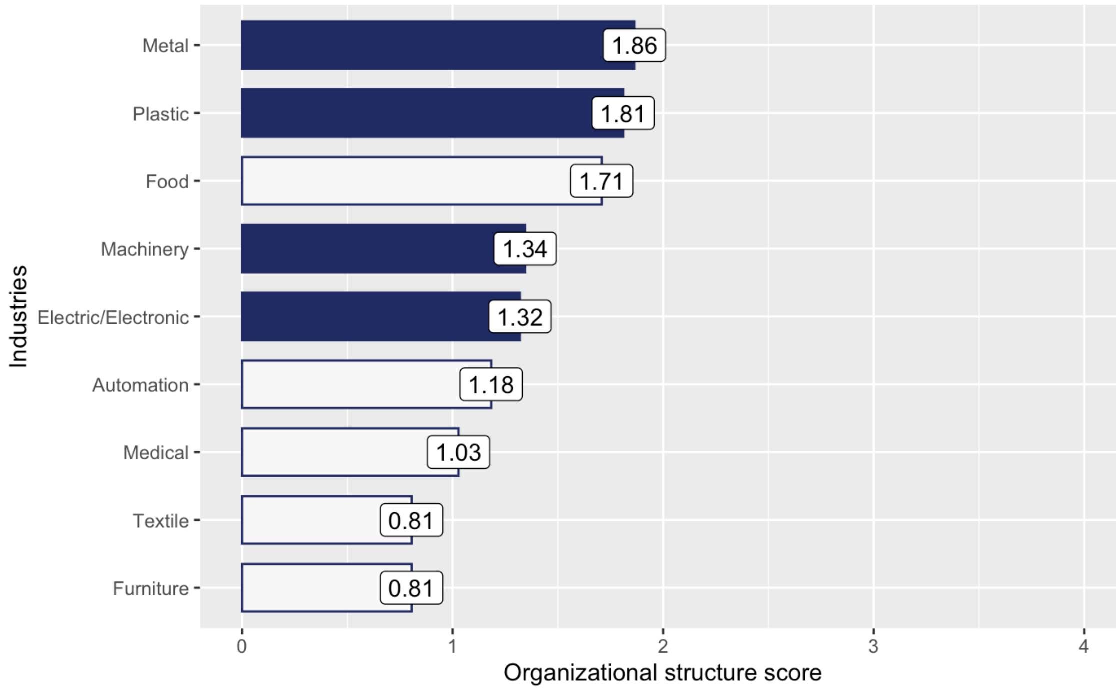



Figure 12. Organizational structure score by industry groups

We conduct ANOVA tests in Figure 13 to see if the mean organizational structure scores are significantly different among different industries. The analysis result shows that the mean organizational structure scores significantly differ between industries (p-value < .05). So, while all industries have rooms for improvement in the organizational structure dimension, furniture, textile, medical and automation industries need urgent re-engineering in their organizational structures.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Organizational Structure Score * Industry | Between Groups | (Combined) | 10.387 | 8 | 1.298 | 2.162 | .038 |
| | Within Groups | | 54.641 | 91 | .600 | | |
| | Total | | 65.028 | 99 | | | |

Figure 13. ANOVA results for the effect of industry on the organizational structure score

### 5.1.2. Customer

There are 12 questions in customer dimension as seen in Appendix A that assess the DX maturity of customer management operations in with a focus on outer relations of the companies with the customers and how these relations are turned into data to be used in the company. As seen in Figure 14, the highest mean score is for Q5 about appearance of the companies on digital platforms and how their customers can reach to them through these digital channels. The main reason behind this result is the credibility effect of having a website to represent the company online and it is quite unlikely not to have a website nowadays. Similarly, Q6 about keeping record of customer communication also has a high mean score that shows the importance given to customer communication. Companies are focusing on customer touching edges more than their inner operations in terms of digital solutions.

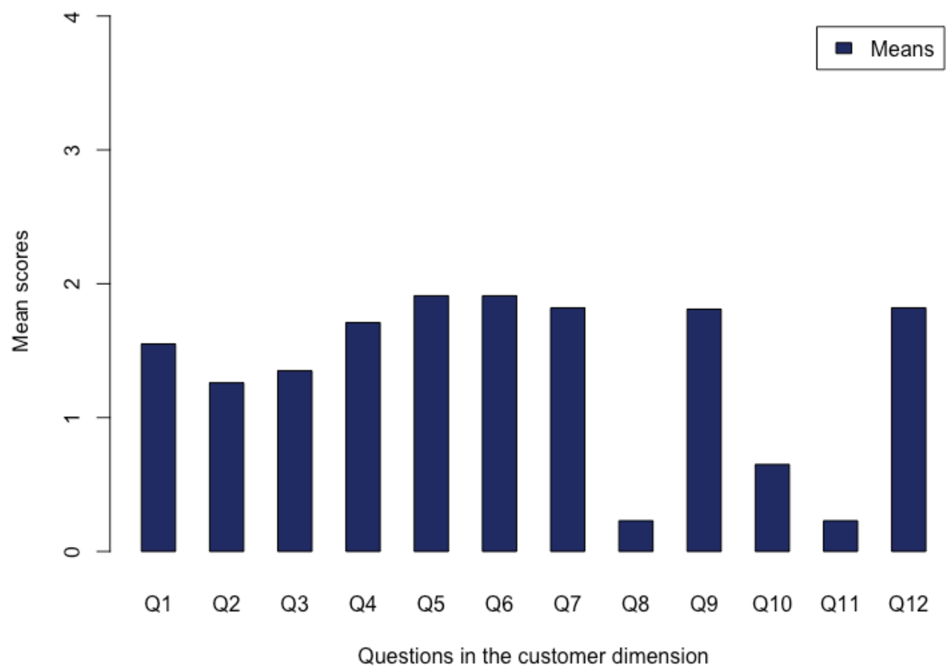



Figure 14. Mean scores of the questions in the customer dimension

There are three questions to assess the sale channels in terms of managing with data, first one is about the sales team, second one is about the dealers and the third layer is the distributors (Q8, Q10, Q11). All these questions have low mean scores as the SMEs mostly do not have multi-layered sales channels and there is no management of these channels with data.

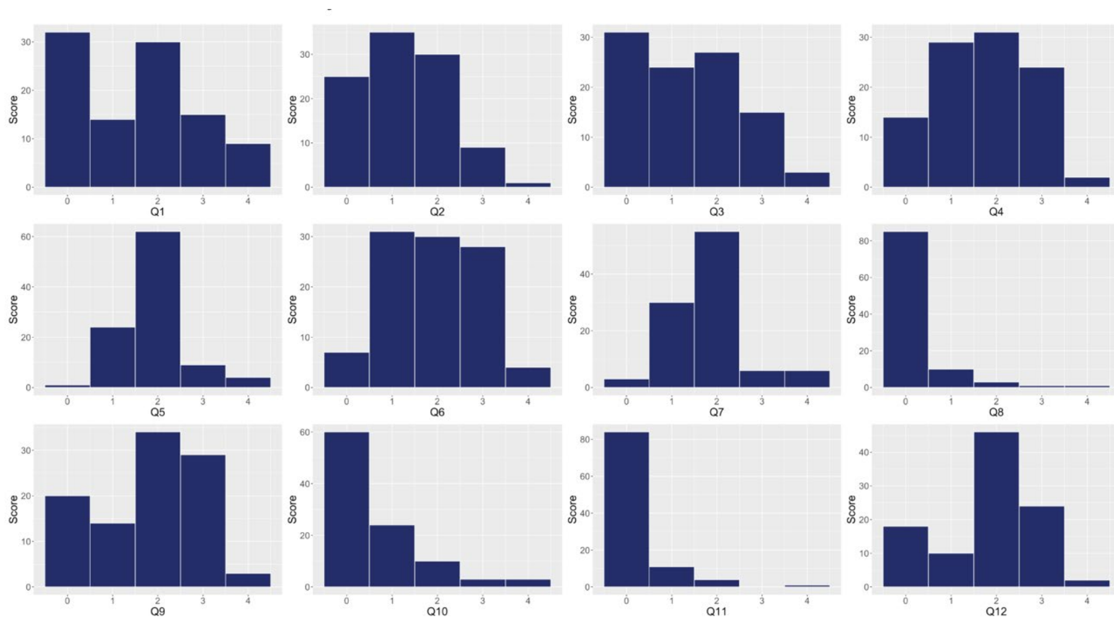



Figure 15. Distribution of question scores in the customer dimension

In Figure 15, distribution of scores in each question is provided. Accordingly, management of sale operations (Q1), pricing quotes (Q4), sale forecast (Q2) and how customer data is shared between departments (Q3) have high dispersion of scores among 5 scoring levels. It can be said that companies are differentiated in their customer related inner operations. Management of customer feedback (Q12) is another well-differentiating question where most of the companies have 2 as score. It can be said that customer feedbacks are gathered in forms of technical service or complaints, but they are not integrated in a system to create managerial insights to improve the products or services.

Customer dimension has an overall mean score of 1.35 that can be seen in Figure 16 which is lower than organizational structure score. The distribution of scores is approximately symmetric with a skewness value of 0.241 and there is only one company with a score higher than 3 whereas there are 11 companies with a score less than 0.5.

The lowest customer score is 0.08 and this company has also the lowest D3A score which is 0.115. The highest customer score is 3.42, however this company has a moderate D3A score which is 2.07.


Figure 16. Distribution of the scores in the customer dimension

The companies are grouped under 3 cluster based on their scores in 12 questions of customer dimension. The smallest cluster is the beginner cluster with 15%, the biggest is intermediate cluster with 47% and the advanced cluster has 38% of companies. The beginner cluster is smaller compared to organizational structure cluster. It can be seen in Figure 16 that beginner cluster has scores smaller than 2, intermediate cluster has scores closer to 3-4 and the advanced cluster mostly has scores greater than 3.

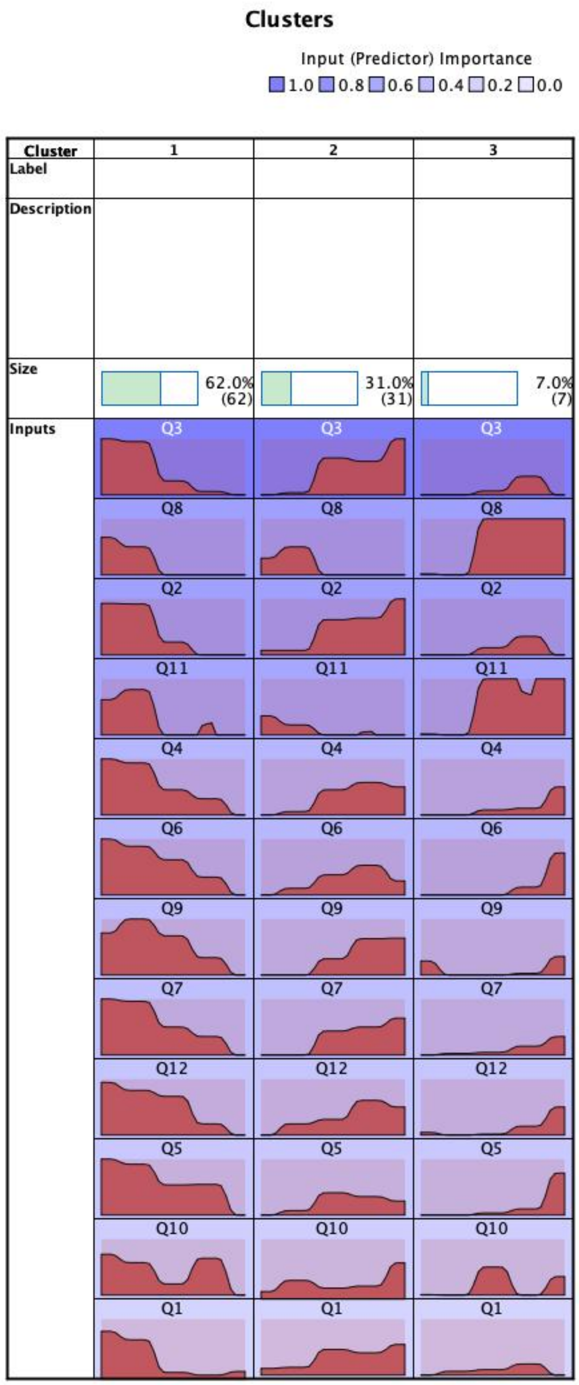



Figure 17. Question score distributions in the clusters for customer dimension

Next, predictor importance of the questions for clustering in Figure 18 is considered to see which questions are more discriminant for the DX maturity of companies in customer dimension.

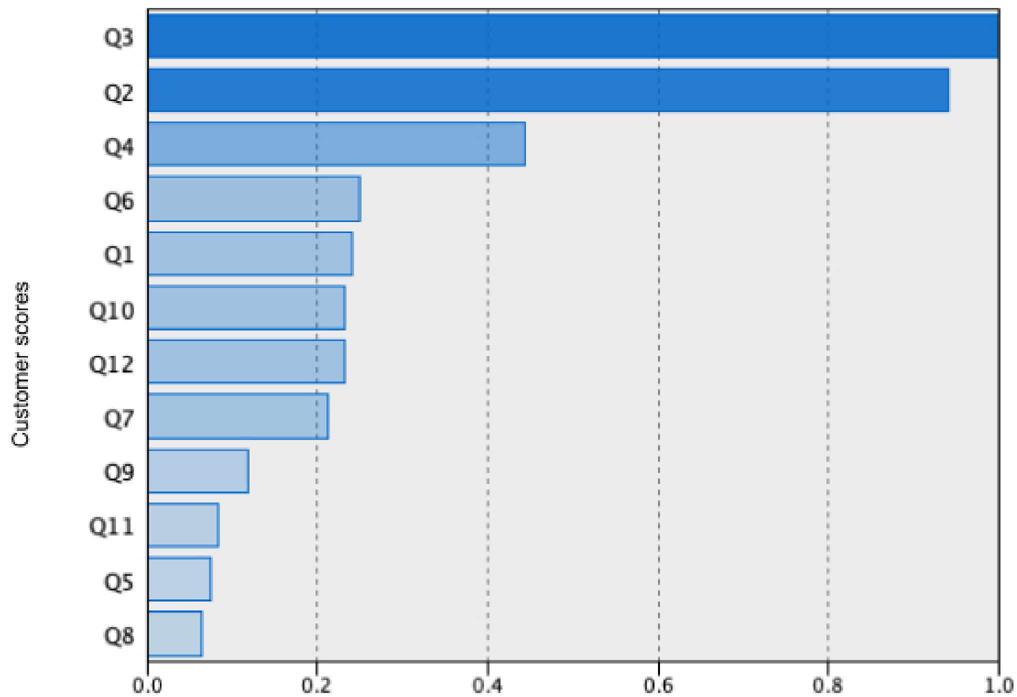



Figure 18. Predictor importance of questions for clustering in the customer dimension

Accordingly, collaboration between department with sales data (Q3) has the highest importance value for clustering as it can be seen in Figure 18. Forecasting sales (Q2) is a particular question about creating a depth insight from sales operations and it also has an important role on differentiating the companies for cluster analysis. Being able to forecast the sales with data and taking decisions on those shows a well-adapted usage of data among different functions of a company and it is a result of a certain level in digital maturity. Hence, beginner and intermediate cluster companies should improve their data usage for sales operations to improve their DX maturity score in customer dimension.

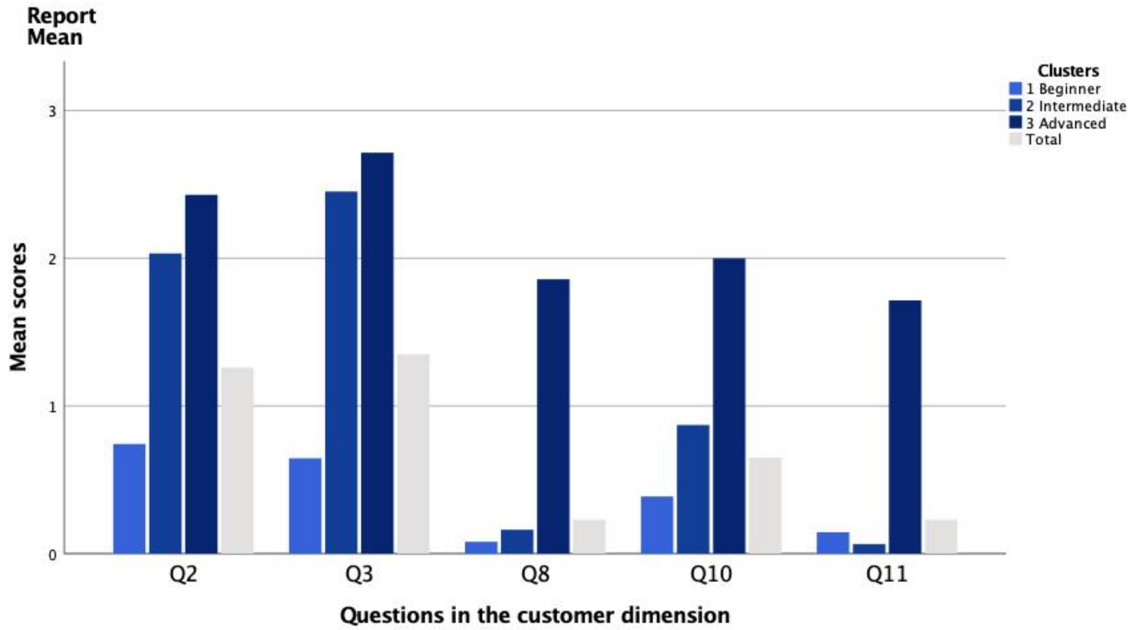



Figure 19. Mean scores of Q2, Q3, Q8, Q10 and Q11 based on clusters

Expectedly sales channels management questions (Q8, Q10, Q11) have the lowest impact on clustering the companies as the distribution of these questions were quite right skewed and the companies did not have high scores.

Customer score increases between the groups of companies with number of employees that is analyzed under four company sizes as it can be seen in Figure 20. The big-sized company group has a mean of 1.93 which is lower than the mean score of big-sized companies in organizational structure dimension which is 2.18. The highest score belongs to a company in the middle-sized company group which shows having an advanced digital maturity in customer relations does not necessarily mean having a certain number of employees yet can be improved with individual efforts.

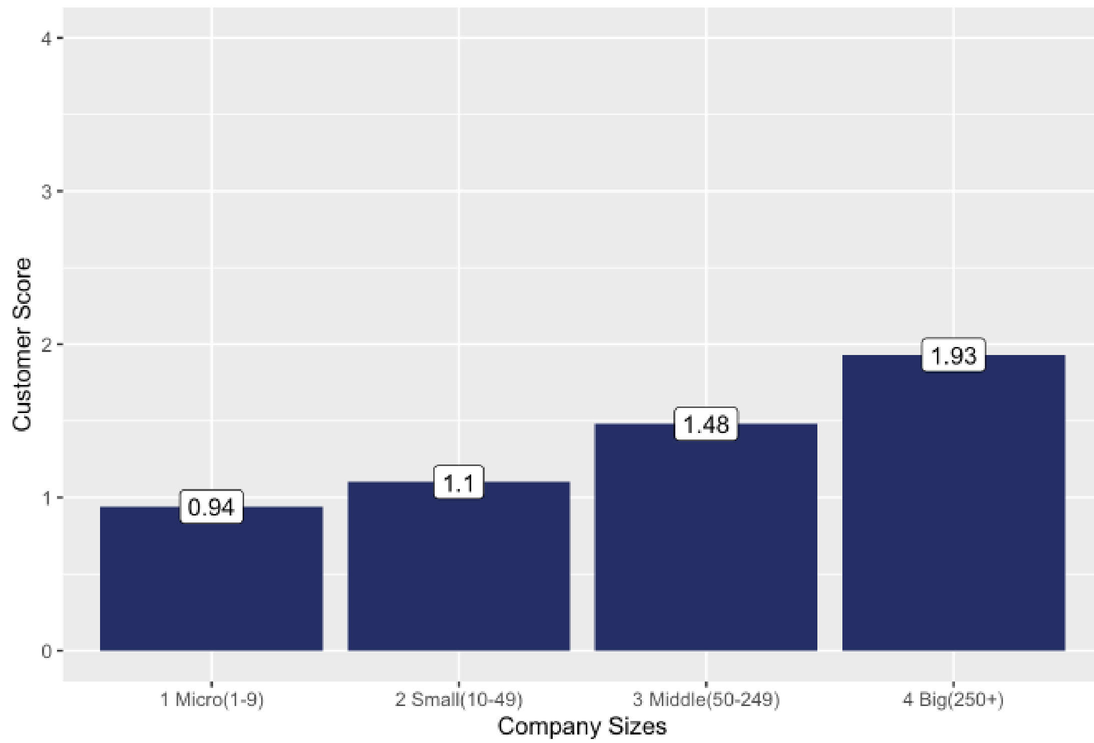



Figure 20. The mean customer scores by company sizes

We conduct ANOVA tests in Figure 21 to see if the difference between mean customer scores is significant among company size groups. The analysis result shows that company size is a highly significant factor (p-value < .01) in the customer score of a company.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Customer Score * Size | Between Groups | (Combined) | 7.622 | 3 | 2.541 | 8.337 | .000 |
| | Within Groups | | 29.258 | 96 | .305 | | |
| | Total | | 36.880 | 99 | | | |

Figure 21. ANOVA results for the effect of company sizes on the customer scores

Industry groups have quite similar mean scores in customer dimension except the food industry. In Figure 22, the mean DX scores for customer dimension for food industry seems to be much higher than all other industries. However, ANOVA test result in the Figure 22 shows that the difference among industry groups is not significant (p-value = .126). Although this is the case, we still want to highlight the success of food industry which is the only industry in service sector. SMEs in food industry act as suppliers in service sector which is closest to the end customers and requires very fast response. As a natural consequence, food industry is expected to score higher in customer dimension than the other pure manufacturing industries. However, food industry constitutes 4% of all companies and this is not enough to make this difference significant. On the opposite side, textile, automation, medical and furniture industries constitute only 17% of all companies and they have relatively poor customer scores, but this difference is not significant too. Nevertheless, metal, electric/electronic, plastic and machinery industries constitute 82% of all companies and they have similar and low customer scores. We realize that suppliers of big manufacturers constitute 25% of all companies and they are all included in these industries. These companies have moderate customer scores since many of their customer related processes are digitalized by the big manufacturers they are supplying. Most of these companies serve to a single customer and they do not have a distribution system. As a result, the companies in these industries have all moderate customer scores. Hence, we conclude that customer scores do not significantly differ between industries.

