Vaasan yliopisto
UNIVERSITY OF VAASA

Ville Helanen

Profitability of Mass Customization in Electrical Motor Manufacturing

Does Customization Improve Product Level Profitability?

School of Technology and Innovations
Master's thesis in Industrial Management
Programme of Industrial Management

Vaasa 2023

UNIVERSITY OF VAASA
School of Technology and Innovations
Author: Ville Helanen
Title of the Thesis: Profitability of Mass Customization in Electrical Motor Manufacturing : Does Customization Improve Product Level Profitability
Degree: Master of Science in Economics and Business Administration
Programme: Industrial Management
Supervisor: Ahm Shamsuzzoha
Year: 2023 **Pages:** 108

ABSTRACT:
The current market environment forces manufacturing companies to produce such customized products that are at the same time relatively cheap and finished with top quality to respond demanding requirements of customers. The concept of mass customization has been presented as a solution that offers economies of scale while producing customer tailored products. The aim of this research is to review the impact of mass customization on product level profitability in complex manufacturing environment. The theoretical framework is constructed on the main themes of mass customization, cost accounting, and product profitability analysis. All these mentioned topic areas are reviewed from the viewpoint of a manufacturing company that produces large variety of customized products with different order fulfillment methods.

The research problem is divided into two separate questions of evaluating available product costing systems in complex manufacturing environment, and seeking evidence if mass customization is profitable in the case company that for this research is made as an assignment. Based on previous research, financial effects of mass customization are not sufficiently studied through empirical research. Furthermore, related research focuses mostly on product configurations and modules, and their effect on operative and technical development instead of financial measures.

The empirical section of this research is conducted as a quantitative single-case study that aims to seek evidence if mass customization of electric motors is profitable for the case company. Operative data is collected from the case company's ERP-system, and it is combined with financial information. This constructed data set is used for performing statistical analysis similar to methods that are applied in econometrics. The collected data set consists of 3900 statistical units thereby constructing a representative sample from the population. The findings show that mass customization is profitable for the case company when customization is measured through customer selected and otherwise optional variant codes, and by comparing profitability levels in between of different engineering groups. As a results, it was discovered that more customized statistical units were seen to be more profitable than those less customized units.

This research contributes filling the recognized research gap of lacking empirical studies related to financial effects of mass customization. In addition, it also presents important information for the case company regarding of how different variant codes and engineering groups affect product level profitability in their manufacturing operations. Furthermore, the presented statistical method offers possibility to analyze and estimate how different product features influence product profitability levels based on statistical methods commonly used in econometrics. Therefore, this research can be seen to have central managerial and practical implications within management accounting practices in manufacturing environments.

KEYWORDS: Mass customisation, manufacturing industry, cost accounting, profitability, statistical methods

VAASAN YLIOPISTO
Tekniikan ja innovaatiojohtamisen akateeminen yksikkö
Tekijä: Ville Helanen
Tutkielman nimi: Profitability of Mass Customization in Electrical Motor Manufacturing: Does Customization Improve Product Level Profitability
Tutkinto: Kauppatieteiden maisteri
Oppiaine: Tuotantotalous
Työn ohjaaja: Ahm Shamsuzzoha
Valmistumisvuosi: 2023 **Sivumäärä:** 108

TIIVISTELMÄ:

Kiristyvä kilpailutilanne markkinoilla sekä vaatimukset räätälöidyistä tuotteista ajavat yrityksiä tarjoamaan asiakaskohtaisia tuotteita saavuttaakseen kilpailuetua muihin kilpailijoihin nähden. Joustavan tuotevalikoiman lisäksi, asiakkaat odottavat samanaikaisesti edullisia hintoja, nopeita toimitusaikoja sekä hyvää laatua tuotteilta. Massakustomoinnin on esitetty tarjoavan mahdollisuuden hyödyntää suuruuden ekonomiaa samalla tarjoten asiakaskohtaisesti valmistettuja tuotteita, jotka täyttävät asiakkaiden erityiset vaatimukset. Tämän tutkimus tarkastelee massakustomoinnin vaikutusta tuotekohtaiseen kannattavuuteen korkean teknologian teollisuusympäristössä. Tutkimuksessa esitetty teoreettinen viitekehys muodostuu massakustomoinnin, kustannuslaskennan sekä kannattavuusanalyysin aihealueista, joita tarkastellaan erityisesti valmistavan tuotannon näkökulmasta. Tutkimuksen tavoitteena on luoda eheä kokonaisuus yhdistäen näitä mainittuja tutkimusaiheita sekä konkretisoida kustomoinnin taloudellisia vaikutuksia empiirisen tutkimuksen avulla.

Tutkielman tutkimusongelma on jaettu kahteen erilliseen tutkimuskysymykseen. Ensimmäinen tutkimuskysymys tarkastelee kustannuslaskennan mahdollisuuksia tuotekustannusten määrittämiseksi ympäristössä, jossa tuotteiden määrä on suuri sekä valmistus monivaiheista. Toinen tutkimuskysymyksistä käsittelee massakustomoinnin vaikutusta kannattavuuteen kohdeyrityksessä. Aikaisempi tutkimus tunnistaa puutteet aikaisemmassa empiirisessä tutkimuksessa liittyen massakustomoinnin taloudelliseen vaikutuksiin sen keskittyessä yleisesti kustomoinnin operatiiviseen järjestämiseen sekä kehittämiseen tuotekonfigurointien ja -moduulien avulla.

Tämän tutkielman empiirinen tutkimus on muodostettu hyödyntäen kvantitatiivista yksittäistapaustutkimusta, jonka tarkoituksena on tutkia tilastollisia menetelmiä hyödyntäen, miten massakustomointi vaikuttaa tuotekannattavuuteen kohdeyrityksen yhdessä tuote- ja kokokategoriassa. Aineisto on kerätty kohdeyrityksen toiminnanohjausjärjestelmästä sekä taloudellisista raporteista, joista on muodostettu yhtenäinen havaintoaineisto. Koottu havaintoaineisto muodostuu yhteensä 3900 havaintoyksiköstä, joiden voidaan nähdä kuvastavan yleistä tilannetta valitussa tapauksessa. Tulokset osoittavat, että massakustomointi parantaa keskimäärin kohdeyrityksen tuotteiden kannattavuutta, kun kustomoinnin mittana käytetään asiakkaiden valitsemien tuoteoptioiden määrää sekä insinööriprosessin muotoa.

Tutkielma osallistuu tunnistetun tutkimusaukon täyttämiseen esittämällä empiirisiä tuloksia kustomoinnin taloudellisista vaikutuksista. Esitelty tilastollinen menetelmä esittää tavan yhdistää kustannuslaskentaa, kannattavuuden analysointia sekä tilastollisia menetelmiä johdon laskentatoimen menetelminä myös muilla massakustomointia hyödyntävillä teollisuudenaloilla lisäten tutkielman hyödyntämisen mahdollisuutta käytännön sekä liikkeenjohdon keinona.

AVAINSANAT: Massakustomointi, tehdasteollisuus, kustannuslaskenta, kannattavuus, tilastomenetelmät

Contents

Figures

Tables

Abbreviations

ABC	**Activity-Based Costing**
ATO	**Assembly-to-order**
CODP	**Customer order decoupling point**
CPA	**Customer profitability analysis**
CVP	**Cost-volume-profit -analysis**
ETO	**Engineer-to-order**
MC	**Mass customization**
MCC	**Mass customization capability**
MTO	**Make-to-order**
PPA	**Product profitability analysis**
ROA	**Return on assets**
TDABC	**Time-Driven Activity-Based Costing**
VC(s)	**Variant code(s)**

1 Introduction

In this first section of the research, general introduction to the topic is given and recognized research gaps are described. Furthermore, objectives, problems, and delimitations of the research subject area are presented, in addition to description of the methodology, data collection, and analysis methods used in this research. Finally, a brief introduction to the case company, in which the empirical part of this research focuses on, is presented.

1.1 Background and theoretical framework

According to Johnsen and Hvam (2019), companies must adapt their operative strategy to answer customer's requirements for increasing demand for customized products. Persson and Lanz (2022) continue that the demand for customized products that are tailored according to customer specific requirements is constantly growing. In addition, manufacturing companies seek improved competitive advantage by offering such products to the markets. However, highly competed markets push manufacturers to cut down their costs at the same time as manufacturing operations and product development become more complex due to the increased product variation. Furthermore, Deshpande (2018) continues that mass customization aims to produce such customized products to the markets with high quality but still with low prices and short lead times. However, producing large variety of customized products with fast schedule, low prices, and good quality is difficult for most manufacturing companies, and it requires implementing advanced manufacturing technologies to be possible. After successful adaptation of mass customization prerequisites, it is seen to result in improved competitive advantage and financial performance.

Li et al. (2022) recognize the conflict between the advantages and disadvantages of mass customization, as higher operative costs are still strongly associated in such complex environment due to increasingly used organizational resources. In addition to increased amount of costs, Myrodia et al. (2021) state that large product variety results in higher costs in the company operations which therefore requires more efficient cost allocation between different product variants to determine the actual product costs for each variant. When determining total product costs, Järvenpää et al. (2017, p. 148) note that traditional costing systems result in too low product costs for highly customized products and too high costs for moderately customized products due to systematic volume error. Furthermore, Quesado and Silva (2021) support the view that traditional costing systems are insufficient in environments that have large product variety, technologically developed manufacturing methods, and increased amount of indirect costs, which has resulted in development of costing systems for improved accuracy in cost allocation. In addition, understanding of total product costs has a highlighted position in management accounting, as product cost information is used for determining product level profitability levels, and to understand of how certain products and their features consume company resources (Järvenpää et al., 2017, p. 36).

Therefore, to describe the interconnectivity in between of costing systems and product profitability analysis, Fisher and Krumwiede (2015) state that availability of accurate cost information is essential for profitability analysis. They describe the importance by giving an example of a manufacturing company that discovered that 30 % of their products were unprofitable after transferring to a more sophisticated costing system. Therefore, a costing system that can sufficiently allocate those increased amount of indirect costs to large variety of differentiated products to determine the total product costs is essentially important in mass customization manufacturing to determine if it is a viable manufacturing strategy to follow. Seeing the major role of product costing and its role in cost management, different possibilities to determine total product costs are reviewed in literature review.

According to Burlina and Di Maria (2020), based on the smile-curve of global manufacturing value chain, low value-adding activities, such as manufacturing operations, are generally produced in countries that have low wages and less trained workers, whereas high value-adding activities are produced in high-skilled areas. However, manufacturers in advanced countries have showed initiatives on retain manufacturing operations in local areas through innovations and job creation. Additionally, de Treville et al. (2017), highlight the requirements for improved profitability when manufacturing activities are organized in high-cost country, as investors and governments are not acceptive for decreased economic performance. To maintain profitability and competitiveness in high-cost manufacturing country, features of responsiveness, automatization, cellular or lean manufacturing were seen to compensate those high costs of manufacturing. Altogether, it is important to discover those profitable products to maintain the economic viability of the company, and to recognize the superior value of customized products that are more fitting to the needs of customers, which can be eventually transferred into higher pricing improving profitability (Shao, 2020; Mikulskienė & Moskvina, 2020; Abdul Manaf et al., 2021). These described sightings describe the significance and relevancy of this research both on macro and microeconomic levels, as sophisticated mass customization can be included in such actions that enable improved value creation for manufacturers when compared to traditional mass customized manufacturing.

This research is built on the subject areas of mass customization, cost accounting, and profitability analysis that together create the scientific framework of this study. Mass customization manufacturing creates a macro concept for the whole research. Therefore, particular attention is given for mass customized product manufacturing environment also when cost accounting and product profitability analysis are later reviewed. This applied framework is presented in the figure 1. below.

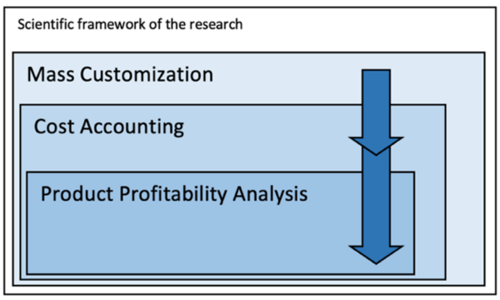

Figure 1. Scientific framework of the research

Particularly, the presented scientific framework of this research is built on recent academic studies and professional literature on mentioned topics to generate a consistent entity of understanding product level profitability within the environment of mass customization, which can be separated from other operating models. The main ideas within the applied scientific framework are presented in the table 1. below.

Table 1. Main themes in the applied scientific framework

Mass Customization
Mass customization can be described as a concept of producing large variety of products with short lead times, good quality, and efficient cost structures, similar to mass production operations, which is recognized to result in improved value creation and thereby increased pricing (Li et al., 2022; Wiengarten et al., 2017; Shao, 2020).
Cost Accounting
Cost accounting has an emphasized role within management accounting as it is seen to generate such financial information that is essential for decision-making within the organization, and it used for recognizing the most profitable products, even though traditional costing systems are seen to be deficient within modern manufacturing environment (Ikäheimo et al., 2019, p. 128–130; Myrelid & Olhager, 2019; Quesado and Silva, 2021).
Profitability analysis
Profitability is the condition of continuity in most companies, and therefore profitability analysis has gained significant position within management accounting practices and research, in which product profitability analysis is often measured through CVP-analysis that has direct connection to determining product costs through costing systems (Abdul Manaf et al., 2021; Järvenpää et al., 2017, p. 101–102; Drury and Tayles, 2006).