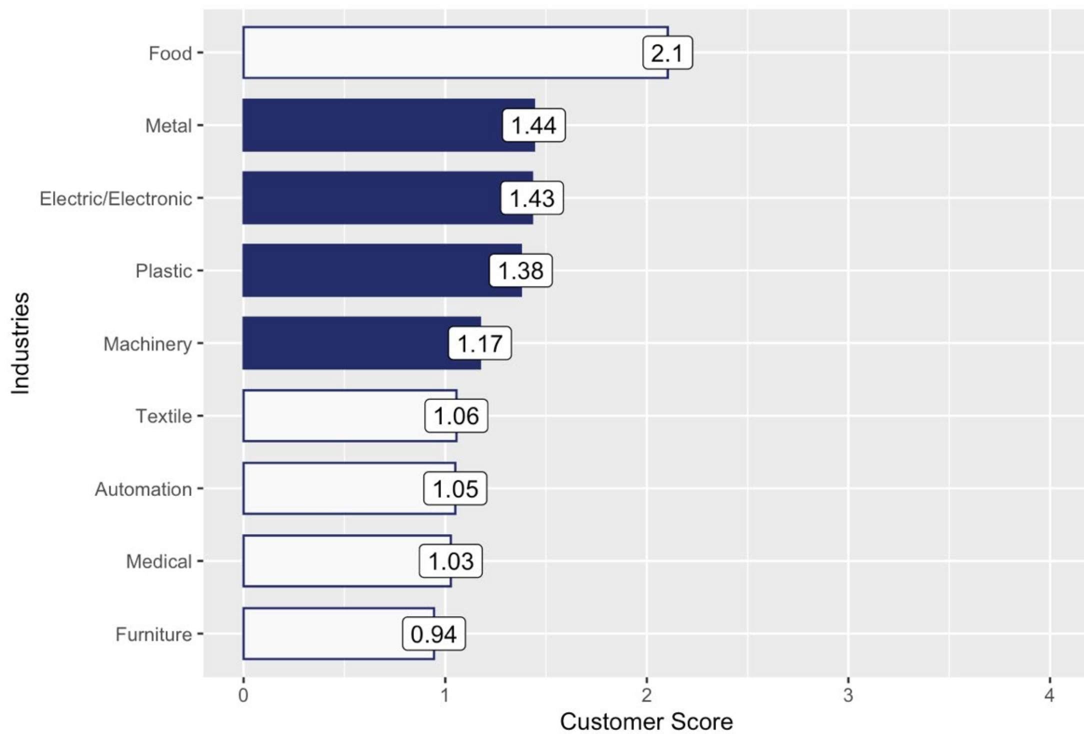



Figure 22. Customer score by industry groups

The low sample size in food industry group caused this difference of food industry to not to be enough for being significant between groups.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Customer Score * Industry | Between Groups | (Combined) | 4.632 | 8 | .579 | 1.634 | .126 |
| | Within Groups | | 32.248 | 91 | .354 | | |
| | Total | | 36.880 | 99 | | | |

Figure 23. ANOVA results for the effect of industry groups on the customer scores

### 5.1.3. Product

Innovation and new product development operations are assessed under 10 questions in product dimension as it can be seen in Appendix A. Mittal et al. (2018) stated one of the special characteristics of SMEs is their higher capabilities of product customization.

Product customization skills are assessed in Q10 in order to verify these capabilities and the scores indeed supported this statement. Q10 has a mean score of 2.95 as it can be seen in Figure 24 which is the highest mean score in product dimension. This result proved being customer oriented and flexible gives SMEs a higher chance to be adapted to changes and if they can support it with data analysis, they have the potential to be one step ahead of big companies.

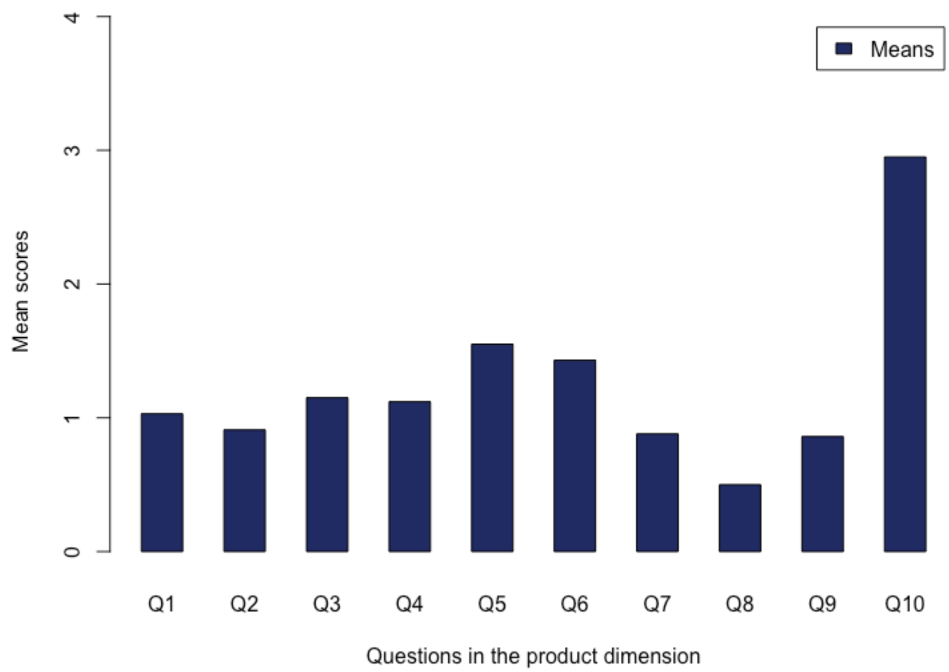



Figure 24. Mean scores of the questions in the product dimension

Another question with a high mean is about the usage of technological tools in product development projects (Q5). SMEs surely have some financial and technical limitations, nevertheless they are catching up with the technological improvements especially if it drives competitive advantage. Using 2D/3D modeling programs increase the efficiency in product development beyond doubt, this high mean score proves that it is widely adapted in SMEs as well.

However, when it comes to the digitalization level of the product itself, we cannot observe the same adaptation of the technology in SMEs. Data collection hardware on products is assessed in Q8 and it has the lowest mean score of 0.5. Since data collection from product is not at a certain level, data analysis is hardly used for taking decisions about the products. It is not very surprising to find that Q9 about the organizational structure in new product development projects and how decisions are made for new products has a mean of 0.89 which is the second lowest mean.

The distribution of scores in each question is presented in Figure 25. Here we observe that more than 40% of companies scored 0 for Q1. Accordingly, it can be said that SMEs mostly do not have dedicated R&D or P&D departments. Almost all of the questions have 0 as the most common except product customization question (Q10).

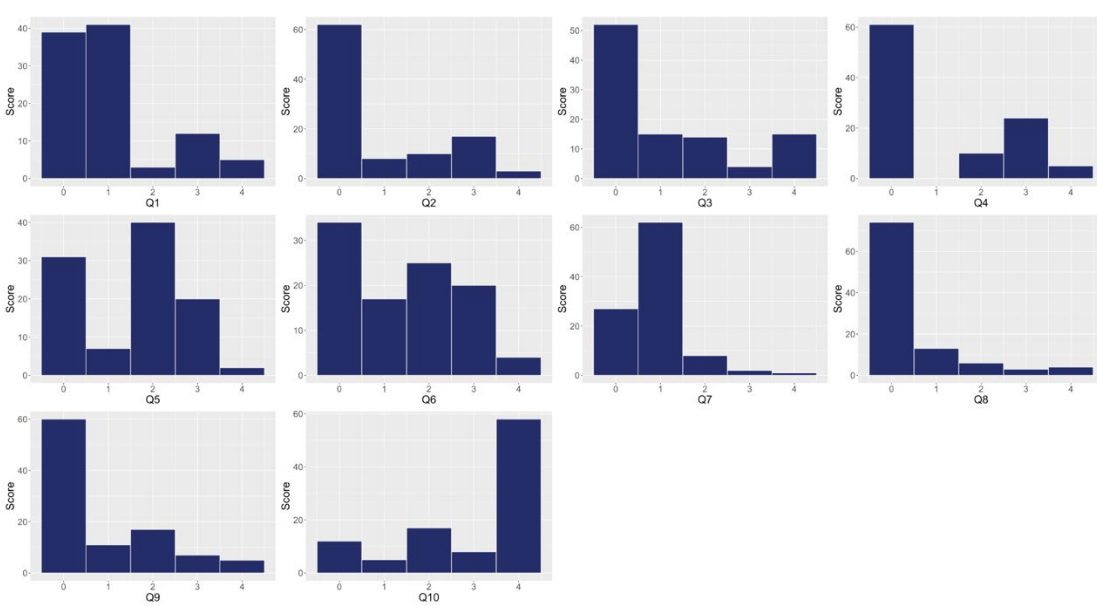



Figure 25. Distribution of question scores in the product dimension

Overall mean score of product dimension is 1.24 as it can be seen in Figure 26 which is lower than both customer and organizational structure dimensions and it is moderately right skewed with a skewness value of 0.576. More than 50% of the companies has a product score lower than the mean and there are only 6 companies with a score higher than 2.5.

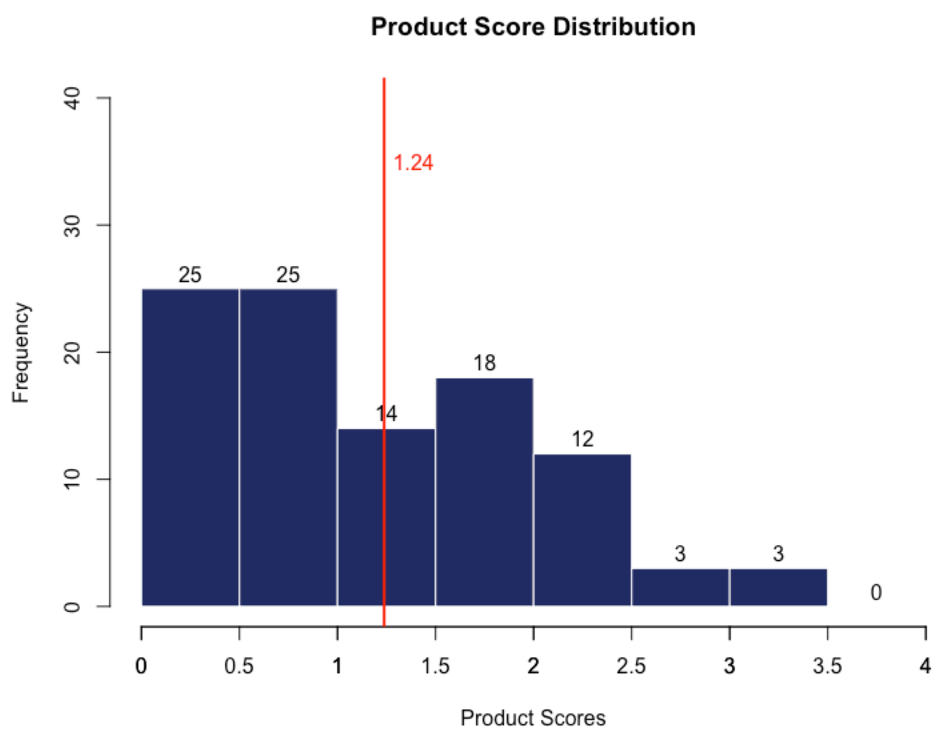



Figure 26. Distribution of the scores in the product dimension

Next, clusters are created based on product question scores with almost equal sizes of 32% for the beginner, 36% for intermediate and 32% for the advanced. It can be seen in Figure 27 that beginner cluster has scores smaller than 2 except Q10, intermediate cluster has scores closer to 2-3 and the advanced cluster mostly has scores greater than 3.

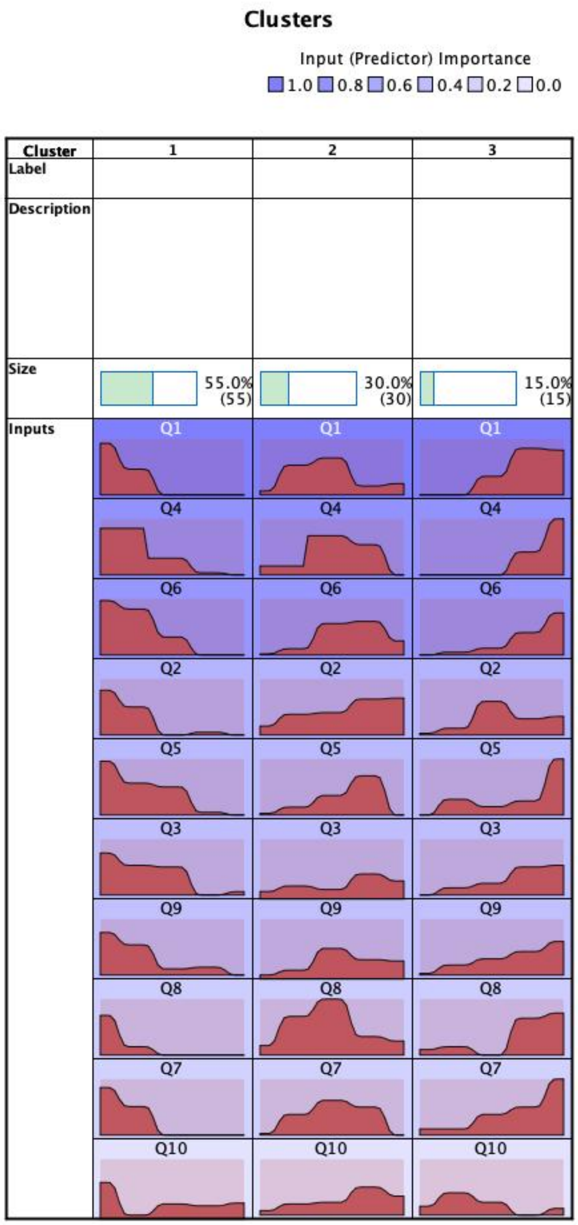



Figure 27. Question score distributions in the clusters for product dimension

Q6 about collaboration and participation in product development projects has the highest importance value on clustering the companies as it can be seen in Figure 28. Following most important questions on clustering are R&D or P&D departments (Q1) and using technological tools in product development (Q5) which are both discussed previously in distribution of scores. It is not surprising to see that the questions with lower variance do not have high importance value in clustering companies like the Q10 about product customization and producing technologies that are used in products.

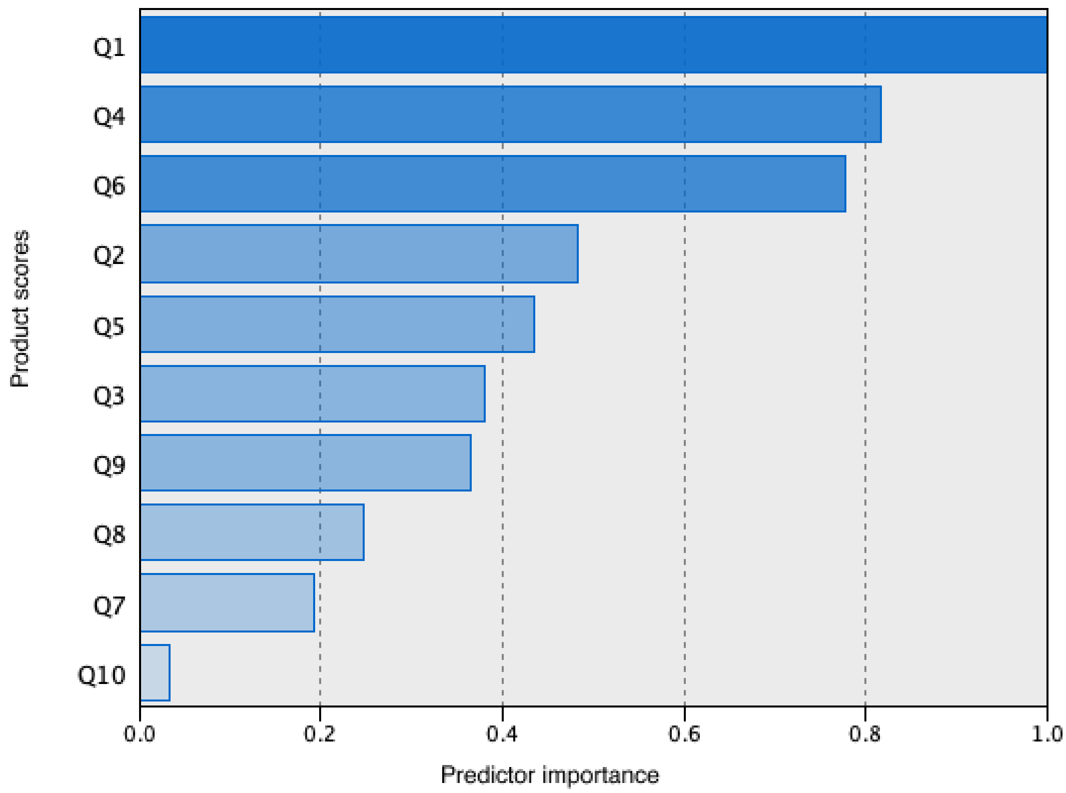



Figure 28. Predictor importance of questions for clustering in the product dimension

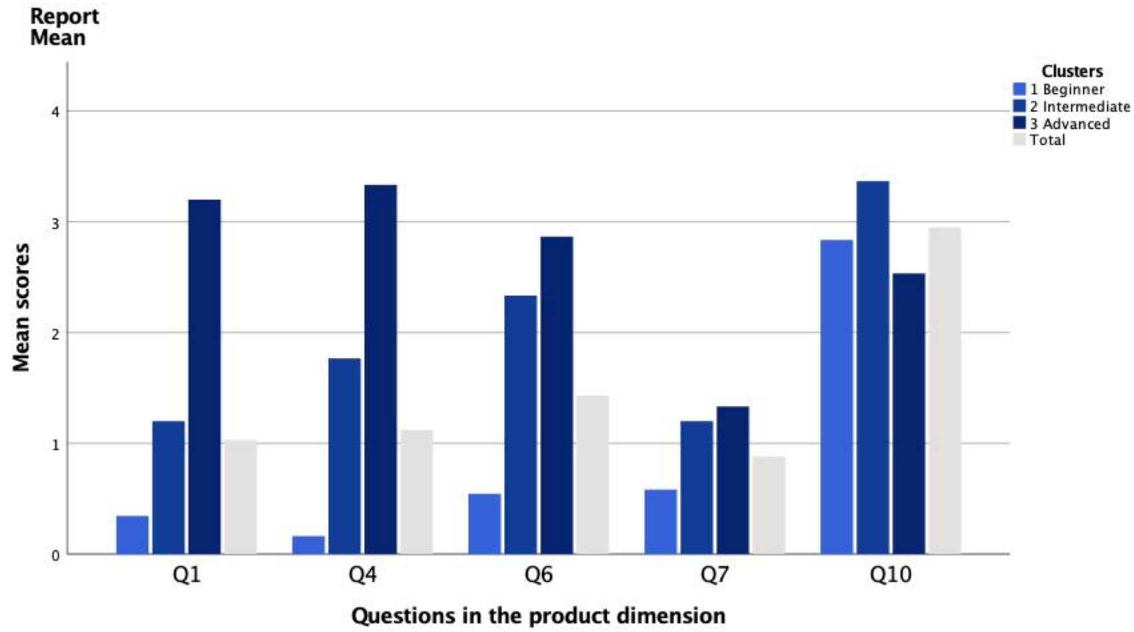



Figure 29. Mean scores of Q1, Q4, Q6, Q7 and Q10 based on clusters

Product mean score is increasing quite slightly between first 3 groups of company size as it can be seen in Figure 30. Big companies constitute 10% of all companies and seem to have higher product scores. We conduct ANOVA tests in Figure 30 to see if the difference between mean product scores is significant among company size groups. The analysis result shows that company size is not a significant factor (p-value = .120) in the product score of a company. This is mainly due to the fact that there are few numbers of exceptionally high scored micro-sized companies and low scored medium-sized companies. High scored micro-sized companies are electric/electronic and automation companies working as the suppliers of global high technology manufacturers as well as military organizations. These manufacturers require high quality standards, availability of patents and R&D activities for suppliers. These suppliers are supported by the big manufacturers they are serving. Hence, they have improved product scores based on their collaboration with these big manufacturers. On the other hand, although middle-sized companies have slightly higher product scores than micro and small-sized companies, they are still very close. These companies are mostly working as suppliers of big local manufacturers and produce product parts that were developed by these manufacturers. Therefore, they do not apply innovative product development processes but perform project-based studies.