In these presented research areas certain research gaps are identified. For example, in mass customization research, financial advancements of mass customization strategy implementation lack consequent empirical studies, as more studies focus on organizational structure capabilities (Wiengarten et al., 2017; Barbosa and Azevedo, 2018). Albeit some research can be found in mass customization product costing accuracy and product profitability (Myrodia et al., 2017), available empirical studies are limited in such context, even though general studies in costing systems can be found. Finally, the lack of research in product profitability analysis is recognized, whereas previous profitability studies focus on company or corporate level profitability (Brierley, 2016; Drury and Tayles, 2006). This research contributes to the recognized research gap by presenting an empirical product profitability analysis within such presented mass customization environment.

1.2 Research objectives, questions, and limitations

The objective of this research is to create a coherent entity that reviews product profitability within mass customization manufacturing environment. These presented concepts of mass customization, cost accounting, and product profitability analysis establish the most important keywords of this research. Additionally, the objective is to offer insights to the latest academic advances in the mentioned scientific framework to the case company to whom this research is made as an assignment. The research questions that this research answers to are divided into two main questions described below.

RQ1: What types of costing systems are commonly available in mass customization environment?

RQ2: Does mass customization as an operating strategy improve the profitability of product line in the case company?

The first research question is centered around different possible product costing systems available for determining total product costs for large variety of products in complex manufacturing environment by allocating increasing number of indirect costs to cost objects. The answer for this first question is provided in the literature review section by examining related academic research, empirical studies and previous literature. The literature has been targeted to consist of recent and good quality research and professional literature. Databases such as ABI Inform, Business Source Premier, Taylor & Francis Online Journal Library, Directory of Open Access Journals, Sage Journals Online, Emerald Journals, IEEE Xplore, Springerlink, and Science Direct (Elsevier) are used for searching such related literature. The second research question is answered through the empirical section of the research by performing statistical analysis based on the data collected from the case company.

The subject of this research is delimited to evaluate mass customization from the viewpoint of a manufacturing company with large variety of highly customized products, whereas hospitality, healthcare, or other service industry organizations are left out from the review. In addition, in the review of cost accounting, main emphasis is given to costing systems that has direct connection to the accuracy of product profitability analysis. Finally, the presented profitability analysis covers only product level profitability which is measured inside of companies through managerial accounting practices. Thus, corporate level profitability, other cost management methods, and performance level evaluations are recognized but excluded from the review of this research.

1.3 Methodology, data collection and analysis

Methodological approach of this research consists of single-case study research design with quantitative research method as an empirical approach. The selected case, that this research has an immediate focus on, is a single motor type and its selected size category in a multinational electric motor manufacturing company, and its product level profitability analysis. The research aims to analyze and describe how different variant codes and customization in overall affect the product level profitability.

This research is funded by the case company in where the empirical study is performed. As the topic of this research is related to profitability, it sets restrictions for data visibility and confidentiality in the results section of this research. Therefore, certain numbers and other identifiable characteristics are blacked or otherwise made unrecognizable. As an example, different product options are described as separate numbers based on their popularity within the sample, profitability measure is left unrecognizable, and censored data is shown as blacked areas. In addition, the name of the case company is not expressed in any part of this research.

The empirical research is performed by utilizing statistical methods together with quantitative data, which is collected through the case company's ERP-system and financial reporting. Thereby, the empirical study combines both manufacturing and operative related data together with financial information. [redacted] [redacted] is set as an individual statistical observation unit that all together form the gathered sample in the selected motor type and size category. The collected data is structured to consist of such units that depict actual customer deliveries that are included in the fiscal year of [redacted]. The size of the sample is 3900 statistical units, which was seen to constitute a representative sample of the selected motor type. Furthermore, the applied statistical methods include analysis of regression, correlation coefficients, and examination of equal means between groups within the sample.

1.4 Case company introduction

This research is done as an assignment for a multinational case company that manufactures electrical motors. The selected business unit for this case study specializes in manufacturing of highly customized electrical motor solutions according to customer requirements. They offer several types of different motors with varying sizes that can be customized according to customers' needs based on 'variant codes' that are predefined and optional product features or options. Mostly these variant codes are standardized for each type of motor. Even though, they are offered as optional extras, in practice they are included in every motor. The case company offers varying customization levels from small adjustments to fully customization of their products, and therefore they operate with hybrid delivery process method that combines assembly-to-order, make-to-order, and engineer-to-order products. As mass customized engineer-to-order products can be seen as an uncommon method to operate, certain emphasis is given to mass customization with engineer-to-order products in the literature review.

As the operating environment of the case company can be described as complex with large variety of advanced products, it complicates determining total product costs for each product. However, implementing an improved costing system is not a strategic goal in the case company, even though they have a need for understanding how varying level of customization on motors based on variant codes affect the product level profitability. The empirical section of this research focuses on describing and comparing profitability levels of differentiated motors through statistical analysis to recognize profitable customization attributes based on the variant codes, their categorization, and different engineering groups. The found results can be seen to support the case company to give attention and make corrective actions to those variants codes that have lower profitability level. In addition, recognizing the most profitable variant codes can be seen as an existing way to promote the total product profitability, which both have an underlined role in managing the profitability of the case company.

1.5 Structure of the research

This research is divided into five major subdivisions. The first chapter presents the background of the topic and introduces recent scientific literature to the topic of this research. Additionally, case company description, methodology, and research questions and limitations are presented. In the second chapter, thorough literature review is presented within the previously presented scientific framework of this research. Therefore, the literature review is divided into four major subchapters based on the framework, in addition to the subchapter of research gap identification. In the third chapter, the applied methodology, in addition to data collection and analysis methods in this research are presented. The fourth chapter consists of the results and conclusions of the empirical study that is conducted in the case company. Finally, the last chapter concludes the whole research, and presents managerial applications, limitations and evaluates the generalizability of the results, in addition to suggestions for further research.

2 Literature review

This literature review presents essential topics and recent scientific research related to the subjects of mass customization, cost accounting, and product profitability analysis. Main emphasis of presented literature is on good quality recent academic research but in addition, related professional books are presented for general introduction of the topics and defining terminology. The literature review is divided into four main subtitles of mass customization, cost accounting, product profitability, and identifying the research gap that together form the scientific framework of this research.

2.1 Mass customization

Based on the term itself, mass customization (MC) can be seen to combine both mass production and customer specific customization at the same time. More specifically, Wiengarten et al. (2017) note that MC has been promoted as viable manufacturing strategy to produce large variety of products to fit customers' requirements with low prices and short lead times enabled by flexible operations. In this first section of the literature review, the concept of mass customization is reviewed from a manufacturing perspective. A special focus is targeted on its financial effects and outcomes on increased operational complexity.

2.1.1 Mass customization and ETO paradigm

Dohale et al. (2022) studied different manufacturing strategies within previous literature in the past 50 years, and note that mass customization is part of third phase of manufacturing strategies which emerged the first decade of 21st century, even though product differentiation started to gain attention already in the 1980s. Manufacturing strategy provides a framework and direction for structural and infrastructural decision-making in manufacturing operations, and it is often reviewed from the perspective of competitive priorities, in addition to manufacturing decisions and performance enhancement. The objective of manufacturing strategy is to improve competitive advantage and operations resilience. Furthermore, MC utilizes advanced production methodologies, and is receptive for technology development, as it aims for improved value creation by developing and improving manufacturing processes. Fogliatto et al. (2012) acknowledge the technology-oriented nature of MC and describe it as a manufacturing strategy that produces large variety of personalized products and services by utilizing modularization, flexible processes, and supply chain member integration. It is seen to improve competitive advantage through increased pricing for customized products and more involved customers. Zhang et al. (2015) continue that MC implementation requires the manufacturing company to perform market analysis to understand the needs of the customers, enable flexible processes within the manufacturing technology, and arrange integrated logistics systems.

To separate MC from mass production, Haug et al. (2019) emphasize that in MC the customization begins often from component level, as mass production manufacturers are also seen to customize their products, but in small amounts. Wiengarten et al. (2017) continue that through low costs and production flexibility, MC is seen to enable companies to produce customer specific products in a cost-efficient manner and answer quickly to the changing needs of customers. In addition, Shao (2020) recognizes the added customer value and higher pricing in products that are more fitting to customer's demand. Finally, Li et al. (2022) note that the concept of MC is seen more specifically to benefit from economies of scale and product differentiation at the same time, in addition to that it is applicable in several industries including consumer goods, high-technology, and medical products. Therefore, MC can be concluded to be a broad manufacturing concept or paradigm that aims for improved value creation by understanding and actively prospecting customer requirements and producing tailored products and services in a similar manner as mass production would operate by utilizing recent advancements in technological development.

According to Cannas et al. (2022), technology development has enabled manufacturers to increase product variety and combine mass customization with increased customer specifications based on engineer-to-order (ETO) delivery process. ETO products are often expensive, large, and complex products that are produced with low volumes, and with high level of customization where engineering is included in the order fulfillment and delivery process. Furthermore, their study shows that ETO companies, that also practice mass customization at the same time, reported that it has improved their ability to react to market's demand for large variety of products that are delivered fast and with good quality. Willner et al. (2016) note that ETO can be seen as an extension to mass customization, and present two differencing views to ETO where products can either be described as new products made specifically for certain customer or tailoring of current and existing products to fit customers' requirements. Even though the definition of ETO is extensive, it is always seen include engineering on every order which separates ETO from the concept of make-to-order (MTO), even though the engineering and design processes can be automized and standardized. The different archetypes and characteristics of ETO manufacturing are presented in the figure 2.

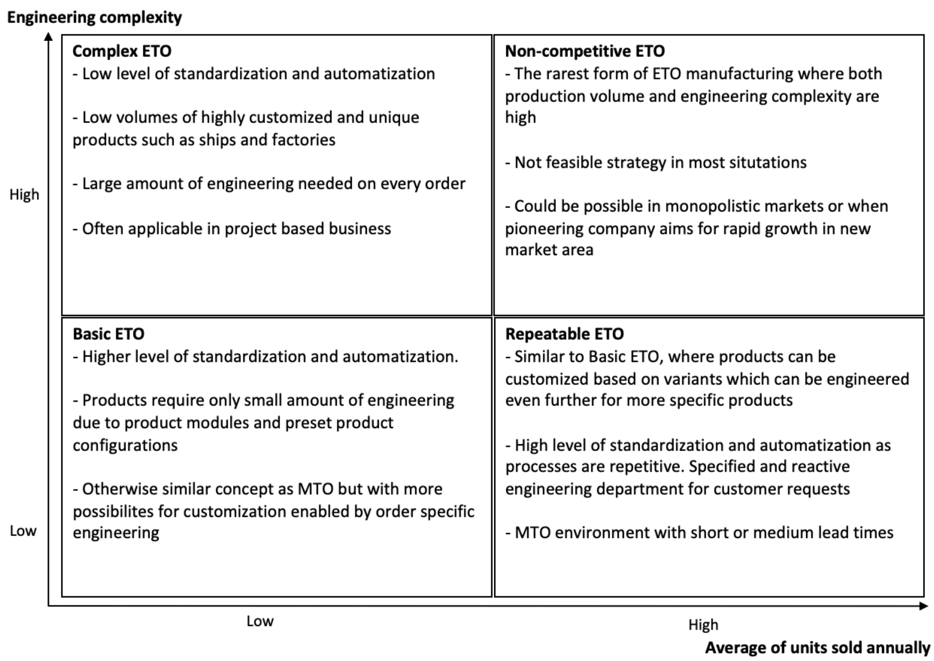

Figure 2. Archetypes of ETO manufacturing (Willner et al., 2016)

Nonetheless, it must be noted that ETO paradigm is not the only possible way to pursue mass customization in manufacturing (Akinc & Meredith, 2015; Johnsen & Hvam, 2019). In addition to ETO, customization is more often performed with different order fulfilment methods, including make-to-stock (MTS), make-to-order or modify-to-order (MTO), make-to-forecast (MTF), configure-to-order (CTO), and assembly-to-order (ATO). From these different methods, ETO offers largest product variety and level of customization, whereas MTS enables very limited amount of customization or possibly none. Otherwise, the remaining order fulfilment methods offer varying customization degrees for products, but not as large variety as ETO offers, it being the most customizable order fulfilment method. However, as customization increases, it affects relatively to the lead time. Furthermore, customer order decoupling point (CODP) can be used for separating these operating methods from each other. Peeters and van Ooijen (2020) present a figure (Olhager, 2003) that demonstrates the differences between customer order decoupling points and order fulfilment methods. This is shown in the figure 3. below. Barbosa and Azevedo (2018) note that MTO and ETO are sometimes combined as a hybrid strategy which enables manufacturing companies to utilize both strategies at the same time and share resources together. Johnsen and Hvam (2019) support the view of combining different methods and note that fully customized ETO products can consist of MTO, CTO, and ETO based solutions together to form an entity of an ETO product. Thus, combination of different operating models can be seen as a viable method to produce large variety of products, as it enables to focus customization on those features that offer highest value creation.