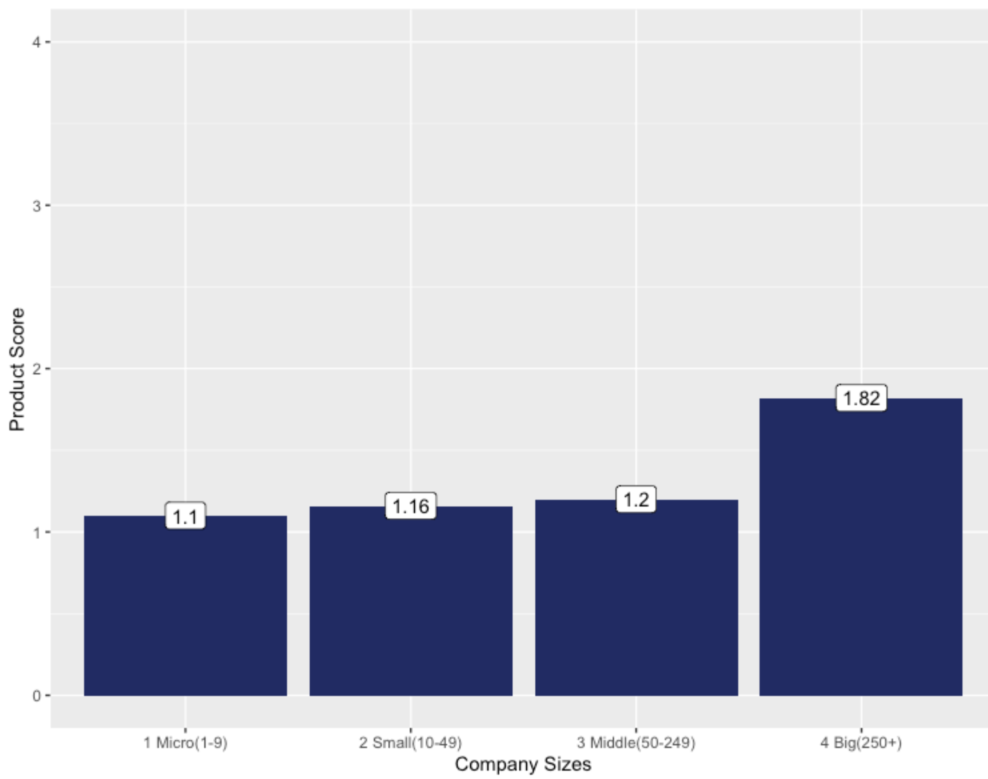



Figure 30. Product score based on company size groups

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Product Score * Size | Between Groups | (Combined) | 3.845 | 3 | 1.282 | 1.997 | .120 |
| | Within Groups | | 61.611 | 96 | .642 | | |
| | Total | | 65.456 | 99 | | | |

Figure 31. ANOVA results for the effect of company sizes on the product scores

Industry group mean scores for product dimension is presented in Figure 32. The highest mean score belongs to the most technology-oriented industries like automation and electric /electronic. On the contrary the industries like food or furniture with low technology need in product have utterly low mean scores. The companies with high scores in product dimension all have operations with a need of relatively smart product parts or processes. ANOVA tests result provided in Figure 33 shows that, mean score differences based on industry groups are significant (p-value < .05). This result indicates that industry or product field directly affects the product score.

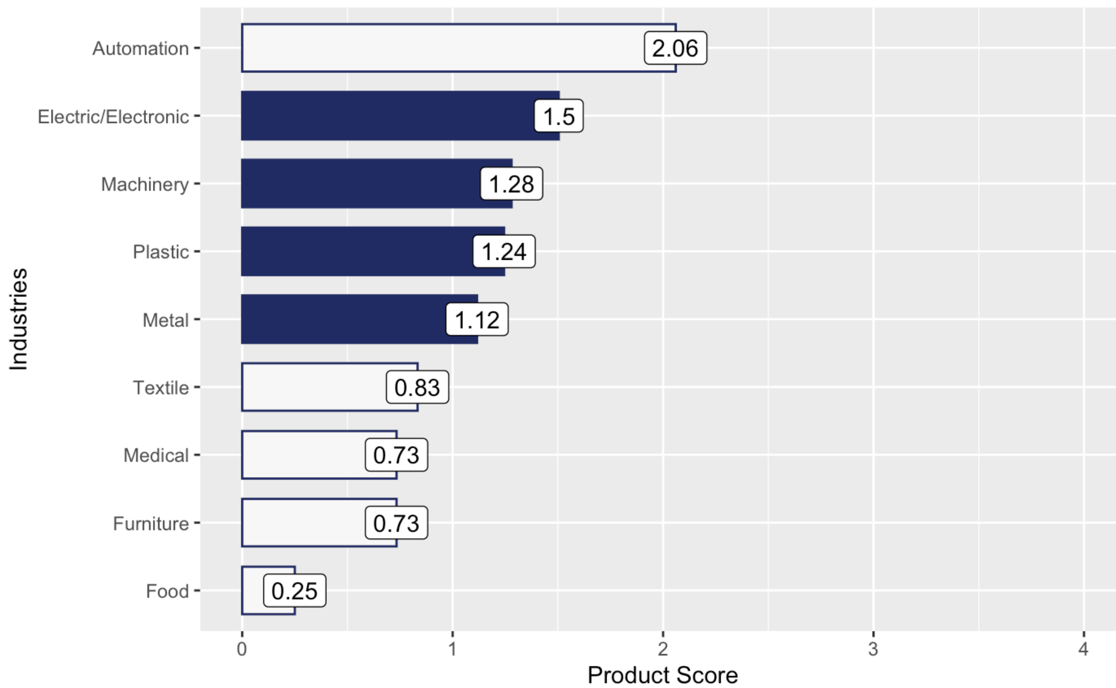



Figure 32. The mean product scores for industry groups

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Product Score * Industry | Between Groups | (Combined) | 11.402 | 8 | 1.425 | 2.399 | .021 |
| | Within Groups | | 54.054 | 91 | .594 | | |
| | Total | | 65.456 | 99 | | | |

Figure 33. ANOVA results for the effect of industry groups on the product scores

### 5.1.4. Supply Chain

Supply chain has 16 questions grouped under planning, material management and delivery management as it can be seen in Appendix A. Q12 about keeping track of stock movements has the highest mean as it can be seen in Figure 34 score as stocks are mostly perceived valuable and the most important aspect of a continuous production.

Companies use digital software in order to keep track of stock movements. Q11 about planning of stocks also has a high mean score because planning material needs also requires digital software as it is quite complicated to foresee needs and avoid over stock.

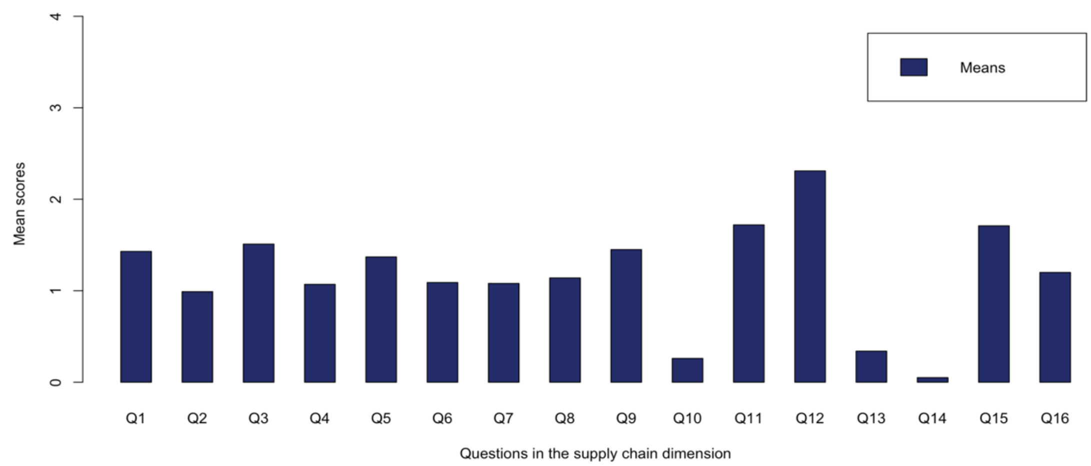



Figure 34. Mean scores of the questions in the supply chain dimension

However, warehouse management is mostly done by hand and the work-in-process stocks are much harder to keep track which explains the low mean scores of Q13 and Q14. Almost all the companies use human force to move stocks without any automated solution and without creating data in between operations for warehouse management.

Distribution of scores for each question is provided in Figure 35. An interesting result that can be observed from the distribution of the scores is the Q6 about purchase orders. Almost 80% of the companies has a score of 1 for this question which shows they use mostly emails to give purchasing orders and register this order in a digital software like excel. The records are used mostly to keep track of the order amounts, but the data created with orders is not structured and cannot be analyzed to evaluate suppliers.

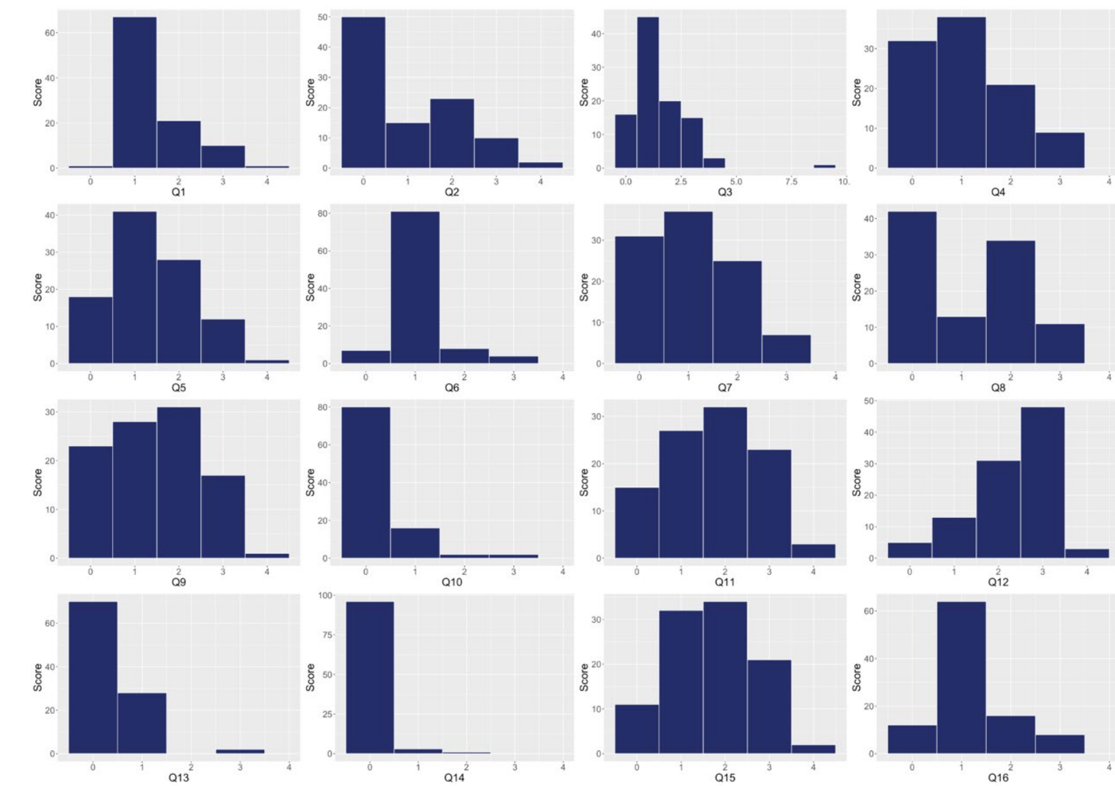



Figure 35. Distribution of question scores in the supply chain dimension

The mean score for supply chain dimension is 1.17, given in Figure 36 which is the lowest among 5 dimensions and the distribution is moderately right skewed with a skewness value of 0.478. Only 2 companies have a score more than 2.5 and more than half of the companies have a score less than mean score 1.17.

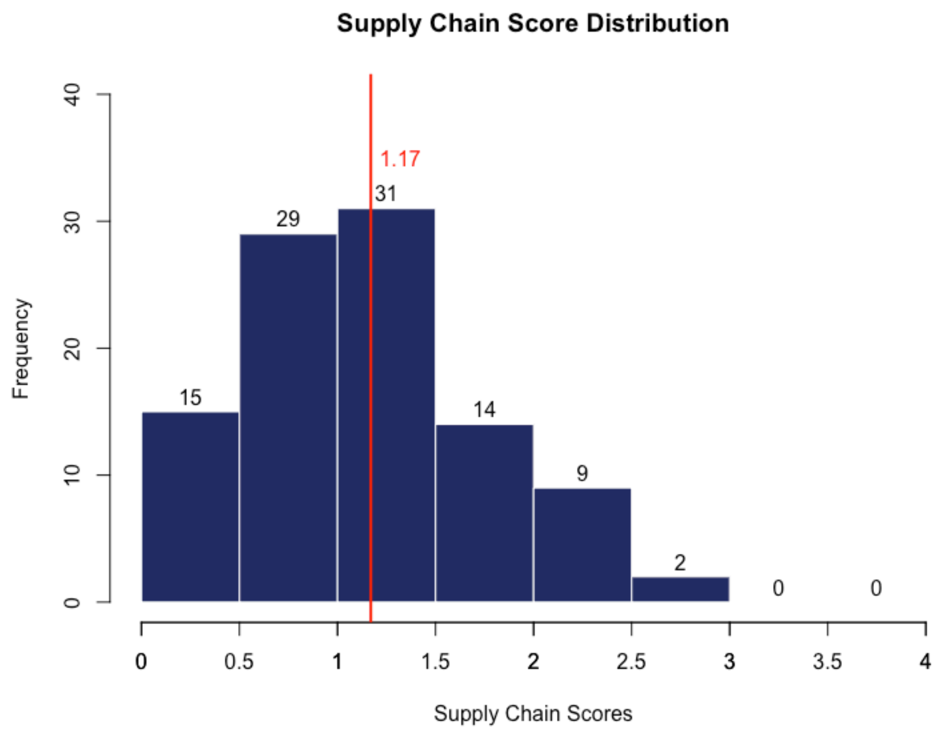



Figure 36. Distribution of the scores in the customer dimension

Three clusters created with supply chain question scores have sizes of 28% for beginner, 39% for intermediate and 33% for advanced. Score distributions for each question under three clusters is provided in Figure 37.

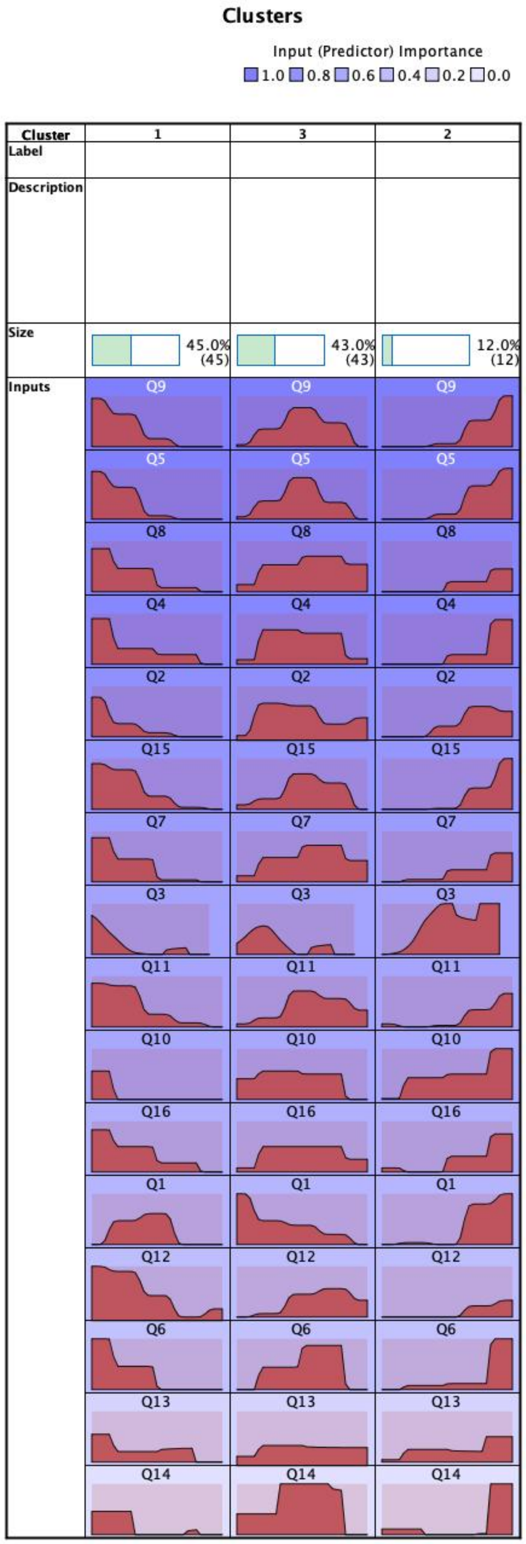



Figure 37. Question score distributions in the clusters for supply chain dimension

Next, predictor importance values for clustering the companies with supply chain management questions are presented in Figure 38. Capacity planning (Q4) has the highest importance value which is related to usage of data analysis in capacity planning and this data is rooted from multiple functions of the company like sales and manufacturing. It is followed by how suppliers are chosen (Q7) and evaluation of suppliers (Q8). Managing suppliers based on data instead of personal relations and experience has an important role in creating fluent operations with the effect of discipline and order. Therefore, the companies managing their suppliers with data take place in the advanced cluster and have higher D3A scores as well.

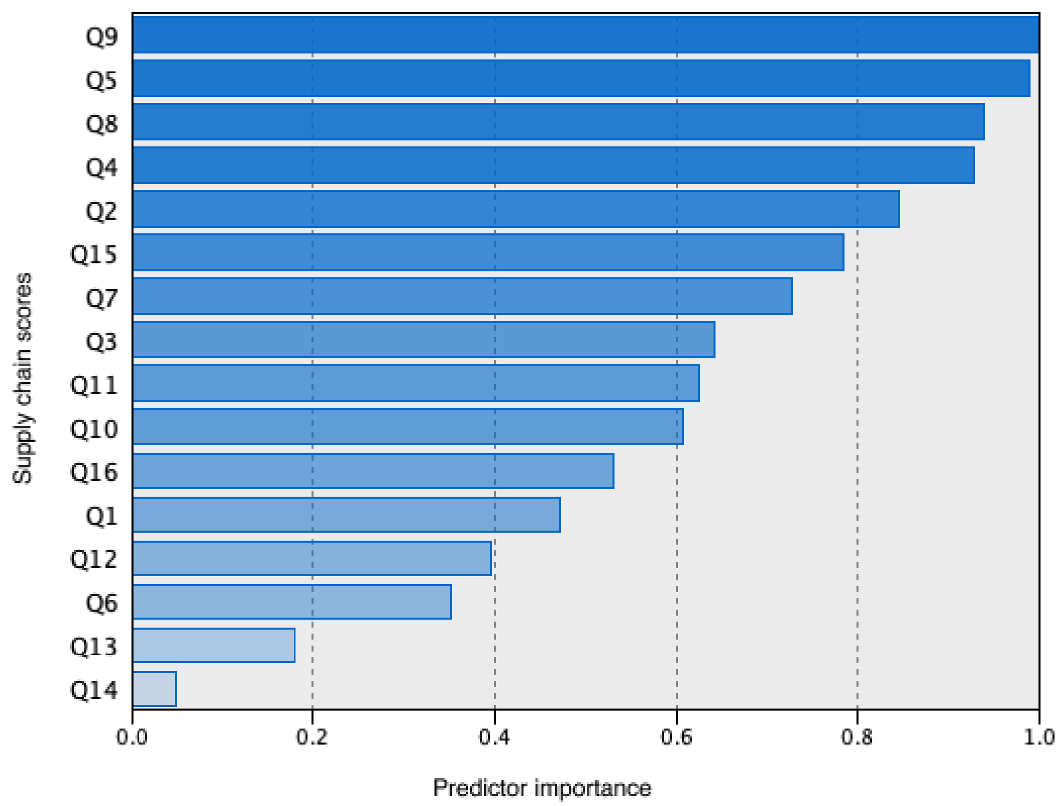



Figure 38. Predictor importance of questions for clustering in the organizational structure dimension

On the contrary, the Q13 and Q14 questions about warehouse management with a high right-skewed distribution have also low impact on clustering the companies. It can be said that smart warehouse management is not a priority yet in SMEs as even the advanced cluster has low scores for these questions as it can be seen in Figure 39.

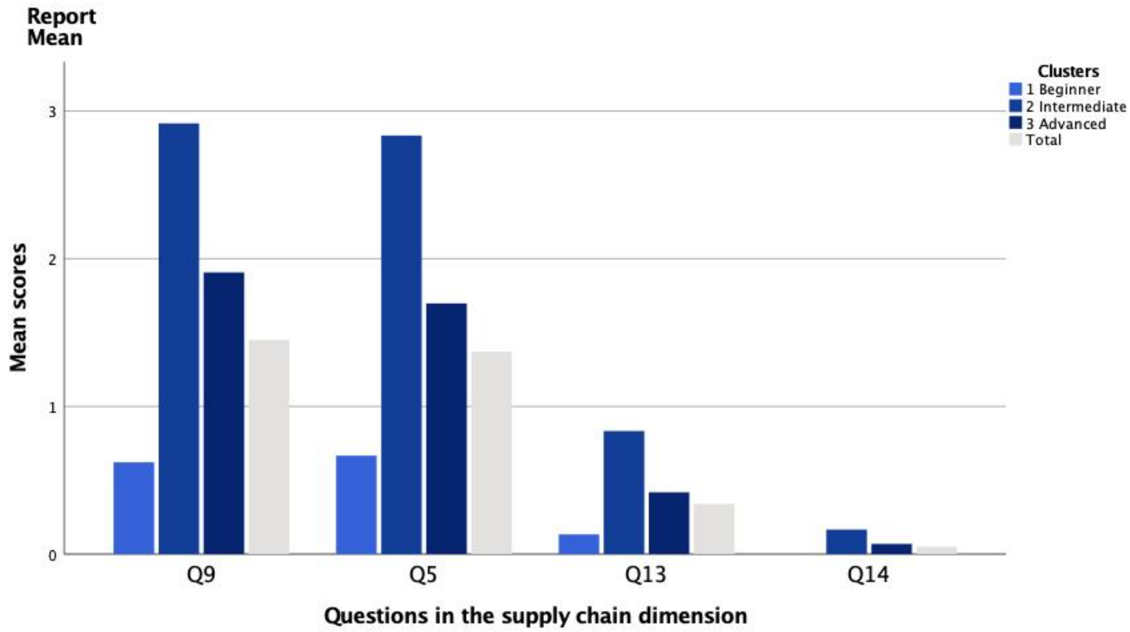



Figure 39. Mean scores of Q9, Q5, Q13, Q14 based on clusters

Similar to other dimensions, supply chain score increases between company size-based groups from micro to big-sized as presented in Figure 40. The difference between groups is highly significant as it can be seen from the ANOVA tests result in Figure 41 (p-value < .01).

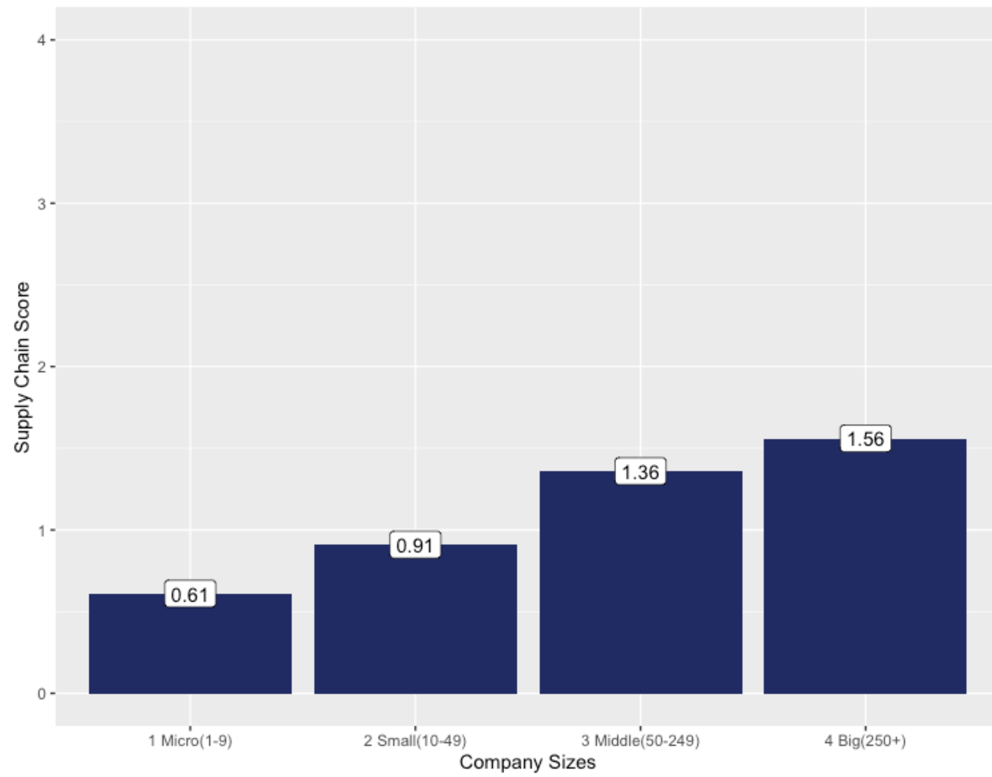



Figure 40. The mean supply chain scores by company sizes

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Supply Chain Score * Size | Between Groups | (Combined) | 7.971 | 3 | 2.657 | 9.132 | .000 |
| | Within Groups | | 27.932 | 96 | .291 | | |
| | Total | | 35.904 | 99 | | | |

Figure 41. ANOVA results for the effect of company sizes on the supply chain scores

Industry based groups comparison result is presented in Figure 42. Similar to customer dimension food industry is the best. As an expected result, machinery and automation had the lowest mean scores as these industries are mostly working with long-term projects rather than production of fast-moving goods which causes relatively slower operations and make companies focus on the product more than processes as even if there are problems they do not occur often.

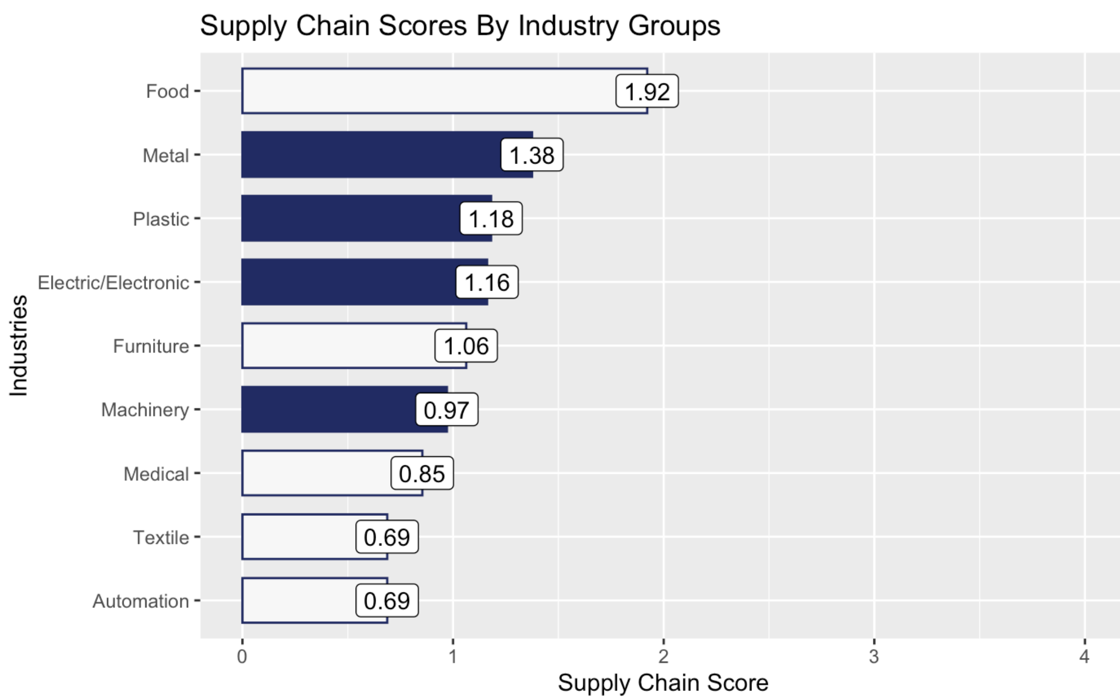



Figure 42. Supply chain score by industry groups

The difference between industry groups is proven to be significant with ANOVA tests result that can be seen from Figure 43 (p-value < .05).

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Supply Chain Score * Industry | Between Groups | (Combined) | 5.886 | 8 | .736 | 2.230 | .032 |
| | Within Groups | | 30.018 | 91 | .330 | | |
| | Total | | 35.904 | 99 | | | |

Figure 43. ANOVA results for the effect of industry groups on the supply chain scores

### 5.1.5. Manufacturing

Manufacturing is assessed with 15 questions provided in Appendix A under three groups of production, quality control and maintenance. The highest mean of the questions is 2.33 that can be seen in Figure 44 from the Q1 that is about how production orders are transferred to production line. It shows that even if the companies do not use all integrated management software, they use a software to create production orders and transfer it to the line mostly printed out. Almost 40% the companies also records data from the production orders at the end of a production day even if it is written on a paper. The second highest mean is on the Q9 which is about responsible department of quality control. Similar to the strategic plan question under organizational structure dimension quality control is a subject that is required by nearly all of the certificates, therefore a dedicated department for quality control exists and it is mostly directly connected to upper management.

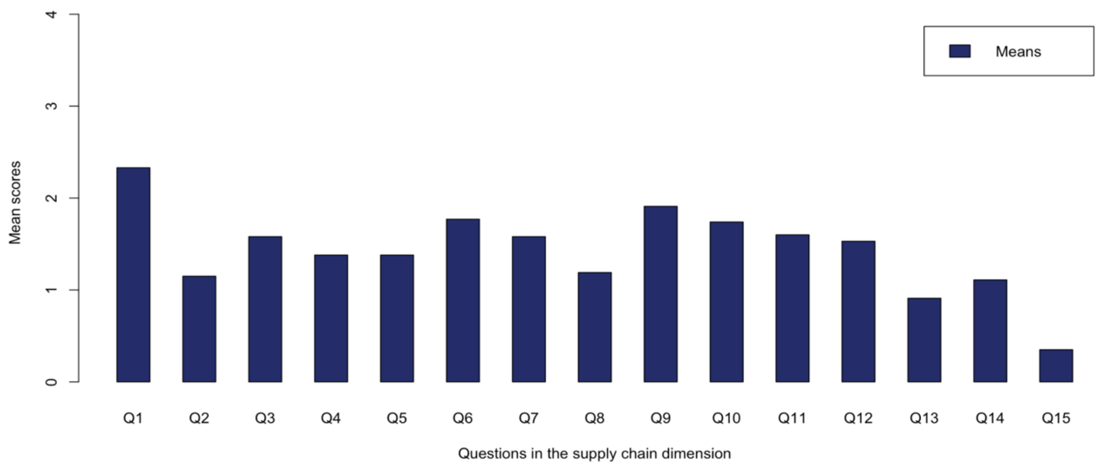



Figure 44. Mean scores of the questions in the manufacturing dimension

Tracking energy consumption among different departments of the company is assessed in Q15 and it has a mean score of 0.35 as lowest under this dimension. Most of the companies do not have specific tracking solutions for energy consumption and the cost is calculated as one for all the operations as it can be seen from the low scores for Q15 in Figure 45. This question also reflects the perception of sustainability of SMEs as they are mostly cost oriented rather than finding solutions for massive energy consumptions or waste.

Maintenance of the machines used in the production is mainly made in case of a malfunction without using advanced methods like predictive maintenance or even periodic planned maintenance operations. Hence the distribution of scores for Q13 about maintenance operations is quite right skewed as it can be seen in Figure 45 and has a quite low mean score of 0.91.

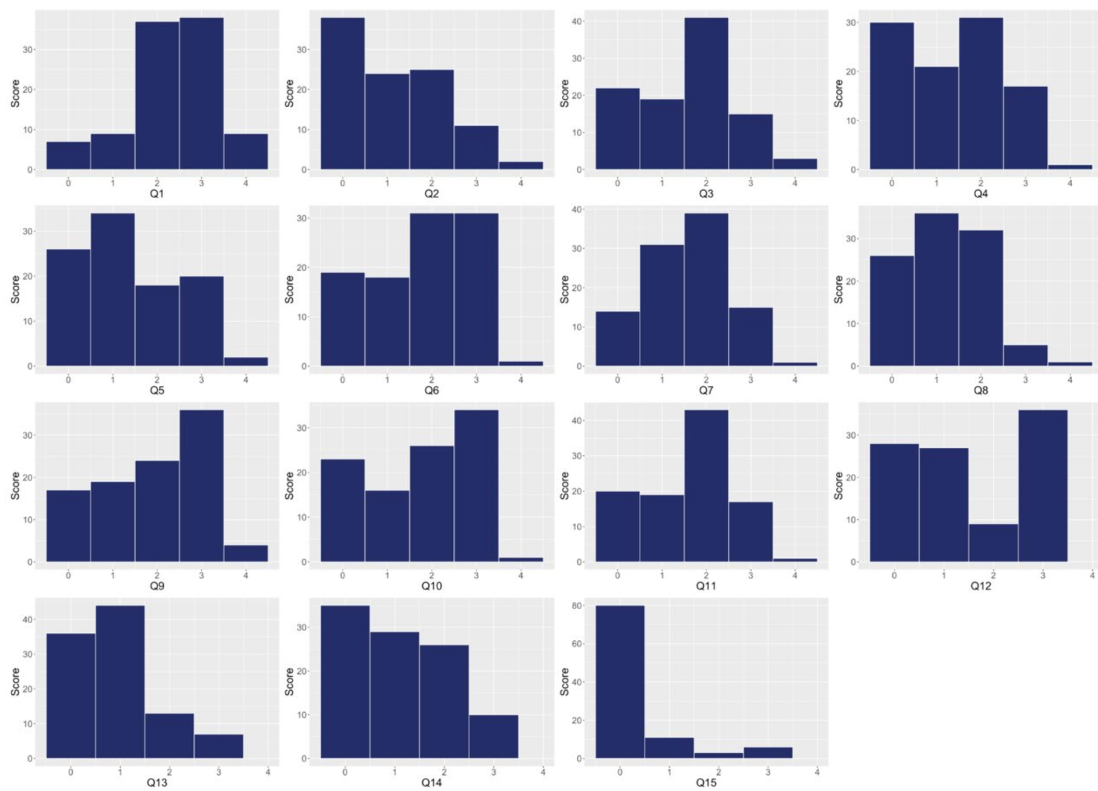



Figure 45. Distribution of question scores in the manufacturing dimension

Manufacturing mean score is 1.43 for 100 companies and the distribution is approximately symmetric as the skewness value is 0.120 (Figure 46). There is one company with a score higher than 3 and this company has 2.63 D3A score which is one of the highest.

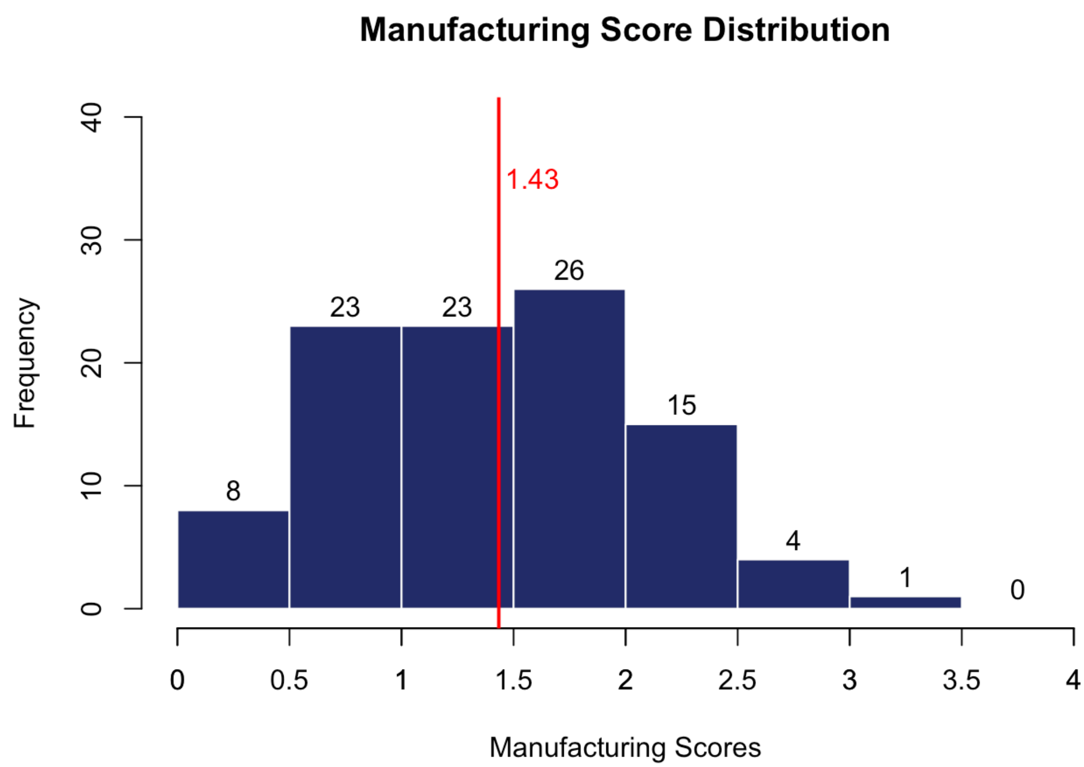



Figure 46. Distribution of the scores in the manufacturing dimension

Next, three clusters are created to analyze important questions, the beginner cluster has 29% of the companies, intermediate cluster has 31% and the advanced cluster has 40% companies. The distribution of scores for each cluster can be seen in Figure 47. Manufacturing dimension is the only dimension where advanced cluster is bigger than intermediate cluster.

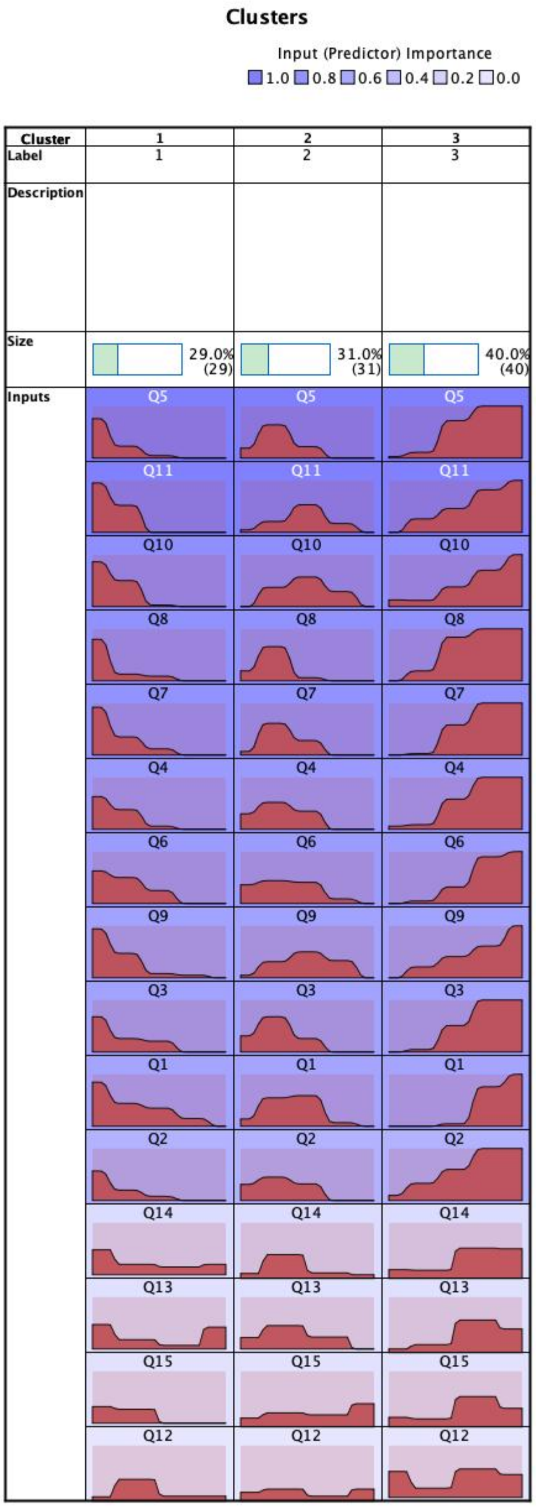



Figure 47. Question score distributions in the clusters for manufacturing dimension

Figure 48 shows the predictor importance values at clustering the companies with manufacturing dimension questions. Keeping track of production process (Q3) has the highest importance value as it clearly declares if there is a software that operators can enter data about production progress, or the managers should go to production area to follow the process. Likewise sharing the production data between different departments (Q8) also have an important role at differentiating companies. Keeping track of downtime of the machines (Q4) is another important question as the data gathered from the machines can be used in data analysis which can generate higher scores in other questions. Questions about maintenance do not have high importance values to create clusters as expressed in the distribution results. Q12 has almost the same mean score for all 3 clusters as it can be seen from Figure 49.