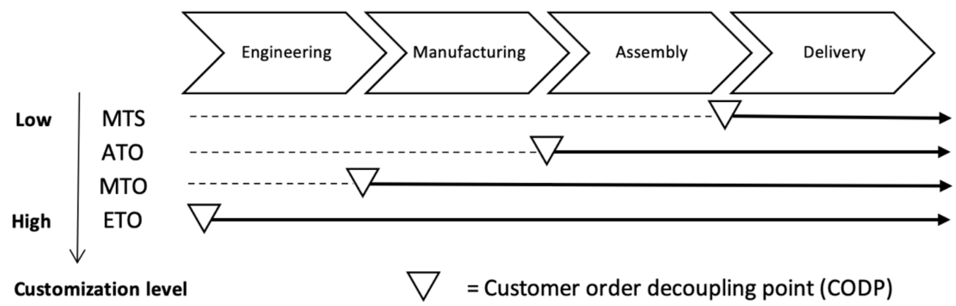

Figure 3. CODPs in different order fulfilment methods (Peeters & van Ooijen, 2020)

2.1.2 Configurable products and product modules

Franke and Hader (2014) note that in mass customizations context, companies must communicate and let customers know what type specifications and characteristics they are able to produce, and then allow customers to choose from the most suitable options from the available configurations. This is supported by Kristianto et al. (2013), who note that in ETO manufacturing, customer requirements and manufacturing capabilities must be aligned to avoid conflicts by setting limits for customization by using configurations to preset design parameter ranges. Cannas et al. (2022) continue that manufacturers must define certain product configurations beforehand to enable engineering, design, and manufacturing tasks to be done tentatively to some extent before the order is placed. In addition, product configurations offer organizations simplified possibility to manage large variety of products. As a result, configurable products are seen to reduce lead times and costs at the same time as quality of products is improved. To further define product configuration systems, Haug et al. (2019) note that they enable selecting valid and pre-defined specifications to customize products. In ETO context, product configurators can be used for creating bill of materials, quotes, and operations plans automatically. In addition, product configurators can include thousands of possibilities but also restriction of how product features can be combined within existing product architectures.

Similar to configurable products and product configurators, Persson and Lanz (2022) describe modularization to include physical and interchangeable modules that can be selected for products to customize them according to customer needs enabling these modules to be managed and configured similar to single products. Li et al. (2016) differentiate product modules to mandatory and optional modules, where mandatory modules form the base of the product, and optional modules enable customer specific customization. Furthermore, Haag and Haag (2019), note that predefined product variants can be used for defining, describing, and communicating specifications of product features in different product configurations, as characteristics must be defined and understood in manufacturing operations, and described and communicated during product deliveries and invoices.

In addition to configurable products, product configurators, and modularization, companies must have mass customization capability (MCC) in order to achieve competitive advantage from MC (Sheng et al., 2022). MCC is described to include all the possibilities for companies to produce and design good quality customized products with short lead times. In order to achieve MCC, companies must perform interorganizational cooperation in a systematic way and improve organizational agility. Furthermore, Korneeva et al. (2021) present a three-level framework for achieving MCC in ETO environment which includes pre-defining product variations, promoting high-functioning and robust process design, and advancing customer integration. The suggested framework is seen as a relevant factor when efficiency in mass customization manufacturing is set as an objective.

As a conclusion, it can be stated that the concept of ETO has similarities with other order product fulfillment and delivery methods, but it is separated from every other delivery process with the order-specific engineering. It enables companies to produce more customer-specific products based on their requirements. In order to achieve the benefits of mass customization and lower production costs together with short lead times and good quality, product configurations must be introduced, and ETO processes need to be automatized and standardized at certain level for improved efficiency.

2.1.3 Financial effects of mass customization

As previously stated, MC aims to produce high variety of products in an efficient way to respond to customer's requirements. However, the customization must be profitable for the manufacturer for it be a viable manufacturing strategy. Thyssen et al. (2006) note that it is obvious that large product variety increases costs and decreases the performance of the company operations as economies of scale diminish, and the amount of support functions will increase. These further required support functions are seen to enlarge the overhead costs in engineering, procurement, production, quality, and after sales. Myrodia et al. (2021) state that variation increases complexity in manufacturing and logistics operations, as supplier base and processes become more diverse, which ultimately increases costs. More specifically, the cost increases are induced from larger inventories, increased need for planning and scheduling, and as more capital is tied into tools and equipment. To further describe the organizational effects of MC, Shamsuzzoha et al. (2010) note that customization increases directly the complexities in manufacturing processes leading to increased costs and lower operative efficiency. Therefore, customization can be seen to increase the resource using in manufacturing companies due to increased operations complexity as the product variety grows.

To overcome these issues of increased costs in customization, Thyssen et al. (2006) suggest modularization as a viable solution. Furthermore, Zhang et al. (2015) add that advanced manufacturing systems, transferring customization into the end of the manufacturing, and modularization can be used for lowering the costs of customization. Total customization costs will be reduced as same components can be used in several product configurations, and therefore it is seen to decrease inventory costs. At the same time, these features are seen to improve cycle time, time-to-market duration, and operational and manufacturing flexibility. The presented view is supported by Persson and Lanz (2022), who note that utilization of modular and configurable product systems will help companies to manage costs, shorten manufacturing lead time, and enable flexibility in the production even though the number of product variants increases. In addition, customized products can be sold with higher prices as they bring more value to the customer since they fulfill their individual requirements. Furthermore, Deshpande (2018) continues that as modularization enables faster time-to-market performance, it improves financial and market performance as products can be sold more in terms of volume for longer time period.

Regardless of the mentioned positive features of MC, Wiengarten et al. (2017) note that the performance benefits of MC are not studied previously enough through consistent empirical studies. However, they report that their global survey indicates that MC strategy enables manufacturers to respond to the changing market requirements and eventually grow their market share due to improved cost and flexibility performance.

Additionally, Persson and Lanz (2022) studied profitability of Swedish manufacturing companies that perform customization in their operations and discovered that the profitability measure of return on assets (ROA) is significantly improved only when modularization is used as a way of performing customization. Therefore, customization without implementation of modularized products was seen to reduce profitability. Furthermore, profitability improvement was seen to result from increased profit margin which affected the measurement of ROA, as significant effect on asset turnover was not found. Furthermore, Deshpande (2018) studied medium and large sizes manufacturing companies in India through questionnaires, and report that companies with good MC capabilities and short time-to-market duration have a positive relationship with good financial and market performance. Therefore, it can be concluded that previous empirical research shows support for the view that customization improves financial performance of those manufacturers, even though more detailed and consistent empirical research is seen to be required for evaluating further implications.

In addition to pure financial performance improvement, Wiengarten et al. (2017) note that MC is seen to increase customer's satisfaction linearly to the level of customization. Shao (2020) supports the view and add that it is a basic assumption in MC that it increases value creation of manufacturing companies as the products fit more closely to customers' requirements. According to Aichner and Gruber (2017), customer satisfaction is seen to increase the number of new customers, create positive word of mouth, and therefore improve the company revenues, profits, and total value. However, in MC environment, customer satisfaction is seen to consist of both product and communication quality, as customer's have a significant role choosing the product customization details. As a conclusion, it can be noted that customization can be thought to also have direct non-financial outcomes, but which can ultimately turn into financial improvements through advanced customer satisfaction and commitment, in addition to lower customer retention and acquisition costs. In addition, as operative costs were seen to grow when product variety increases, the assumed higher pricing and improved profitability through value added by the customization must eventually exceed the increased costs so that the MC manufacturing strategy can be seen as financially viable operations strategy.