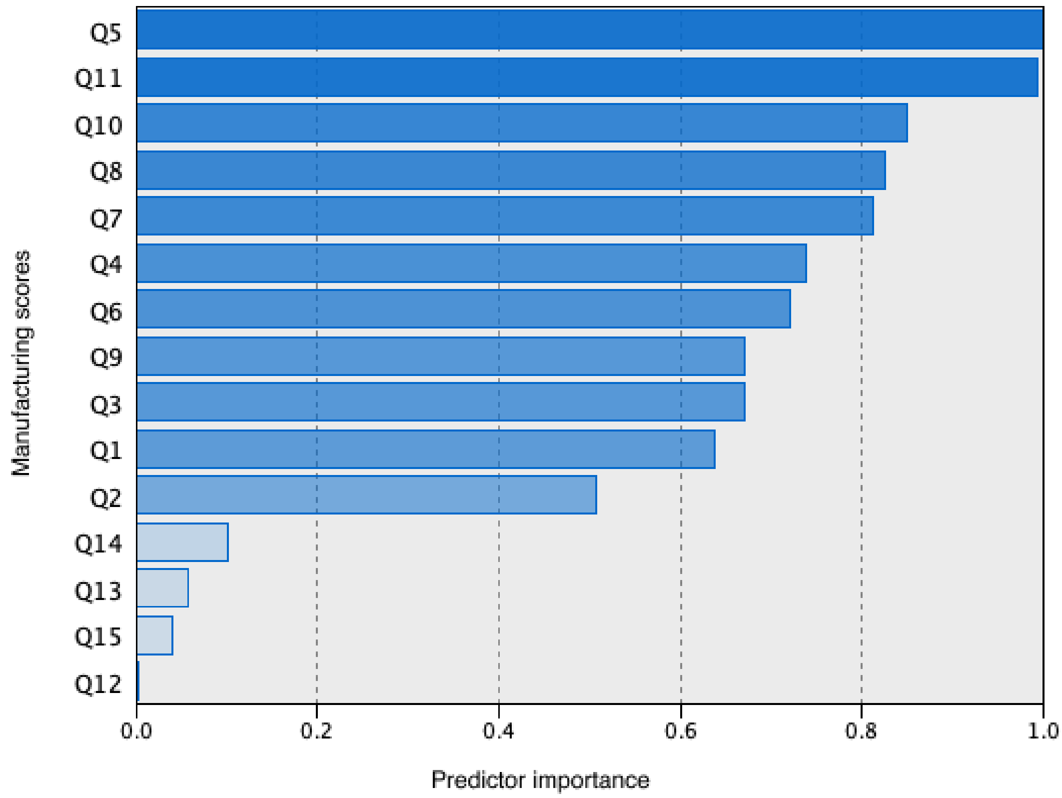



Figure 48. Predictor importance of questions for clustering in the organizational structure dimension

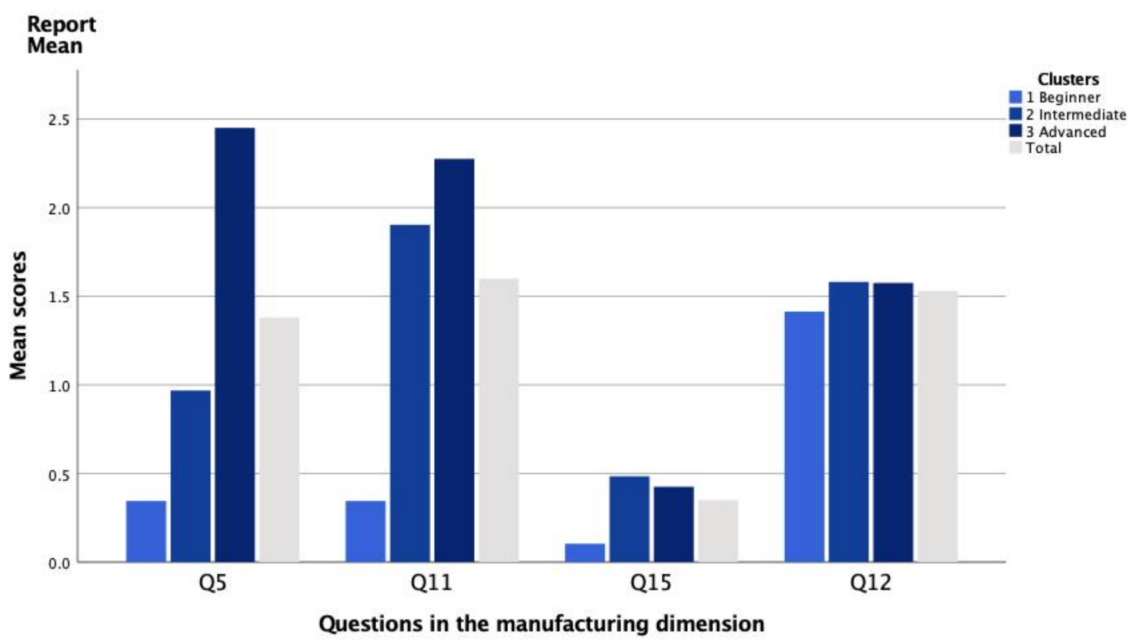



Figure 49. Mean scores of Q5, Q11, Q15, Q12 based on clusters

As all the other dimensions manufacturing dimension mean score is getting higher with number of employees. The mean score for micro-sized companies is 0.79, 1.06 for small-sized companies, 1.65 for middle-sized companies and 2.09 for big-sized companies as it can be seen from Figure 50. The difference between groups is highly significant proven with ANOVA tests results in Figure 51.

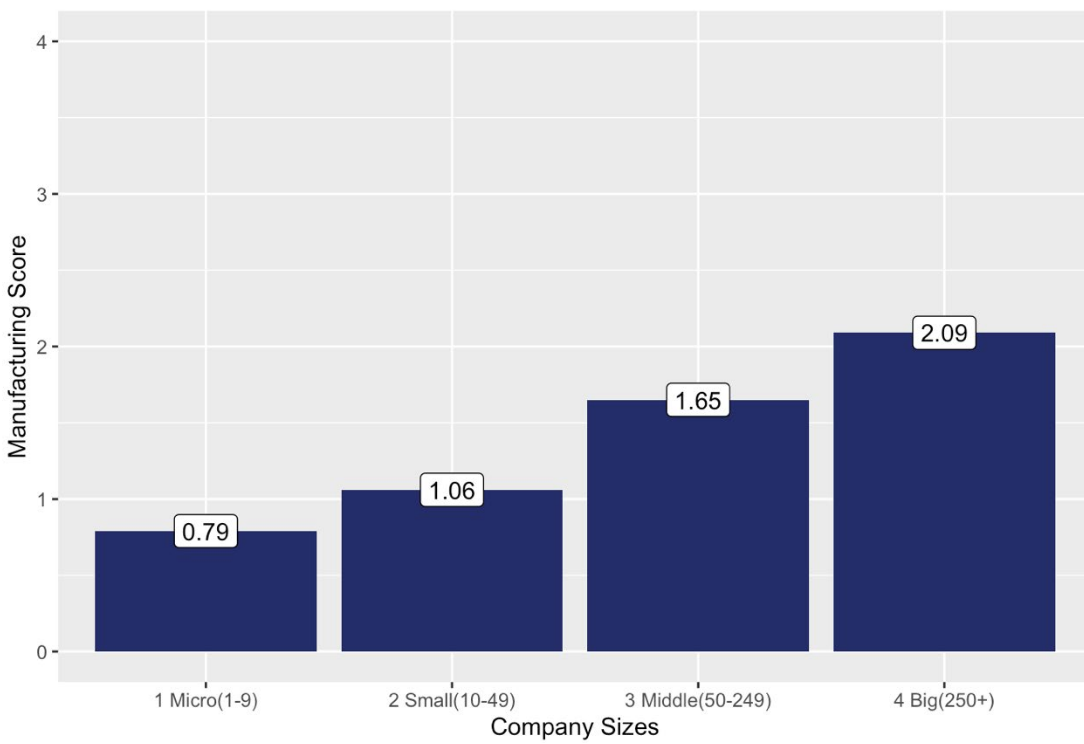



Figure 50. The mean manufacturing scores by company sizes

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Supply Chain Score * Size | Between Groups | (Combined) | 7.971 | 3 | 2.657 | 9.132 | .000 |
| | Within Groups | | 27.932 | 96 | .291 | | |
| | Total | | 35.904 | 99 | | | |

Figure 51. ANOVA results for the effect of company sizes on the manufacturing scores

The industry-based groups have different order compared to other dimensions and the plastic industry is the leader for manufacturing dimension with a mean score of 1.72 followed by metal industry with a mean score of 1.65 (Figure 52). Automation industry has the lowest mean score with 0.85 followed by textile industry with 0.87. The nature of automation industry is long-term projects with low repetitive actions. Therefore, the low scores can be expected for automation industry. However, textile industry needs to be improved as it has bigger opportunities in terms of automation of the processes and having digital information flow from the production. The difference is significant between groups as shown in ANOVA tests result in Figure 53 (p-value < .05).

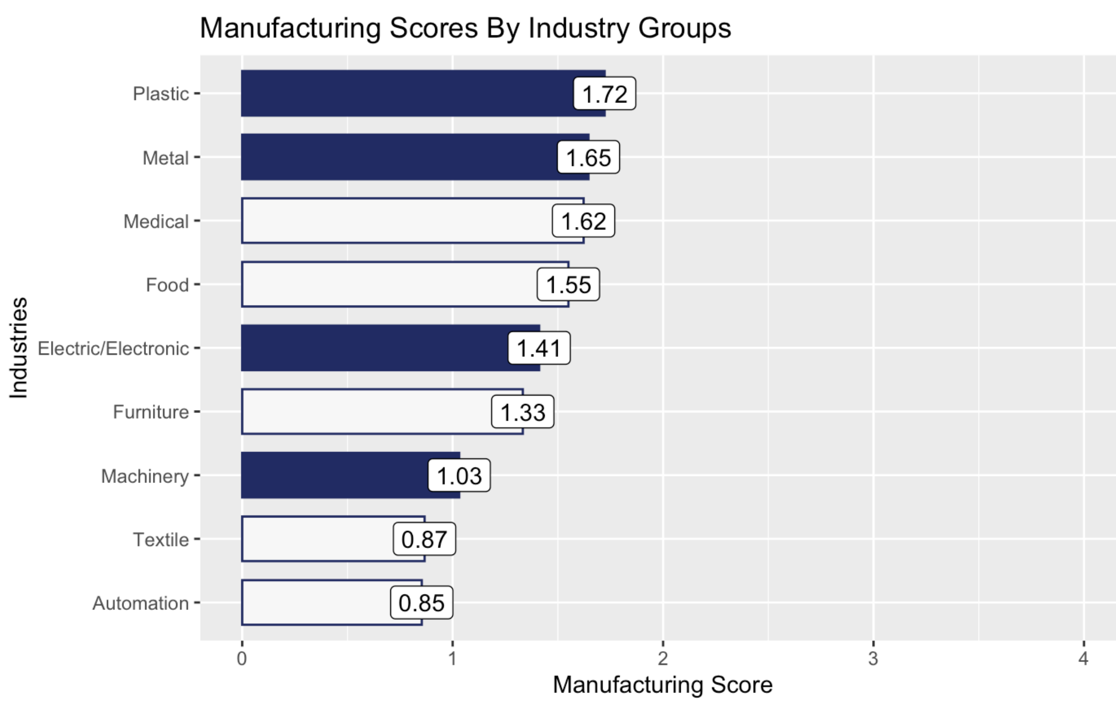



Figure 52. Customer score by industry groups

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Manufacturing_score * Industry | Between Groups | (Combined) | 7.901 | 8 | .988 | 2.300 | .027 |
| | Within Groups | | 39.081 | 91 | .429 | | |
| | Total | | 46.982 | 99 | | | |

Figure 53. ANOVA results for the effect of industry groups on the manufacturing scores

## 5.2. D3A Score Analysis

Using the similar steps, we followed to analyze the dimension scores in Section 5.1, now we scrutinize the overall digital performances of companies in relation to their DX dimension performances.

We start by interpreting the dimension scores of the companies to identify the most improved and the weakest areas in the overall digital performances of companies.

Then, we calculate the D3A scores of companies as the arithmetic means of their DX dimension scores. D3A score is an evaluation of the overall digital performance of a company. We explore the mean and the distributions of the D3A scores and generate insights about the overall performance of SMEs.

Next, the companies are clustered with respect to their DX scores in five DX dimensions. We use the two-step clustering algorithm with continuous D3A scores. Overall clustering enables us to see which dimensions are more important in differentiating the SMEs' overall digital maturity levels. It also helps us to explore the current state of the DX maturities of SMEs under study.

We further improve our analyses to explore the impacts of company size and industry on the D3A scores. The changes in the D3A scores of companies with respect to the company sizes and industries are analyzed by ANOVA tests to see if these factors significantly affect the overall digitalization levels of companies.

### 5.2.1. Dimensional Performances

We illustrate the dimensional performances of companies by a radar chart in Figure 54. The highest digitalization levels are realized at the organizational structure dimension (mean = 1.52) and then in the manufacturing dimension (mean = 1.43). Indeed, the latter is quite expected since all 100 SMEs are coming from the manufacturing industry. However, it is not very intuitive that the SMEs have their highest digital performances in the organizational structure dimension. This performance might be caused by the requirements for export activities of standard institutions and governmental obligations which eventually lead SMEs to improve their organizational structure. For instance, ISO quality certificates needs organizational structure declaration and strategic plan for at least five years which help SMEs to score higher in organizational structure dimension of D3A. High scores in the organizational structure point out a potential of DX awareness among SMEs which is very promising for their future digital progress.


Figure 54. Mean DX dimension scores of 100 SMEs

The weakest digital performance of the SMEs is realized at the supply chain dimension (mean = 1.17). Low scores in the supply chain dimension are quite expected in SMEs, since they do not have improved end-to-end integration capabilities. Collaboration and data integration in the supply chain require financial capacity and knowhow, and these are the weak characteristics of SMEs (Mittal et al., 2018).

We see that the digital performances of 100 SMEs are very low in all DX dimensions; highest being realized at the organizational structure score as 1.52 and the lowest is recognized at the supply chain dimension as 1.17. Manufacturing dimension (mean = 1.43), customer dimension (mean = 1.35) and product dimension (mean = 1.24) scores are less than moderate. We realize that SMEs need to improve their capabilities in all DX dimensions towards the targets generated by an I4.0 vision.

5.2.2. Distribution of D3A scores

The overall mean D3A score of 100 companies is calculated as 1.34. We realize a quite symmetric and bell-shaped distribution of the D3A scores in Figure 55 with the skewness 0.176. The highest D3A score is 2.75 and it belongs to a middle-sized company from electric/electronic industry group. On the other side, the lowest D3A score is 0.11 and it is the score of a micro-sized company from plastic industry group. There are only 3 companies that have D3A scores higher than 2.5. These companies come from X, Y and Z industries. We observe that 60% of SMEs have D3A scores which are less than the overall average 1.34.

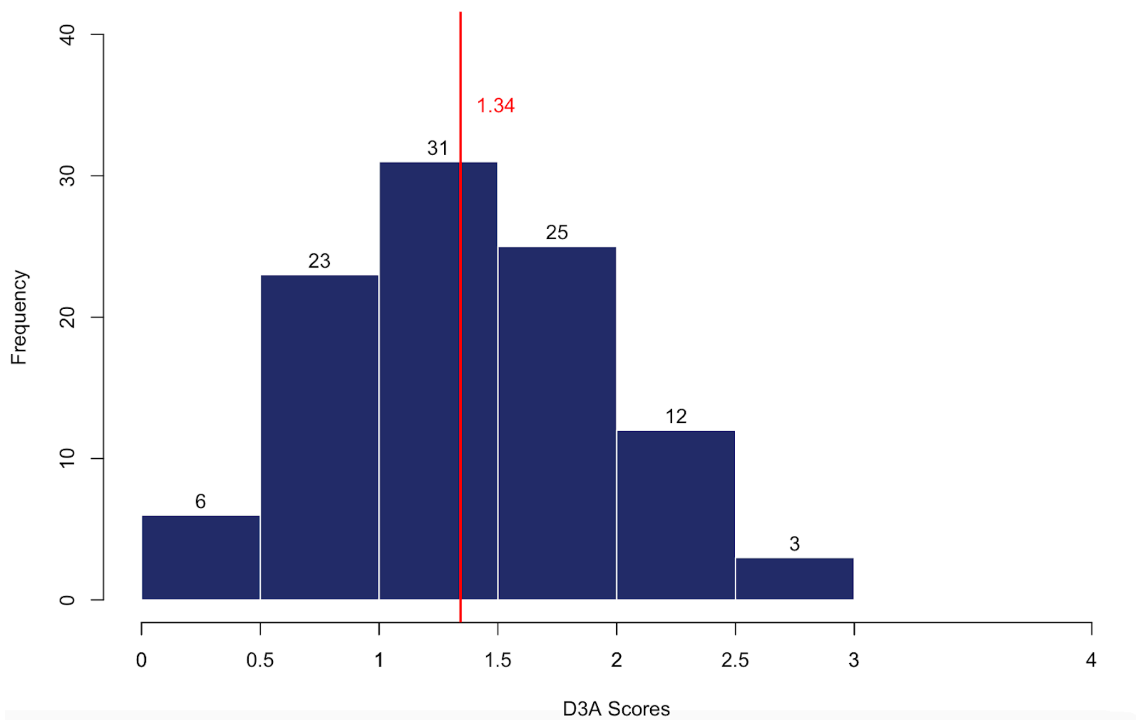



Figure 55. Distribution of D3A scores of 100 SMEs

The discussions for the poor performance of SMEs in all DX dimensions and the overall D3A scores call our attention to the urgent need to identify the critical areas that will support SMEs in fast and effective DX of their processes.

### 5.2.3. Clustering of Companies with D3A score

Now we group 100 SMEs under three clusters based on their scores in five DX dimensions by using the two-step clustering algorithm. Accordingly, 40% of the companies are placed under the first cluster with a mean D3A score of 0.80 that represents the beginners; 41% of the companies are placed in the second cluster with a mean D3A score of 1.48 which are the intermediate companies and the rest 19% of the companies are in the third cluster with a mean D3A score of 2.16 that represents the advanced group as it can be seen in Table 3.

The distribution of dimension scores based on clusters are provided in Figure 56. Beginner cluster scores are mostly between 0-1 and closer to 0, intermediate cluster scores are mostly around 2 and advanced cluster scores are mostly around 3. Product dimension score distribution is relatively flatter which means beginner cluster has companies with high product dimension scores or advanced cluster has companies with low product dimension scores. This result shows that product dimension is not good at differentiating the companies.