2.2 Cost accounting in manufacturing organizations

According to Pellinen (2019, p. 9), it is self-evident that managers are analytically striving to create superior utility, and through accounting, the idea of utility can be measured in monetary values. However, the amount of possible utility is restricted by limited resources, including skilled workers, good products, and ideas, in addition to money and capital. Therefore, cost accounting enables the possibility to perform calculus in monetary terms to optimize the amount of utility while taking restrictions into consideration. This section reviews the concept of product costing within the framework of management accounting in manufacturing and MC environment. Furthermore, the aim of this section of the literature view is to find the best suited costing systems within the MC context that can include large product variety and complex manufacturing operations that complicate the product costing process. Finding a suitable costing method and system in such context has a significant role as accurate product cost information is required when product profitability levels are analyzed.

2.2.1 Management accounting

For all organizations, whether they are aiming for profit of not, it is important to understand their financial position. Nothhelfer (2017, p. 5–7) notes that accounting can be generally divided into financial and management accounting based on the type of financial information that they produce. The key difference between financial and management accounting is the target audience of the financial information. Management accounting produces information for internal usage, and financial accounting for external audiences. Atkinson et al. (2004, p. 4) specify investors, creditors, and governmental operators as such external entities that are interested in the information produced by financial accounting. Furthermore, the emphasis of financial accounting is on its formality of the information production and historical viewpoint in the past accounting period. According to Järvenpää et al. (2017, p. 19–20), the most important information that financial accounting produces are the financial statements which include income statement, balance sheet, attachments, and cash flow statement. Financial accounting is strictly regulated by regionals laws and regulations, and the compliance and reliability of financial statements are audited by external auditors for improved reliability. In addition to regional laws, Ikäheimo et al. (2019, p. 30) highlight the compliance of financial accounting by requirements for publicly listed companies to follow International Accounting Standards (IAS) and International Financial Reporting Standards (IFRS). In conclusion, financial accounting can be seen to produce regular, locally and globally regulated, and standardized financial information for external audiences that focuses on financial performance of the company in the past.

In contradiction to financial accounting, Ikäheimo et al. (2019, p. 126) describe management accounting to produce financial information that supports management on three different levels including decision-making, managing personnel, and ensuring adequacy of resources. These aspects can be evaluated from strategic, operative, and forecasting premises. Management has a need for forecasting and evaluating financial situation of the company in the future based on the current or foreseen development, as it enables to act correctively if undesirable results are seen possible. Atkinson et al. (2004, p. 4–5) emphasize the internally directed, future-oriented, subjective, and unregulated nature of management accounting. Management accounting information is also used for understanding non-financial performance measures of the company such as success of new products, overall quality, process times, and customer satisfaction that can be measured also in non-monetary terms. In addition, management accounting information helps organizations to improve profitability, cut down costs, and improve their processes, as managers and employees can base their decision-making on financial information. This idea is supported by Bhimani et al. (2015, p. 5), who note that the most important objective of management accounting is to increase value creation of the company.

Pellinen et al. (2019, p. 10) emphasize the importance of understanding the terminology of cost accounting. Atkinson et al. (2004, p. 34–36) define cost as the monetary value of goods and services that are acquired with profit motive. In manufacturing, costs can be divided into direct and indirect manufacturing costs. Direct manufacturing costs include material and labor costs that are traced directly to the product by their resource or material using, whereas indirect manufacturing costs are formed by overhead costs such as marketing, R&D, aftersales, and other non-direct costs that are indirectly related to the product. To determine the indirect costs of a product, a cost allocation method must be used. Furthermore, total product costs include all the manufacturing costs including both direct and indirect costs in total. Bhimani et al. (2015, p. 31, 34) define cost object as a separately defined item, such as a product or service, to which costs can be assigned in monetary terms. In addition, variable costs can be defined as costs that change proportionally to the product volume, whereas fixed costs stay the same and do not change according to the production volume. Finally, cost assignment can be seen to present the process where indirect costs are assigned, and direct costs traced to the cost object.

According to Järvenpää et al. (2017, p. 15, 36–38), management accounting has developed towards more strategic position in organizations, as it supports company operations within the whole value chain. These strategic dimensions include strategic cost management, activity-based costing, target cost management, key performance indicators, lifecycle costing, and market analysis. Moreover, management accounting supports decision-making in several circumstances that are summarized in the table 2 below.

Table 2. The roles of management accounting (Järvenpää et al., 2017, p. 36–38)

Decision-making situation	Support from management accounting
Investment decisions	Investment profitability evaluation, disinvestment analysis
Product decisions	Pricing and product profitability analysis, product costing, make-or-buy-analysis
Customer related decisions	Customer profitability analysis
Process development decisions	Analyzing the effect of process performance improvement on profitability
Strategic decisions	Strategy evaluation calculations, growth potential analysis, understanding competitors
Environmental and social decisions	Evaluating the effect of operations on social and environmental goals

Therefore, it can be concluded that management accounting practices produce such financial and non-financial information that supports decision-making, planning, and forecasting of company operations throughout the whole organization from operative to strategic level. Management accounting information is subjective, and its extent and accuracy can be adjusted based on the needs of the organization itself as it is the only user that takes advantage of it. However, the created financial information must be accurate and useful in order to bring value to the decision-making.

2.2.2 Costing systems in general

According to Ikäheimo et al. (2019, p. 128–130), even though management accounting generally consists of several important assignments in company's decision-making, cost accounting can be seen to present the foundation of management accounting, since it produces relevant information for the other uses. In addition, Pellinen (2019, p. 43–44) continue that product costing has a major emphasis in cost accounting, as it produces relevant information for company's decision-making. Consequently, product cost information is used for inventory valuation which is eventually used in financial statements that are produced by financial accounting, thereby creating a connection between management and financial accounting. Furthermore, Fisher and Krumwiede (2015) add that generally accepted accounting principles (GAAP) and IAS require using a reasonable and systematic costing system that can be used for determining the costs of goods sold to be used in financial reporting. In general, Hoozée and Hansen (2018) state that all costing systems are fundamentally used for understanding of how product costs are generated by resource using. In manufacturing industry, costing systems follow a certain schematic structure, where indirect costs are assigned for specific operations which are allocated eventually to cost objects for calculating total product costs. However, costing systems must rely on estimated information when costs are allocated to cost objects since fully accurate costing system would be too expensive for companies to construct, and it would not therefore serve the management needs. Chen and Wang (2007) support the presented view and note that the purpose of product costing is to estimate the overall costs of a product which eventually helps with pricing the product.

Furthermore, Bhimani et al. (2015, p. 4) define cost management as planning of costs in general and cutting away costs that do not increase value for the customer. Therefore, cost management presents a broader concept that includes cost accounting as one of its managing mechanisms. This is supported by Radionova et al. (2019), who describe costing systems to be included in cost management methods and add that product costing is a complex process as costs arise from multiple sources, and companies must apply a suitable costing system to fit their needs. Furthermore, as this research has a focus on cost accounting and applicable methods in complex manufacturing, less emphasis in given for other cost management tools. Therefore, other cost management methods are excluded from this review, as they do not particularly present a practice for allocation costs but a paradigm for managing costs in overall.

Atkinson et al. (2004, p. 79, 123) divide costing systems into three general groups including job-costing, process-costing, and activity-based costing (ABC) based on their nature, even though they all allocate costs to cost objects but in a dissenting practice. Bhimani et al. (2015, p. 32, 57–58, 86, 318) share the idea of two traditionally used costing systems but refer (ABC) systems as more exact approach for product costing. In job-costing, allocation of indirect costs is done by assigning the partial cost of each manufacturing transaction to the cost object that is responsible for the resource using. Process-costing is often used in homogenous mass production where resource costs can be allocated to cost objects by dividing overall costs and using averages as an allocation method. ABC utilizes calculating the sum of costs in each activity, and then assigns those costs to cost objects based on their usage of those needed activities for producing the product or service. However, costing systems are often mixed as hybrid models to aim for more accurate costing instead of using single system only. General idea of the relationship between different costs and how these costs are allocated and traced into cost objects is presented in the figure 4. below. Additionally, to these mentioned costing systems, Järvenpää et al. (2017, p. 131–132) note that standard costing enables an easy practice to determine product costs based on standardized costs for direct material and labor. Furthermore, standard costing enables easy comparison and analysis between standard and actualized costs based on changes in prices and quantities.

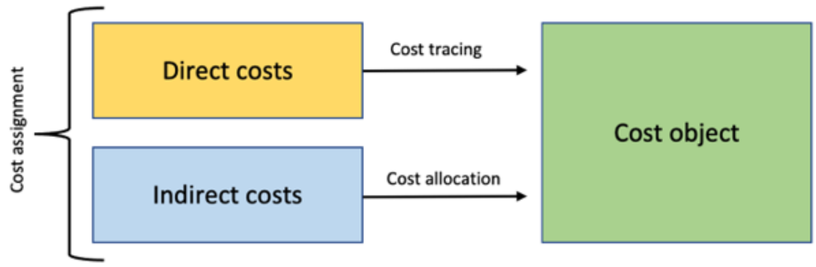

Figure 4. Basic principle of costing systems (Bhimani et al., 2015, p. 32)

As a conclusion, costing systems can be thought to construct a framework and methodology on how indirect costs are allocated to products, services, and other cost objects in a sufficiently accurate way that it supports decision-making in the company. As a result of the costing process, an estimated total cost of a cost object is determined. Manufacturing companies can choose and combine different costing systems based on their operating model, product offerings, and available resources in order to fulfill their needs for cost information. However, the traditional costing systems are not explicitly suitable for every type of manufacturing operations, and improved costings systems are presented in previous literature as more suitable alternatives in more complex manufacturing environment that has large product variety.

2.2.3 Available costing methods for mass customized products

Afonso et al. (2021) note that traditional costing systems are not sufficient in current complex manufacturing environment, and therefore do not support managerial decision making. In addition, traditional manufacturing operations can be unreliable and therefore result in high variability which eventually affect the product cost calculations as they do not include variation in the costing. Furthermore, Myrelid and Olhager (2019) emphasize the importance of accurate product costing in manufacturing industry as it helps to recognize the most profitable products and that deficiencies in traditional product costing systems in modern and complex manufacturing must be acknowledged. According to Chiarini and Vagnoni (2017), current manufacturing environment is described to be digitalized, market oriented, and complex with frequently changing environment. This view is shared by Quesado and Silva (2021), who add that traditional costing systems have been critiqued for not fulfilling organization's requirements, which has led to development of costing systems. Therefore, new costing systems have been introduced for current environment to be suited better in the needs of manufacturing organizations. In addition, ABC has been developed further during the recent years, and it has been a common subject for research. As a conclusion, previous research shows support to the view that traditional costing systems are not fully functional in MC environment, which has led to the development of improved costing systems.

In previous literature, advanced costing system suggestions are found to be more suitable in more complex manufacturing environment. These include lean accounting, throughput accounting, time-driven activity-based costing (TDABC), and mathematical models for cost estimation and data modeling in previous and already existing costing systems (Myrelid & Olhager, 2015; Vedernikova et al., 2020; Niazi et al., 2006; Afonso et al., 2021). However, Quesado and Silva (2021) suggest ABC as a viable and particularly competent costing system also in complex manufacturing environment. In adequately, lean accounting, which is based on value stream costing, is only suitable in well-established lean manufacturing organizations (Myrelid & Olhager, 2015; Ruiz-de-Arbulo-Lopez et al., 2013). Moreover, throughput accounting, that is based on weakest links of manufacturing operations and theory-of-constraints (TOC), enables to determine the rate of the best economic performance at where the organization can operate usually in short-term, and therefore do not perform as a costing system that estimates total product costs (Jassem, 2021; Novak et al., 2016). Even though, lean organization could utilize MC as a manufacturing strategy, it must be excluded from the viable costing systems for MC as it is applicable only in lean organizations, which reduces its suitability in most organizations. Therefore, the remaining applicable costing systems in MC environment include ABC, TDABC, and the mathematical models for cost estimation. These mentioned costing systems are reviewed to understand their mechanisms and suitability in MC manufacturing environment with large product variety and ETO products.

(a) Activity-Based Costing

Even though Atkinson et al. (2004, p. 79) mentioned ABC as one of the common costing systems, Quesado and Silva (2021) suggest ABC as a viable costing system also in complex manufacturing environments since it is seen to overcome issues in traditional costing systems with more precise cost allocation. In addition, ABC is seen to be best suited costing system in companies that have large amount of indirect costs, large product range, and diversified customers requiring tailored services. MC. Laith Akram et al. (2017) continue that ABC is well-applicable in organizations that have complex operations with several products and machines. These views can be seen to support the applicability of ABC in MC manufacturing. The superiority of ABC is supported by Järvenpää et al. (2017, p. 147-150), who note that based on previous literature and practice, ABC is the most efficient model for allocating indirect costs to cost objects. By comparing job-costing and process-costing to ABC, it aims to prevent systematic volume error which results from insufficient manufacturing indirect cost allocation in those traditional costing systems where differences in production resource using is not typically considered. Due to the systematic volume error, costs are often miscalculated for customized products as too low, and too high for standardized products. Therefore, usage of traditional costing systems in MC environment can be seen to results in increased costing errors both in standardized and broadly customized products.

According to Järvenpää et al. (2017, p. 147–148), ABC deploys resource drivers and cost drivers to allocate indirect costs. Resource drivers simulate resource using as precisely as possible and allocate costs from resource using to activities based on time-consumption, batch quantity, order related changes, or actual resource consumption. From the activities, the costs are eventually allocated to cost objects by using cost drivers. Bhimani et al. (2015, p. 318) continue that identifying related activities is necessary when implementing ABC. Additionally, ABC performs particularly well in allocating indirect costs, as direct costs can be traced easily to cost objects. Thyssen et al. (2006) describe that resource drivers are used for creating activity cost pools based on indirect resource costs. In addition, the hierarchical nature of resource drivers and cost drivers in activity-based cost models have an emphasized position, as they aim to avoid allocating costs arbitrary to wrong cost objects. In the ABC hierarchy, each hierarchy level has separated activities, that enables more stable costing at lower levels regardless of activity fluctuation on higher costing levels.