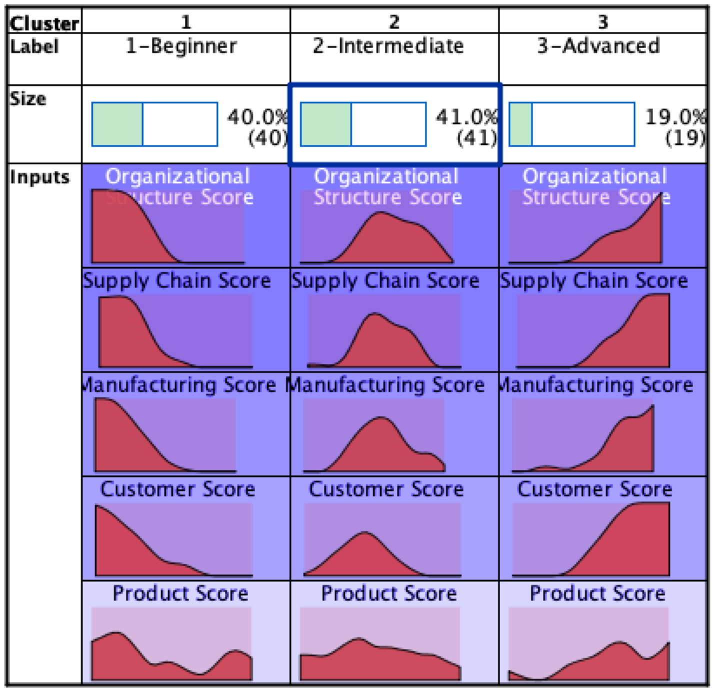



Figure 56. Dimension score distributions in the clusters for D3A score

We provide mean scores of five dimensions based on clusters in Table 3 where columns that are higher than mean score are highlighted. Accordingly, the average scores for organizational structure dimension significantly increase as 0.7, 1.9 and 2.5 among the three clusters. The average scores of clusters are closer to each other for customer, supply chain and manufacturing dimensions. Product dimension's mean scores are relatively lower than other dimensions for intermediate and advanced cluster. On the other hand, beginner cluster has a higher mean score than organizational structure, supply chain and manufacturing score.

Another interesting insight from the mean comparisons shown in Table 3 is that manufacturing dimension cluster average scores are higher than D3A average scores for each cluster. However, supply chain average scores are lower than D3A average scores for each cluster. This shows that supply chain dimension scores pulled down the D3A scores of companies in general.

Table 3. Mean Scores of Five Dimensions Based on Clusters

| Clusters | Organizational Structure Score | Customer Score | Product Score | Supply Chain Score | Manufacturing Score | D3A Score |
|---|---|---|---|---|---|---|
| 1 | 0.72 | 0.94 | 0.90 | 0.65 | 0.83 | 0.79 |
| 2 | 1.85 | 1.37 | 1.30 | 1.24 | 1.64 | 1.48 |
| 3 | 2.45 | 2.18 | 1.81 | 2.04 | 2.25 | 2.15 |
| Total | 1.51 | 1.35 | 1.23 | 1.16 | 1.43 | 1.33 |

Next, predictor importance of each dimension is provided in Figure 53. Organization dimension score has the highest importance score at clustering the companies whereas product dimension score has the lowest impact. As we discussed beforehand for the distribution of the scores for product dimension, it can be said that product development practices may vary depending on the field of the product. Therefore, product dimension scores do not directly reflect the DX maturity of the companies.

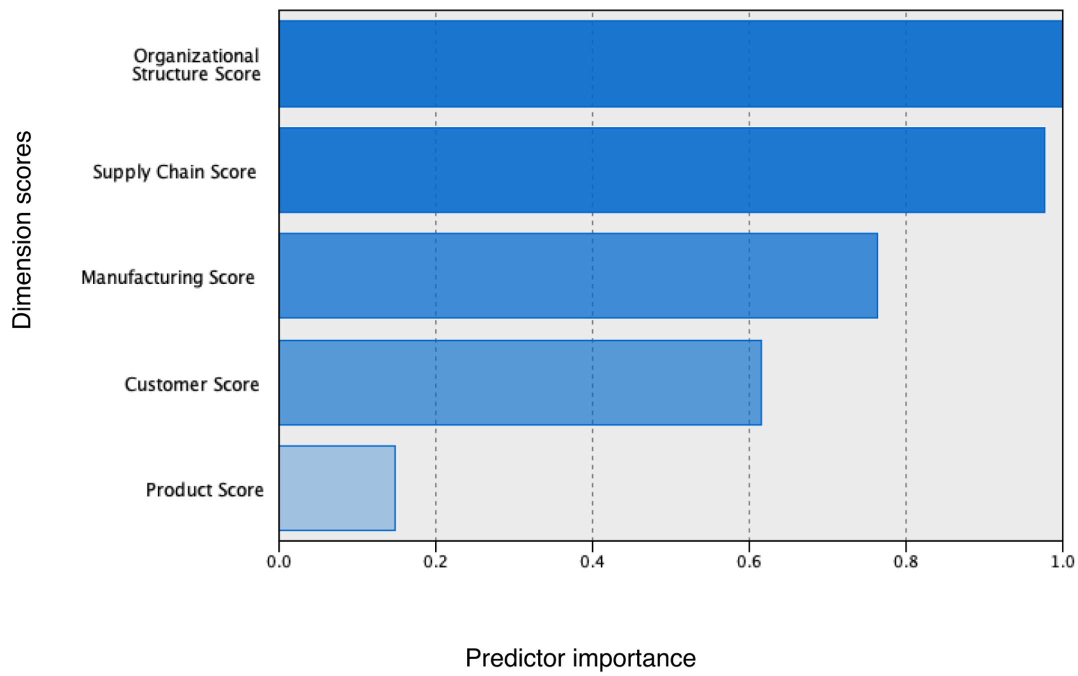



Figure 57. Predictor importance of dimensions for clustering with D3A scores

5.2.4. Impacts of company size and industry

Similar to our observations in the DX dimension scores in the above section, mean D3A scores increase with the company sizes as seen in Figure 58. Micro-sized companies have a mean of 0.86, small-sized companies have a mean of 1.06, middle-sized companies have a mean of 1.49 and finally big-sized companies have a mean score of 1.91. Furthermore, we statistically prove that company size is a very significant factor (p-value $< .001$) in the overall digital maturity of SMEs. This follows from the ANOVA analysis we provide in Figure 59.

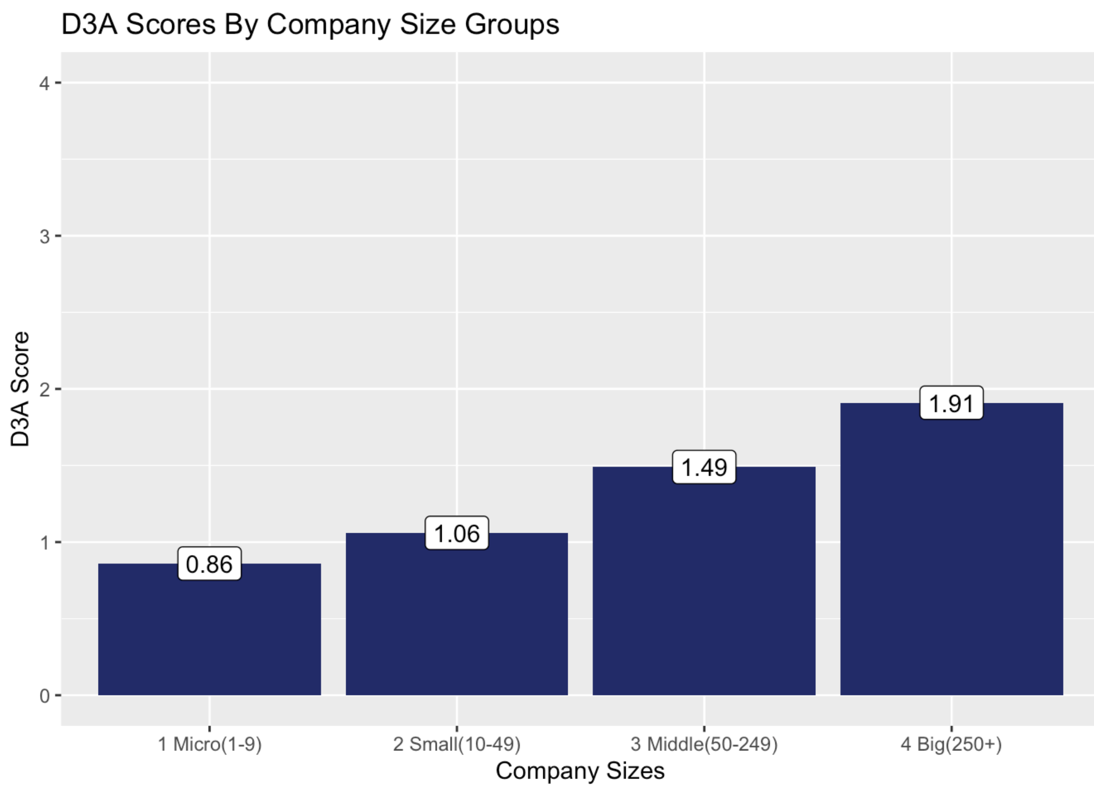



Figure 58. D3A scores by company size groups

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| D3A Score * Size | Between Groups | (Combined) | 9.211 | 3 | 3.070 | 13.308 | .000 |
| | Within Groups | | 22.149 | 96 | .231 | | |
| | Total | | 31.360 | 99 | | | |

Figure 59. ANOVA results for the effect of company sizes on the D3A scores

The digital performances of industries are compared with respect to their mean D3Ascores in Figure 60. The highest mean of D3A scores is in food industry (mean = 1.51) and metal industry (mean = 1.49) whereas the lowest mean of D3A scores is, in textile industry (mean = 0.85), noting that food industry has less than 10 companies in our sample, we can conclude that the metal industry has the highest digitalization level among nine manufacturing industries.

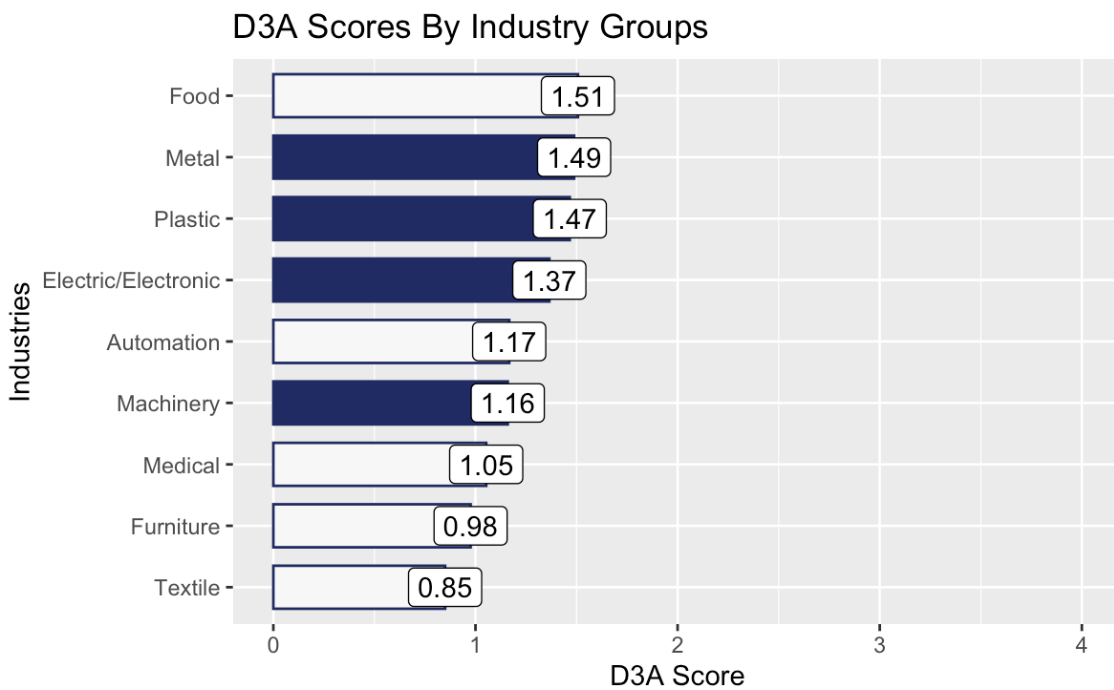



Figure 60. D3A scores by industry groups

However, ANOVA analysis we provide in Figure 61 shows that the difference between industry groups is not significant enough to statistically point out digitally improved industries (p-value = .234). It is an expected outcome as the size of industry-based groups are not equal and the companies under the same industry group do not have common DX background and practice.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| D3A Score * Industry | Between Groups | (Combined) | 3.306 | 8 | .413 | 1.340 | .234 |
| | Within Groups | | 28.054 | 91 | .308 | | |
| | Total | | 31.360 | 99 | | | |

Figure 61. ANOVA results for the effect of industries on the D3A scores

# CHAPTER 6:

# ANALYSIS OF FACTORS THAT AFFECT THE DX MATURITY

Several hypotheses about digital maturity of SMEs are developed during the theoretical development process of D3A and the detailed statistical analyses of the dimensions. In this section, we generate managerial insights by studying the relationships between the DX scores in different dimensions and exploring the factors that affect the DX maturity levels of companies such as company size, industry, and the level of innovation.

Throughout the rest of the statistical tests in this section, significance levels less than 1% ($p < 0.01$) are referred to as highly significant and are considered as very strong evidence to prove our hypothesis. Significance levels between 1% - 5% ($.01 \leq p < .05$) are significant. Significance levels between 5% - 10% ($.05 \leq p < .10$) imply weak significance and show suggestive evidence for our hypothesis. Finally, significance levels greater than or equal to 10% ($p \geq .10$) provide little or no real evidence for the hypothesis that we want to show.

## 6.1. The relationship between DX dimensions

D3A score has positive correlations with all DX dimensions as we expect. Here, we analyze these relations with Pearson correlation tests to generate more managerial insights. Figure 62 includes the cross correlations among the DX dimension scores as well as the D3A scores. The highest positive correlation between the DX dimension scores is observed among supply chain and manufacturing dimensions with $r = .756$ (p-value $< .01$). In manufacturing dimension, DX maturity is mainly assessed with the level of vertical integration whereas in the supply chain dimension both end-to-end integration and horizontal integration are evaluated. The highly significant positive correlation between these two dimensions indicates that the level of vertical, horizontal, and end-to-end integration are related to each other. It can be said that companies invest in the digitalization of manufacturing systems and collecting data from inner operations can share the insights gained from these processes with other parties of the value chain, thus have higher digitalization maturity in supply chain operations as well.

| | | Organizational Structure Score | Customer Score | Product Score | Supply Chain Score | Manufacturing Score | D3A Score |
|---|---|---|---|---|---|---|---|
| Organizational Structure Score | Pearson Correlation | 1 | .716** | .421** | .755** | .726** | .907** |
| | Sig. (2-tailed) | | .000 | .000 | .000 | .000 | .000 |
| | N | 100 | 100 | 100 | 100 | 100 | 100 |
| Customer Score | Pearson Correlation | .716** | 1 | .390** | .709** | .563** | .823** |
| | Sig. (2-tailed) | .000 | | .000 | .000 | .000 | .000 |
| | N | 100 | 100 | 100 | 100 | 100 | 100 |
| Product Score | Pearson Correlation | .421** | .390** | 1 | .244* | .285** | .557** |
| | Sig. (2-tailed) | .000 | .000 | | .015 | .004 | .000 |
| | N | 100 | 100 | 100 | 100 | 100 | 100 |
| Supply Chain Score | Pearson Correlation | .755** | .709** | .244* | 1 | .756** | .874** |
| | Sig. (2-tailed) | .000 | .000 | .015 | | .000 | .000 |
| | N | 100 | 100 | 100 | 100 | 100 | 100 |
| Manufacturing Score | Pearson Correlation | .726** | .563** | .285** | .756** | 1 | .851** |
| | Sig. (2-tailed) | .000 | .000 | .004 | .000 | | .000 |
| | N | 100 | 100 | 100 | 100 | 100 | 100 |
| D3A Score | Pearson Correlation | .907** | .823** | .557** | .874** | .851** | 1 |
| | Sig. (2-tailed) | .000 | .000 | .000 | .000 | .000 | |
| | N | 100 | 100 | 100 | 100 | 100 | 100 |

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 62. Cross correlations between dimensions and D3A score

The lowest correlation between D3A scores and DX dimension scores is achieved at the product dimension with r = .557 (p-value < .001) whereas the highest correlation between D3A scores and DX dimension scores is achieved at organizational structure dimension r = 0.907 (p-value < .001) where both are highly significant. The latter supports the generally accepted finding in the literature that the lack of organizational structure and management capabilities act as boundaries for the success of DX (Mittal et. al, 2018). This leads us to establish our first hypothesis for the correlation of organizational score with other dimensions' scores and D3A score.

$H_1$ – Companies with higher organizational structure scores have better performances in other DX dimensions and have more improved D3A scores.

Pearson correlation analysis in Figure 62 shows that all dimension scores and the D3A scores have positive correlations with the organizational structure scores. These strong correlations prove that companies who have high scores for organizational structure dimension, score higher in all other dimensions, hence have higher D3A scores as well. Therefore, $H_1$ is accepted. We can state that organizational structure affects the overall DX maturity. Having a strategic plan and taking decisions according to this plan enhances the collaboration between upper management and employees which leads a company to score higher in organizational structure dimension. DX roadmaps can be generated following this strategic plan to follow which areas to focus in the first place. The application of DX projects must be addressed to support business model of the company and strategic goals in order to have a high return of investment that would eventually lead more projects to be applied successfully. Having said that, the vision of the upper management that is reflected in this strategic plan is crucial to implement digital tools successfully for all the departments of the company.

## 6.2. The effect of company size and industry group on DX dimension scores and D3A score

Next, we provide the overall conclusion of the analyses made in Chapter 5 and summarize the effect of company size and industry groups on the DX dimension scores and D3A scores of companies. We compare the mean scores of all five DX dimension scores and D3A scores between the categoric variables of company size and industry groups. Hypotheses 2 and 3 are established to see if these comparisons between groups of company sizes and industries are statistically significant.

$H_2$: D3A scores and DX dimension scores differ between company size groups.

We apply ANOVA tests to observe the effect of company size on D3A scores and DX dimensions. The ANOVA results in Figure 63 shows that company size highly affects the DX scores in the organizational structure, customer, supply chain and manufacturing dimensions, as well as the D3A scores of companies. However, the effect of company size on product dimension is not significant (p-value = .120 > 0.10). Larger companies tend to have more improved performances in all DX dimensions as well as D3A scores (Figures 10, 19, 39, 49, 57). However, this result is not apparent in product dimension, although in Figure 30 big companies seem to have higher product dimension scores. As explained in Chapter 5.1.3 company size is not a significant factor on product dimension scores due to the exceptionally high scored micro-sized companies and low scored medium-sized companies.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Organizational Structure Score * Size | Between Groups | (Combined) | 16.520 | 3 | 5.507 | 10.898 | .000 |
| | Within Groups | | 48.508 | 96 | .505 | | |
| | Total | | 65.028 | 99 | | | |
| Customer Score * Size | Between Groups | (Combined) | 7.622 | 3 | 2.541 | 8.337 | .000 |
| | Within Groups | | 29.258 | 96 | .305 | | |
| | Total | | 36.880 | 99 | | | |
| Product Score * Size | Between Groups | (Combined) | 3.845 | 3 | 1.282 | 1.997 | .120 |
| | Within Groups | | 61.611 | 96 | .642 | | |
| | Total | | 65.456 | 99 | | | |
| Supply Chain Score * Size | Between Groups | (Combined) | 7.971 | 3 | 2.657 | 9.132 | .000 |
| | Within Groups | | 27.932 | 96 | .291 | | |
| | Total | | 35.904 | 99 | | | |
| Manufacturing Score * Size | Between Groups | (Combined) | 14.677 | 3 | 4.892 | 14.538 | .000 |
| | Within Groups | | 32.305 | 96 | .337 | | |
| | Total | | 46.982 | 99 | | | |
| D3A Score * Size | Between Groups | (Combined) | 9.211 | 3 | 3.070 | 13.308 | .000 |
| | Within Groups | | 22.149 | 96 | .231 | | |
| | Total | | 31.360 | 99 | | | |

Figure 63. ANOVA results for the effect of company sizes on the dimension scores and D3A score

$H_3$: DX Dimension scores and D3A scores differ between industry groups

We apply ANOVA tests to observe the effect of industries on D3A scores and DX dimensions. ANOVA tests in Figure 64 show significant results for the effect of industry groups on organizational structure, product, supply chain and manufacturing dimension scores (p-value < .05). Customer dimension is the only one out of five dimensions where the industry group-based comparisons are not significant (p-value = .126 > 0.10). Hence, the company performances in the DX dimensions for organizational structure, product, supply chain and manufacturing differ significantly between industries, whereas the DX performance in the customer dimension as well as the overall D3A performances of companies do not significantly differ between industries.

In Figure 22, the mean DX scores for customer dimension for food industry seems to be significantly larger than all other industries. Although this difference is not statistically significant, we still want to highlight the success of food industry which is the only industry in service sector. SMEs in food industry act as suppliers in service sector which is closest to the end customers and requires very fast response. As a natural consequence, food industry is expected to score higher in customer dimension than the other pure manufacturing industries. As explained in Chapter 5.1.2 food industry has much higher customer scores but it constitutes only 4% of all companies which is not enough to make this difference significant. On the opposite side, textile, automation, medical and furniture industries have relatively poor customer scores, but this difference is not significant neither as they constitute 17% of all companies.

The mean D3A scores of industries differ between 0.85 (textile industry) and 1.51 (food industry) in Figure 60. However, these deviations are not statistically significant. D3A scores depend on five dimension scores, four of which are significantly affected by the industry group. However, the customer dimension score is not significantly affected by the industry group which might be the reason why the overall D3A scores do not significantly differ between industries.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Organizational Structure Score * Industry | Between Groups | (Combined) | 10.387 | 8 | 1.298 | 2.162 | .038 |
| | Within Groups | | 54.641 | 91 | .600 | | |
| | Total | | 65.028 | 99 | | | |
| Customer Score * Industry | Between Groups | (Combined) | 4.632 | 8 | .579 | 1.634 | .126 |
| | Within Groups | | 32.248 | 91 | .354 | | |
| | Total | | 36.880 | 99 | | | |
| Product Score * Industry | Between Groups | (Combined) | 11.402 | 8 | 1.425 | 2.399 | .021 |
| | Within Groups | | 54.054 | 91 | .594 | | |
| | Total | | 65.456 | 99 | | | |
| Supply Chain Score * Industry | Between Groups | (Combined) | 5.886 | 8 | .736 | 2.230 | .032 |
| | Within Groups | | 30.018 | 91 | .330 | | |
| | Total | | 35.904 | 99 | | | |
| Manufacturing Score * Industry | Between Groups | (Combined) | 7.901 | 8 | .988 | 2.300 | .027 |
| | Within Groups | | 39.081 | 91 | .429 | | |
| | Total | | 46.982 | 99 | | | |
| D3A Score * Industry | Between Groups | (Combined) | 3.306 | 8 | .413 | 1.340 | .234 |
| | Within Groups | | 28.054 | 91 | .308 | | |
| | Total | | 31.360 | 99 | | | |

Figure 64. ANOVA results for the effect of industry groups on the DX dimension scores and D3A score

## 6.3. The effect of innovation levels on the D3A scores of companies

Innovation skills are the key to create dynamic business models to adapt to the technological advancements. However, as discussed in Chapter 2, SMEs lack the innovation culture and strategy to improve themselves (Terziovski, 2010). Under this obstacle, we still wonder if more improved innovation culture leads to higher digitalization in SMEs.

The product dimension of D3A framework focuses on assessing the level of innovation of a company to see if they can easily adapt to the changing needs of the customer and improve their operations accordingly. We analyze the effect of innovation from the perspective of new product development processes (Q9), having an R&D center (Q1) and level of academic collaborations (Q3) (Appendix A). We establish hypotheses 4, 5 and 6 to see if these measurements have significant effects on D3A scores.

$H_4$: Innovation practices of companies have impacts on D3A scores.

Q9 of product dimension is addressing directly to the innovation level of the company with decision making processes and management of new product development processes (Appendix A). Scores are given increasingly depending on using data in new product development decisions and collaboration between departments. A company with a score 0 in this question means the decisions are made by the managers without analyzing the performance of the products analytically whereas a score 4 means the new product decisions are made based on analytical insights and participation of the employees. Innovation is addressed with a focus on the application of new product ideas in a collaborative process without a direct hierarchy. The ANOVA test in Figure 65 shows that innovation levels of companies are highly significant on D3A scores ($p < .01$). Therefore, $H_4$ is confirmed. In Figure 66, we plot the mean D3A scores for increasing levels of innovation. So, companies that generate new product ideas collaboratively, based on analytical insights from sales or customer feedback tend to have more improved digital maturities realized in higher D3A scores.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| D3A_score * Q9 | Between Groups | (Combined) | 9.923 | 4 | 2.481 | 10.993 | .000 |
| | Within Groups | | 21.438 | 95 | .226 | | |
| | Total | | 31.360 | 99 | | | |

Figure 65. ANOVA results for the effect of the level of innovation in a company on product dimension and D3A score

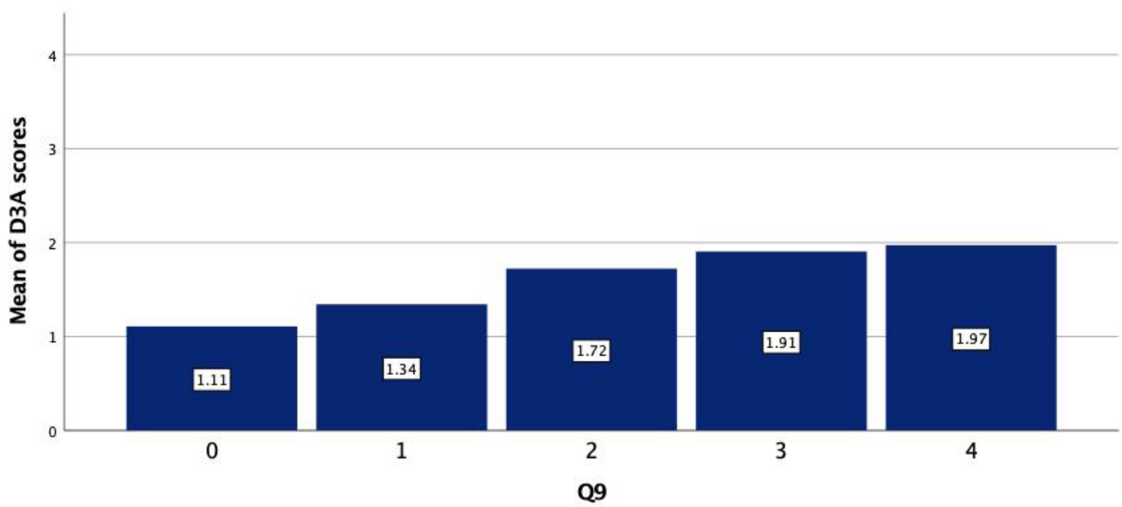



Figure 66. Mean D3A scores for Q9 in product dimension

Turkish government offers generous incentives like tax deductions and exemptions with special laws to companies with R&D projects. Companies need to prove that their R&D centers are eligible to develop new products, materials, supplies, devices, equipment, procedures, and systems through new methods in order to gain these incentives. In our sample, companies with R&D centers are mostly from electric/electronic industry as the nature of the production requires new technical information. In $H_5$ we analyze the effect of having an R&D center with the D3A scores of companies.

$H_5$: Qualification of R&D departments have impacts on D3A scores.

Q1 in the questionnaire is used to assess the qualification of R&D department (Appendix A). The qualification of R&D department goes from having a dedicated department for R&D to having this department as a separate R&D center. A company is scored 0 if there is no R&D department at all, scored between 1-3 evaluating the independence of this department, and finally it is scored 4 if there is an R&D center that is located in a technopark. We test this hypothesis by ANOVA in Figure 67. ANOVA test result shows that the scores for Q1 in product dimension have highly significant impacts on D3A scores of companies (p-value < .001). Hence, $H_5$ is accepted. In Figure 68, we plot the mean D3A scores for increasing qualifications of R&D departments. D3A scores of the companies tend to increase while the qualifications of R&D departments are scored between 0-3. Surprisingly companies scored 4 for this question have lower D3A scores. Score 4 shows that the R&D center is located in a technopark. Technoparks are government supported organizations built in technology development zones as defined in law no: 4691 to encourage R&D based companies by providing them high quality office area and support services. They also play an important role in university-industry-government cooperation and provide support for relatively smaller companies and startups. However, the related law was updated recently so that the companies would be able to open R&D centers in technoparks with small number of employees such as less than 10. This encouraged several companies to open R&D centers not for innovation purposes, but just to achieve savings in taxes by being located in technoparks. Hence, such companies do not have improved DX levels that are achieved through higher innovation levels. Therefore, even though having an office in a technopark provides better innovation and collaboration opportunities for companies, it does not directly mean that they have more improved digital maturity in their operations and organizations.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| D3A_score * Q1 | Between Groups | (Combined) | 9.215 | 4 | 2.304 | 9.883 | .000 |
| | Within Groups | | 22.145 | 95 | .233 | | |
| | Total | | 31.360 | 99 | | | |

Figure 67. ANOVA results for the effect of having an R&D center on dimension scores and D3A score

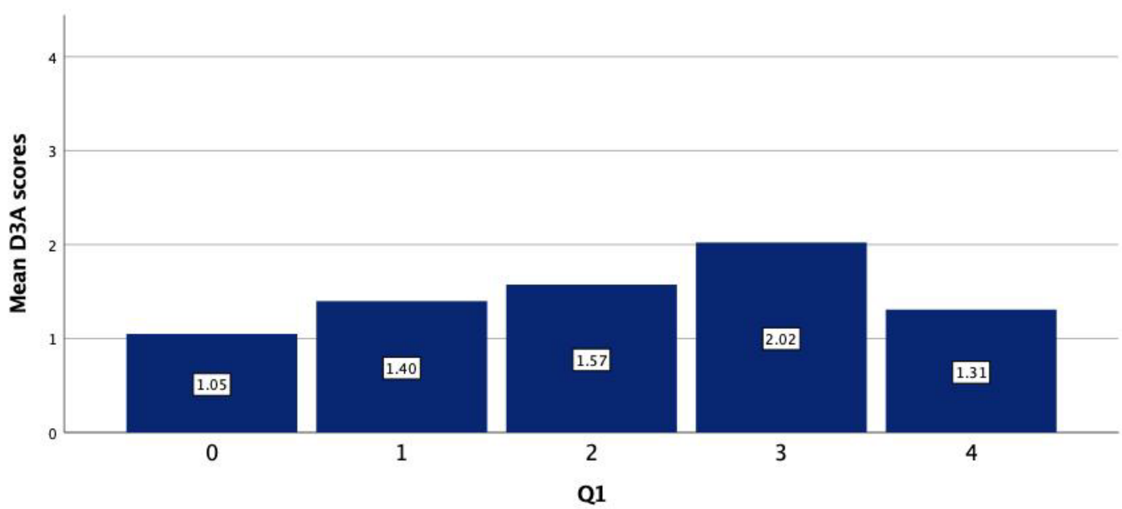



Figure 68. Mean D3A scores for qualification of R&D departments (Q1)

Lack of alliances with universities or other research institutions affects SMEs' research and development capabilities, which causes innovation to be a challenge in

SMEs (Mittal et al., 2018). The effect of academic collaborations on D3A scores of companies is analyzed in $H_6$.

$H_6$: Academic collaborations for R&D have impacts on D3A scores.

In the Q3 of product dimension, the collaborations with academic institutions are assessed. A company is scored between 0 and 4 depending on the level of academic collaborations for R&D with scores, 0: no collaborations, 1: internships, 2: consultancies, 3: academic projects with universities, 4: funding academic projects with universities. To generate more distinctive classes of academic collaborations we prefer to combine score categories 3 and 4. We provide the ANOVA test result in Figure 69 to see the effect of academic collaborations on D3A scores and find that this impact is highly significant (p-value $< .001$). Hence, $H_6$ is also confirmed. In Figure 70, we plot the mean D3A scores to observe the impact of increasing levels of academic collaborations. Accordingly, companies which have connections with academical institutions have higher D3A scores than the companies with no collaborations. Generating academic collaborations through student internships and using consultancies contribute similarly to the DX maturity of companies. Strikingly, the highest contribution to the DX maturity of the companies is achieved through generating joint projects with the universities and funding them. This finding is very critical in the sense that it proves the importance of academy-industry collaboration in digitalization of companies. Nevertheless, it highlights our efforts in this joint research between academia and industry where we aim to generate a DX assessment tool for the SMEs.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| D3A_score * Q3 | Between Groups | (Combined) | 6.103 | 4 | 1.526 | 5.739 | .000 |
| | Within Groups | | 25.257 | 95 | .266 | | |
| | Total | | 31.360 | 99 | | | |

Figure 69. ANOVA results for the effect of academic collaborations on D3A score

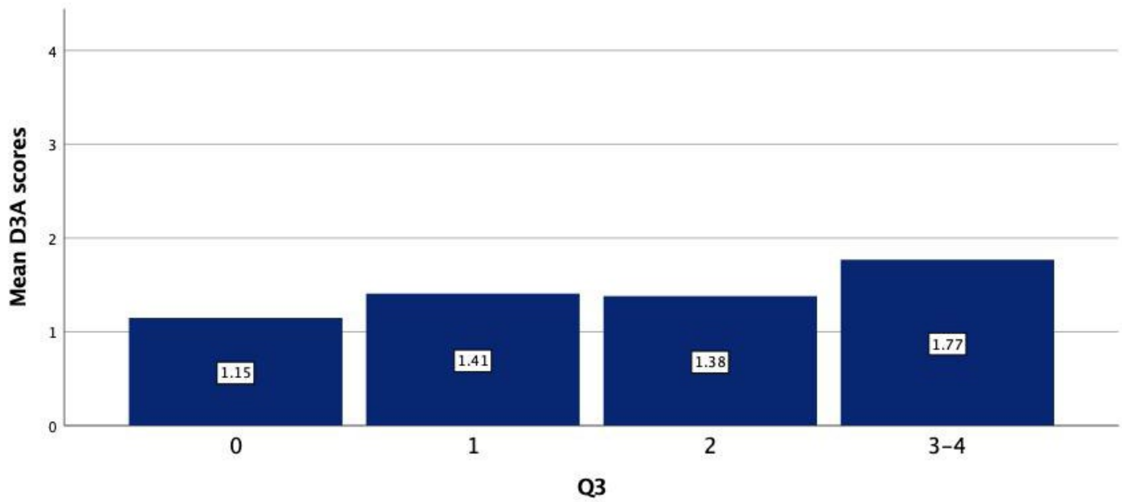



Figure 70. Mean D3A scores for academic collaborations for R&D (Q3)

## 6.4. The effect of product customization levels on the D3A scores of companies

Mittal et al., 2018 state that product customization skills are important in agile production and SMEs are more flexible than MNEs in this field. Product customization skills are one of the major competitive advantage of SMEs. Digital systems make these customizations easier and prevents mistakes during the processes. Producing custom products requires frequent changes in supply chain operations based on continuous information flow from customer operations. In particular, we expect that product customization ability of a company should be related to its digitalization in the DX dimensions for customer, supply chain and product. In $H_7$, we test the effect of product customization skills of a company on these dimension scores along with the overall D3A scores.

$H_7$: Product customization skills of companies have impacts on customer, supply chain, product dimension scores and D3A scores

Product customization skills are assessed in Q10 of the product dimension. We provide ANOVA test results in Figure 71 to analyze the effect of product customization skills on customer, supply chain, product dimension scores and D3A scores. We observe that these impacts are all very insignificant on customer, supply chain and D3A scores (p-value >> .10). We explain this with the argument that almost all the companies have high product customization abilities with Q10 scores changing between 3-4. So, the effect of high product customization on customer and supply chain dimension scores and D3A scores are not very apparent. However, product customization abilities still have significant effects on product dimension scores (p-value = .015). In Figure 72, we plot the mean product dimension scores for increasing levels of product customization abilities. We observe that companies that have no product customization capabilities (Q10 score = 0) are considerably weaker in product dimension scores. Companies with better product customization skills tend to have more improved DX scores in product dimension, but this impact seems to be very moderate.

| | | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|---|
| Customer_score * Q10 | Between Groups | (Combined) | .582 | 4 | .145 | .381 | .822 |
| | Within Groups | | 36.299 | 95 | .382 | | |
| | Total | | 36.880 | 99 | | | |
| Supply_score * Q10 | Between Groups | (Combined) | 1.500 | 4 | .375 | 1.036 | .393 |
| | Within Groups | | 34.403 | 95 | .362 | | |
| | Total | | 35.904 | 99 | | | |
| Product_score * Q10 | Between Groups | (Combined) | 7.904 | 4 | 1.976 | 3.262 | .015 |
| | Within Groups | | 57.552 | 95 | .606 | | |
| | Total | | 65.456 | 99 | | | |
| D3A_score * Q10 | Between Groups | (Combined) | .370 | 4 | .092 | .283 | .888 |
| | Within Groups | | 30.991 | 95 | .326 | | |
| | Total | | 31.360 | 99 | | | |

Figure 71. ANOVA results for the effect of product customization skills on dimension scores and D3A score

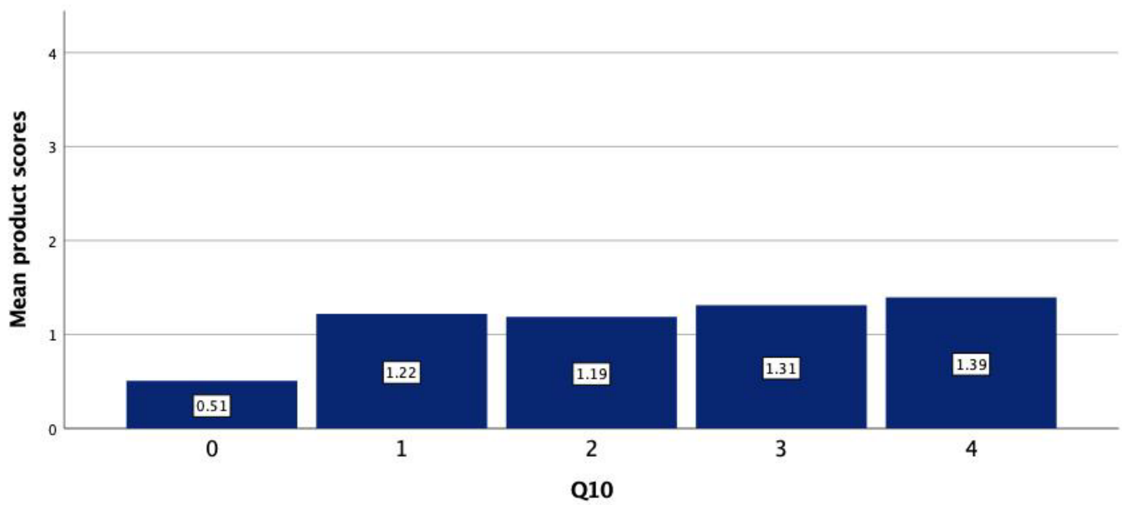



Figure 72. Mean D3A scores for Q10 in product dimension

# CHAPTER 7:

# RESULTS

In this section we provide an overall analysis of SMEs in our region by company size and by industry. We also provide general findings on the significant factors that affect the digital maturity of SMEs.

The overall mean of D3A scores of 100 companies is 1.34 over 4 and the highest score is 2.75 whereas the lowest score is 0.11. Supply chain dimension has the lowest mean score (1.17) whereas organizational structure dimension has the highest mean score (1.52) among the five DX dimensions. The low scores in supply chain dimension show that the communication between different parties of the value chain is not digitally managed and end-to-end integration is poor. The high scores in organizational structure dimension show the potential of digital maturity advancements as it reflects the digital readiness of the SMEs. There are no companies that have high scores in product, customer, supply chain or manufacturing dimensions without being advanced in organizational structure dimension which proves the importance of digital awareness and the management effect in DX maturity. Manufacturing dimension has the second highest mean score (1.43) which shows the effort of SMEs in investing on advanced technology for production. Customer score has a lower mean score as 1.35 showing the lack of data usage in customer management processes. Lastly, product dimension has a mean score of 1.24 that proves the challenges of SMEs face in innovative product development processes.

We group the companies under three main clusters based on their scores in 5 DX dimensions. The clusters represent the beginners, the intermediate and the advanced groups of companies in DX maturity. The advanced cluster has the lowest number of companies (19%) with a mean D3A score of 2.15 while the intermediate and beginner clusters are almost the same size, i.e., 41% and 40% with mean D3A scores of 1.48 and 0.79. Advanced cluster companies have the most improved scores in all DX dimensions. Intermediate cluster companies have moderate scores in all DX dimensions. However, the scores in product dimensions may be at all levels. Beginner cluster companies have very poor scores in all dimensions. Surprisingly, there are many companies with high product dimension scores in this cluster.

Companies come from nine main industry groups. Figure 73 provides the comparative evaluations of the DX performances of these industries in various DX dimensions as well as overall D3A scores. Let us recall that overall D3A scores and customer dimension scores are not found to be significantly different between industry groups. Nevertheless, food industry has the highest mean D3A score (1.51) and textile industry has the lowest mean D3A score (0.85). We briefly explain the DX performances of industry groups below in descending order of their mean D3A scores. In Figure 73 we interpret the mean scores as very poor: 0-0.5, poor: 0.5-1, moderate: 1-1.5, high: 1.5-2, very high: 2-4.

Food industry (D3A score = 1.51) has a very high performance in customer dimension. It has high scores in organizational structure, supply chain and manufacturing dimensions whereas it has a very poor score in product dimension. Its customer and supply chain dimension scores are the highest among others. The performance of the food industry is the poorest among all industries in product dimension.

Metal industry (D3A score = 1.49) has high scores in organizational structure and manufacturing dimensions. Indeed, it has the highest organizational structure scores among all industries. It has moderate scores for customer, product, and supply chain dimensions where the product is its poorest DX dimension.

Plastic industry (D3A score = 1.47) shows a similar performance with metal industry where the lowest performance in plastic industry is the supply chain dimension instead of product dimension. It has its highest performances in organizational structure and manufacturing dimensions whereas it has moderate scores for customer, product, and supply chain dimensions.

Electric/electronic industry (D3A score = 1.37) has moderate performances in all DX dimensions. However, it attains its highest performance in product dimension and this score is the second best among all industries. It has its lowest performance in supply chain dimension.

Machinery industry (D3A score = 1.17) has moderate scores in all DX dimensions. Its supply chain score is lowest, and it is poor. It receives its highest performance in organizational structure dimension.

Automation industry (D3A score = 1.16) has highly deviating scores. Its product score is very high, and it is the highest among all industries. It has moderate scores in organizational structure and customer dimensions whereas supply chain and manufacturing dimension scores are poor.

Medical industry (D3A score = 1.05) has moderate scores in organizational structure and customer dimensions whereas it has poor scores in product and supply chain dimensions. Surprisingly it has very high scores in manufacturing dimension which is the third highest score in all industries.

Furniture industry (D3A score = 0.98) has moderate scores in supply chain and manufacturing dimensions where the latter is its most improved dimension. It has poor scores in organizational structure, customer, and product dimensions.

Finally, textile industry (D3A score = 0.85) has poor scores in all DX dimensions except customer dimension where it has a moderate score.


Figure 73. Company evaluations by industry

Companies are in four different company sizes. Figure 74 provides the comparative evaluations of the DX performances of companies in various sizes. Let us recall that company size has significant effects on the D3A scores and all dimension scores except product dimension. However, performance ranking of companies in all dimensions are the same, i.e., mean D3A scores increase with the company sizes in all dimensions. In Figure 74, we interpret the mean scores as very poor: 0-0.5, poor: 0.5-1, moderate: 1-1.5, high: 1.5-2, very high: 2-4.

Big-sized companies have the highest scores for all dimensions and D3A scores. The scores in organizational structure and manufacturing dimensions are very high, whereas the scores are high in customer, product, and supply chain dimensions.

Middle-sized companies have high scores in organizational structure and manufacturing dimensions. They have moderate scores in customer, product, and supply chain dimensions.

Small-sized companies have moderate scores in all dimensions except supply chain dimension where they have poor scores.

Finally, micro-sized companies have poor scores in all dimensions except product dimension. We notice the moderate product scores which are higher relative to other dimensional scores of micro-sized companies. As discussed above these companies mostly belong to the beginner cluster of companies that include companies with both high and low product scores.

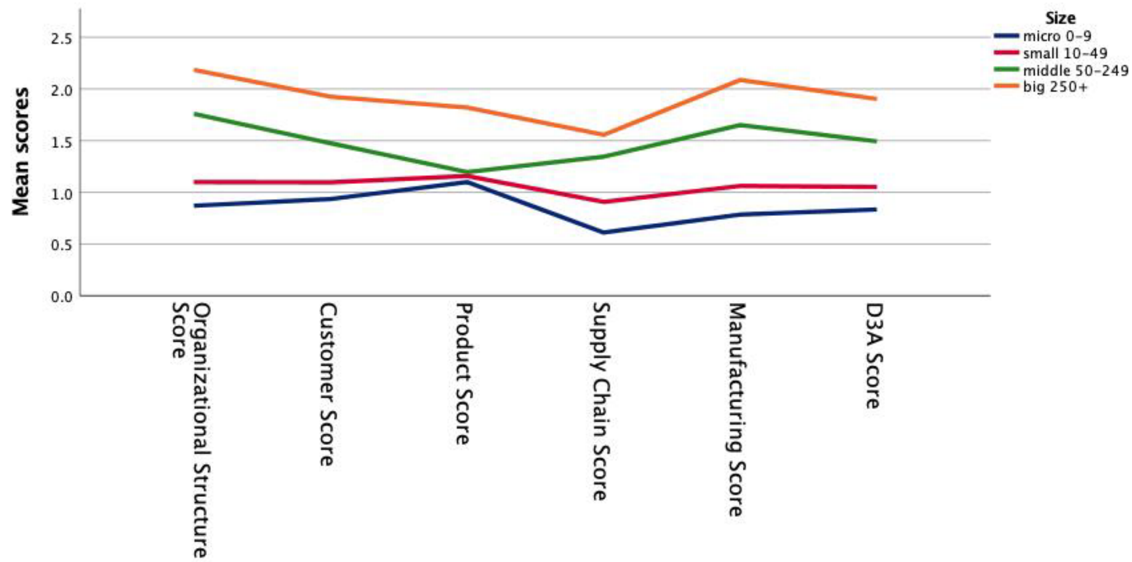



Figure 74. Evaluation by company size

Next, we summarize the most important findings in terms of the factors that affect the DX performances of companies in Table 4. These results are important in guiding SMEs in generating their DX road maps.

Table 4. Relationship between DX maturity scores and the factors affecting DX maturity

| Factors | DX Maturity Scores | | | | | |
|---|---|---|---|---|---|---|
| | Organizational Structure | Customer | Product | Supply Chain | Manufacturing | D3A |
| Company Size | ✔ | ✔ | ✕ | ✔ | ✔ | ✔ |
| Industry | ✔ | ✕ | ✔ | ✔ | ✔ | ✕ |
| Innovation practices | | | | | | ✔ |
| Qualification of R&D centers | | | | | | ✔* |
| Academic collaborations | | | | | | ✔ |
| Product customization skills | | ✕ | ✔ | ✕ | | ✕ |
| | | | | ✕ : Rejected<br>✔ : Approved<br>✔* : Approved under conditions | | |

The overall digitalization level of a company is related to its performance in five DX dimensions. However, organizational structure of the company is the most essential of these since companies with higher organizational structure scores have better performances in other DX dimensions as well. So, organizational structure has the highest impact on the overall digitalization levels realized in D3A scores. On the other hand, product score has the lowest impact on D3A scores since micro-sized SMEs acting as suppliers of global companies might have high product scores and low D3A scores, whereas big-sized family-owned companies with traditional management styles might have low product scores and high D3A scores.

Innovation culture of a company has significant impacts on its D3A score since improvements in new product development processes usually require higher digitalization levels in companies. Innovation practices of companies, qualification of R&D departments and academic collaborations for R&D have highly significant impacts on D3A scores. Companies that generate new product ideas collaboratively, based on analytical insights from sales or customer feedback have more improved digital maturities. R&D departments that are managed more independently tend to have higher D3A scores. However, R&D centers that take place in technoparks do not lead to higher digital maturity scores in companies. The research projects that bring industry and academy together play an important role on the general advancements of industries towards generating better digital practices. Nevertheless, questions that are related to the collaboration level of companies are recognized as critical in differentiating companies in all DX dimensions.

SMEs have high product customization capabilities since they can adapt special product needs and process updates faster. Since product customization level does not appear to be a differentiating factor among SMEs, these skills do not have significant effects on customer and supply chain dimension scores or D3A scores, but they still have significant impacts on product dimension scores. Companies with better product customization skills tend to have more improved DX scores in product dimension, but this impact seems to be very moderate.

# CHAPTER 8:

# CONCLUSION

The main objective of the research is to design a comprehensive digital maturity model to assess different levels of digital maturity of SMEs in our region and to find out the factors that affect the digital maturity levels of companies. The generated framework consists of five DX dimensions: organizational structure, customer, product, supply chain and manufacturing that are assessed with 65 questions in total. The assessment framework is implemented on 100 SMEs in four OIZs and the results of the comprehensive analysis are presented.

During the research study, the companies were interviewed face to face with industry experts and several DX areas were discussed with the company executives. The assessment process itself created a DX awareness in SMEs by locating their position among their competitors. It also highlighted the role of executives in initiating and implementing the DX vision. Nevertheless, these discussions clarified the aim of DX and the role of SMEs for the success of DX of the supply chain.

The development process of the framework fulfills the eight principles of a DX maturity model to ensure that the framework is considered as a design science artifact (Becker et al., 2009). D3A is introduced by the government to be accomplished in university and industry collaboration where the aim is to generate a DX maturity model and assess regional SMEs. The model is developed based on the existing models with appropriate scientific methods. The model is developed iteratively with pilot studies and expert feedbacks. The development process and the results are documented and publicly presented.

This study provides important academic contributions as well as valuable insights for industry. D3A is proven to be a reliable and valid framework that can be used in evaluating the DX maturity of SMEs. The factors that affect the digital maturity of SMEs can be used to generate insights for SMEs to evaluate improvement areas in their DX roadmap. Furthermore, the assessment results provide a general understanding of the DX maturity of SMEs in our region.

We are aware that our study had also limitations. First, there might be limitations of working with regional data. The model is planned to be applied in other regions of the country to be able to make more comprehensive analysis. Secondly, some industries had low number of companies. Increasing the number of companies in these industries will provide stronger results. Thirdly, SMEs should be supported in creating their own DX roadmaps based on the results of the assessment which is ahead of the scope of the study for the moment. Further research can be done on the implementation of DX strategy and generation of roadmaps for SMEs.

APPENDIX A

ORGANIZATIONAL STRUCTURE QUESTIONNAIRE

| Organizational Structure | |
|---|---|
| 1 | How do you take business decisions? |
| 2 | Do you have a written strategic plan? |
| 3 | Do you have a strategy for digital transformation? |
| 4 | Are your business processes defined? |
| 5 | How is the collaboration between departments? |
| 6 | How do you keep financial records? |
| 7 | Who is responsible of IT infrastructure in your company? |
| 8 | Do you have cyber security systems in your company? |
| 9 | Do you have access to corporate data outside of office? |
| 10 | How do you manage of your employees self-development and education progress? |
| 11 | How do you do improve your employees’ digital skills? |
| 12 | How do you make your employees' propose new ideas and improvements about work? |
| Customer | |
| 1 | How do you manage your sale and marketing operations? |
| 2 | How do you forecast your sales? |
| 3 | How is the sales data shared between departments? |

| | |
|---|---|
| 4 | How do you give pricing quotes? |
| 5 | What can your customers do on digital platforms? |
| 6 | How do you keep record of the meetings with your customers? |
| 7 | How do you take orders? |
| 8 | How do you manage your dealers' performance? |
| 9 | How do you manage your customer projects? |
| 10 | How do you manage the performance of your sales team? |
| 11 | How do you manage your distributors' performance? |
| 12 | How do you manage the customer feedback, returns, complaints and technical assistance? |
| Product | |
| 1 | Do you have an R&D or P&D department? |
| 2 | Do you have patents or patent applications? |
| 3 | Do you collaborate with academic institutions in your product development and innovation projects? |
| 4 | Do you have any R&D projects with support? |
| 5 | How do you manage your product development projects? |
| 6 | Who is taking place in product development projects? |
| 7 | Do you produce technologies that is used in your products? |
| 8 | Do you have data collection hardware like censors or chips on your products? |
| 9 | How do you take decisions and manage new product development processes? |
| 10 | Are you able to do customizations in your products? |
| Supply Chain | |

| | |
|---|---|
| 1 | Which production planning method are you using? |
| 2 | How do you update production plan in case of a last minute change from a client, supplier or you? |
| 3 | How do you decide lot sizes for production? |
| 4 | How do you manage capacity planning? |
| 5 | How do you manage material needs? |
| 6 | How do you manage your purchase orders? |
| 7 | How do you choose your suppliers? |
| 8 | How do you evaluate the performance of your suppliers? |
| 9 | How is the data shared inside the company between production and the other departments like sale, purchase, warehouse or delivery? |
| 10 | How is the data shared outside the company between production and the other parties in the supply chain like suppliers, logistic companies or clients? |
| 11 | How do you manage your stock planning? |
| 12 | How do you keep track of your stocks? (Raw materials, spare parts or finished products) |
| 13 | How do you manage your warehouse? |
| 14 | How do you manage your work-in-process stocks? |
| 15 | How do you create working orders for delivery? |
| 16 | How do you plan deliveries? |
| Manufacturing | |
| 1 | How do you send production orders to production line? |
| 2 | How do you manage scheduling / rescheduling? |
| 3 | How do you keep track of your production? |

| | |
|---|---|
| 4 | How do you keep track of machine operations and stops during production? |
| 5 | How do you keep track of your operators and operations of blue collar workers? |
| 6 | How do you keep track of stock movements in production line? |
| 7 | How do you keep track of your production performance / realization? |
| 8 | How is the production data shared between departments? |
| 9 | Who is responsible of quality control? |
| 10 | How do you manage quality problems in material, products and processes? |
| 11 | How do you keep data of quality problems in material, products and processes? |
| 12 | Who is responsible of machine maintenance? |
| 13 | Which methods are you using for maintenance? |
| 14 | How do you manage maintenance planning and scheduling? |
| 15 | How do you keep track of your energy consumption? |

APPENDIX B

RELIABILITY STATISTICS FOR FIVE DIMENSIONS

| Dimensions | Item-Total Statistics | Scale Mean if Item Deleted | Scale Variance if Item Deleted | Corrected Item-Total Correlation | Cronbach's Alpha if Item Deleted |
|---|---|---|---|---|---|
| Organizational Structure | Q1 | 16.59 | 79.901 | .789 | .904 |
| | Q2 | 16.87 | 80.175 | .683 | .908 |
| | Q3 | 16.91 | 82.588 | .637 | .910 |
| | Q4 | 16.23 | 79.007 | .745 | .905 |
| | Q5 | 16.14 | 76.283 | .758 | .904 |
| | Q6 | 15.99 | 79.343 | .615 | .911 |
| | Q7 | 16.24 | 77.497 | .653 | .910 |
| | Q8 | 16.60 | 80.101 | .631 | .910 |
| | Q9 | 16.83 | 80.183 | .546 | .915 |
| | Q10 | 17.22 | 79.729 | .662 | .909 |
| | Q11 | 17.49 | 85.141 | .601 | .912 |
| | Q12 | 17.09 | 81.093 | .675 | .908 |
| Customer | Q1 | 14.70 | 43.485 | .483 | .851 |
| | Q2 | 14.99 | 43.505 | .718 | .830 |
| | Q3 | 14.90 | 40.394 | .809 | .821 |
| | Q4 | 14.54 | 43.645 | .643 | .835 |
| | Q5 | 14.34 | 48.530 | .453 | .849 |
| | Q6 | 14.34 | 43.499 | .680 | .833 |
| | Q7 | 14.43 | 46.753 | .544 | .843 |
| | Q8 | 16.02 | 49.636 | .392 | .852 |
| | Q9 | 14.44 | 47.905 | .277 | .864 |
| | Q10 | 15.60 | 46.263 | .476 | .847 |
| | Q11 | 16.02 | 50.525 | .312 | .856 |
| | Q12 | 14.43 | 43.904 | .615 | .837 |
| Product | Q1 | 11.35 | 52.614 | .717 | .825 |
| | Q2 | 11.47 | 53.322 | .587 | .835 |
| | Q3 | 11.23 | 53.431 | .488 | .846 |
| | Q4 | 11.26 | 50.376 | .658 | .828 |

| | | | | | |
|---|---|---|---|---|---|
| | Q5 | 10.83 | 52.971 | .682 | .827 |
| | Q6 | 10.95 | 50.694 | .773 | .818 |
| | Q7 | 11.50 | 59.323 | .571 | .842 |
| | Q8 | 11.88 | 56.491 | .560 | .839 |
| | Q9 | 11.52 | 54.313 | .572 | .837 |
| | Q10 | 9.43 | 60.813 | .146 | .878 |
| Supply Chain | Q1 | 17.29 | 88.713 | .445 | .920 |
| | Q2 | 17.73 | 78.765 | .748 | .912 |
| | Q3 | 17.21 | 79.541 | .624 | .918 |
| | Q4 | 17.65 | 80.775 | .805 | .910 |
| | Q5 | 17.35 | 81.301 | .768 | .911 |
| | Q6 | 17.63 | 89.427 | .538 | .919 |
| | Q7 | 17.64 | 82.738 | .705 | .913 |
| | Q8 | 17.58 | 79.781 | .737 | .912 |
| | Q9 | 17.27 | 79.876 | .760 | .911 |
| | Q10 | 18.46 | 89.079 | .526 | .919 |
| | Q11 | 17.00 | 80.808 | .694 | .914 |
| | Q12 | 16.41 | 84.608 | .587 | .917 |
| | Q13 | 18.38 | 90.339 | .416 | .921 |
| | Q14 | 18.67 | 94.466 | .162 | .924 |
| | Q15 | 17.01 | 81.040 | .750 | .912 |
| | Q16 | 17.52 | 86.757 | .573 | .917 |
| Manufacturing | Q1 | 19.18 | 92.493 | .686 | .893 |
| | Q2 | 20.36 | 91.101 | .679 | .893 |
| | Q3 | 19.93 | 90.207 | .748 | .891 |
| | Q4 | 20.13 | 89.468 | .760 | .890 |
| | Q5 | 20.13 | 89.003 | .770 | .890 |
| | Q6 | 19.74 | 90.962 | .683 | .893 |
| | Q7 | 19.93 | 91.924 | .771 | .891 |
| | Q8 | 20.32 | 92.806 | .743 | .892 |
| | Q9 | 19.60 | 90.707 | .652 | .894 |
| | Q10 | 19.77 | 89.452 | .710 | .892 |
| | Q11 | 19.91 | 91.315 | .736 | .891 |
| | Q12 | 19.98 | 103.697 | .061 | .919 |
| | Q13 | 20.60 | 99.677 | .361 | .904 |
| | Q14 | 20.40 | 98.121 | .385 | .904 |

| | | | | | |
|---|---|---|---|---|---|
| | Q15 | 21.16 | 103.954 | .132 | .910 |

# APPENDIX C

## MULTICOLLINEARITY ANALYSIS FOR FIVE DIMENSIONS

| Dimension | Question | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| Organizational Structure | Q1 | .287 | 3.485 |
| | Q2 | .422 | 2.372 |
| | Q3 | .487 | 2.052 |
| | Q4 | .362 | 2.765 |
| | Q5 | .333 | 3.005 |
| | Q6 | .478 | 2.091 |
| | Q7 | .528 | 1.896 |
| | Q8 | .494 | 2.025 |
| | Q9 | .541 | 1.849 |
| | Q10 | .407 | 2.460 |
| | Q11 | .477 | 2.094 |
| | Q12 | .470 | 2.127 |
| Customer | Q1 | .637 | 1.570 |
| | Q2 | .407 | 2.457 |
| | Q3 | .259 | 3.855 |
| | Q4 | .482 | 2.077 |
| | Q5 | .639 | 1.565 |
| | Q6 | .416 | 2.407 |
| | Q7 | .585 | 1.709 |
| | Q8 | .417 | 2.397 |
| | Q9 | .768 | 1.301 |
| | Q10 | .610 | 1.639 |
| | Q11 | .376 | 2.656 |
| | Q12 | .490 | 2.042 |
| Product | Q1 | .380 | 2.630 |
| | Q2 | .637 | 1.569 |
| | Q3 | .631 | 1.585 |
| | Q4 | .429 | 2.330 |
| | Q5 | .278 | 3.592 |
| | Q6 | .207 | 4.825 |
| | Q7 | .615 | 1.627 |

| | | | |
|---|---|---|---|
| | Q8 | .584 | 1.713 |
| | Q9 | .577 | 1.732 |
| | Q10 | .873 | 1.146 |
| Supply Chain | Q1 | .632 | 1.583 |
| | Q2 | .353 | 2.829 |
| | Q3 | .479 | 2.089 |
| | Q4 | .282 | 3.541 |
| | Q5 | .294 | 3.404 |
| | Q6 | .498 | 2.007 |
| | Q7 | .220 | 4.541 |
| | Q8 | .199 | 4.977 |
| | Q9 | .343 | 2.912 |
| | Q10 | .533 | 1.878 |
| | Q11 | .375 | 2.666 |
| | Q12 | .513 | 1.949 |
| | Q13 | .495 | 2.020 |
| | Q14 | .609 | 1.642 |
| | Q15 | .307 | 3.255 |
| | Q16 | .534 | 1.872 |
| Manufacturing | Q1 | .359 | 2.785 |
| | Q2 | .410 | 2.441 |
| | Q3 | .295 | 3.389 |
| | Q4 | .275 | 3.640 |
| | Q5 | .262 | 3.810 |
| | Q6 | .292 | 3.424 |
| | Q7 | .238 | 4.202 |
| | Q8 | .245 | 4.073 |
| | Q9 | .359 | 2.787 |
| | Q10 | .237 | 4.211 |
| | Q11 | .220 | 4.545 |
| | Q12 | .817 | 1.224 |
| | Q13 | .306 | 3.266 |
| | Q14 | .305 | 3.280 |
| | Q15 | .896 | 1.115 |

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