As a result of more accurate product costing, Pham et al. (2021) found in their research that ABC implementation improved financial performance in Vietnamese companies in uncertain business environment. The effect on improved financial performance is supported by Charaf et al. (2022), who detected in their study that ABC implementation affected positively the performance of Moroccan companies, as it enhanced decision-making, overall quality, communication, and customer satisfaction within the company. In contradiction to these reported positive effects of ABC, Laith Akram et al. (2017) found no significant difference in profitability based on financial ratios in manufacturing companies in Jordan before and after implementation of ABC. Therefore, previous literature suggests ABC as beneficial in complex operations, but not all empirical evidence support the view.

Regardless of the mentioned positive features, ABC has been critiqued for its high implementation costs and maintenance needs, non-compliance to other financial reporting methods, demanding requirements for information systems and personnel in order to implement ABC, in addition to that current systems are seen as satisfactory (Barros & Ferreira, 2017; Pietrzak et al., 2020). Therefore, no need for improved costing systems have been seen which has resulted in low implementation level of ABC. Furthermore, Barros and Ferreira (2017) continue that ABC consumes too much time in organizations when activities and their resource drivers are evaluated through subjective surveys. Therefore, it has increased inflexibilities and decreased the accuracy of the whole costing system. Moreover, Mazbayeva, et al. (2022) note that previous studies recognize the low and variating level of ABC implementation. In advanced and western countries, the implementation level has been averaging between 32–78 % in different studies, whereas in developing countries the average has been 4–20 %.

Chen and Wang (2006) note that implementation of ABC in MC environment is difficult due to the complexity induced issues related to growing number of activities and understanding their interconnectivity and relationships within the operations. However, they contribute to the cost model discussion in MC context by presenting a reversed ABC based solution for determining product costs and tackling the mentioned problems. The proposed model is a generic activity-dictionary-based-costing model that aims to overcome these issues by integrating information of activities, product families, knowledge of production, and accounting data. As a result, the model utilizes closed-loop framework for determining total product costs based on design specifications of the product. Furthermore, it also enables estimating costs of new products based on previous cost information and estimated activity consumption. Zhang and Tseng (2007) also present an ABC framework for MC products that enables product costing for products with multifaceted features and characteristics. The model is based on generic bill-of-material for a product that can be modified based on required customization, and the variations effects on required activities in the product manufacturing can be built in the model resulting in more accurate costing. These examples demonstrate the applicability of ABC in MC manufacturing, and that successful implementation in such environments exists in previous research. As a conclusion, ABC cannot be excluded in the review of applicable systems in MC manufacturing environment as it is still a viable and detailed method in product costing, and its effects are multidimensional within the organization instead of only producing more accurate cost information, even though the barriers for implementation are high.

(b) Time-Driven Activity-Based Costing

During recent years, ABC has been developed further, and it has been a major subject for research (Quesado & Silva, 2021). For example, Barros and Ferreira (2017) describe time-driven activity-based costing (TDABC) as an improved version of common ABC system, as it easier and cheaper to implement, and it can include complexity and variability of the company operations in the product costing also in manufacturing industry. TDABC is built on allocating resource costs directly to cost objects by utilizing capacity cost rate and the actual time used for completing the activity. The concept of capacity cost rate is defined in the equation (1) below where the numerator includes the resources used in the activity, and denominator describes the actual time that is spent to perform the activity in the defined cost center. After these two parameters, are defined, they are multiplied to assign indirect costs to cost objects based on time equations, where the multiplier is defined as cost-driver rate. Furthermore, Namazi (2016) notes that TDABC do not participate in the first cost assignment process that is included in ABC, and instead focus entirely to assign costs from resources to cost object using time as a cost driver.

$$Capacity\ cost\ rate = \frac{Cost\ of\ capacity\ supplied}{Practical\ capacity\ of\ the\ resources\ supplied} \tag{1}$$

According to Barros and Ferreira (2017), the strength of TDABC is that it does not require making subjective and time-consuming surveys for personnel when comparing to common ABC. This is seen to improve the accuracy of the costing, but also cut down the costs. Stout and Propri (2011) continue that TDABC bases the cost allocation solely on time estimates, and therefore does not require collecting subjective and time-consuming data to form the resource pools that are necessary in common ABC. Furthermore, TDABC has similar positive features as ABC, since it enables costing in complex business environments, but with improved maintainability of the costing process. However, TDABC does not guarantee more precise costing, but it offers transparent way to allocate costs based on resource consumption on each activity. Namazi (2016) also compares TDABC to ABC and add that TDABC implementation is seen to enable companies to improve their costing processes by more accurate costing in complex and variating operations environment by simply driving costs from resources to cost objects by estimating the time spent. In addition, it reveals how the capacity is used within the operations, as capacity cost rate calculations determine how much of the free capacity is utilized within the operations. Regardless of the positive effects, TDABC is only applicable if time can be used as a sole cost-driver, and it also requires data collection from the operations, and managers time estimations may be inaccurate. In addition, it lacks empirical evidence of how accurate the costing is.

According to Öker and Adigüzel (2016), TDABC can be implemented in manufacturing environment, even though it is easier to apply in service industry. They base their view on difficulties to measure capacity in manufacturing environment based on time. However, Barros and Ferreira (2017) note that even though TDABC is mostly studied in service industry, their study proposed that is well applicable in manufacturing industry, and it can include variations in the processes. Soufhwee et al. (2019) stated in their study where TDABC was implemented in automotive part manufacturing company costing process simulation, that TDABC was more accurate costing system when compared to the previously used conventional ABC. The main benefit of TDABC was that the resource drivers were based on accurate measures resulting in better cost allocation. Furthermore, the costing results could be enhanced with improved data collection, processing, and simulation based on the concept of Industry 4.0. In a study comparing costing error between ABC and TDABC, Hoozée and Hansen (2018) found out TDABC to provide more accurate cost information only in situations when resources can be easily traced to activities, for example in specialized manufacturing. In other situations, traditional ABC had lower costing error. Therefore, TDABC can be thought to be well suited in MC manufacturing environment if time can be used as the main resource driver and the resource costs can be driven straightforwardly to activities. It is seen to enable similar benefits as ABC but with cost-efficient and otherwise easier implementation and maintenance processes, which can be seen as an improvement to traditional ABC.

(c) Cost estimation models

In addition to separate costing models for determining calculated product costs, cost estimation models and more developed data modelling methods have been presented in previous literature. To describe cost estimation methods, Ning et al. (2020) note that they differ from cost calculations, as in cost estimations organizations do not have the required manufacturing details to determine the direct and indirect costs of the production processes, and therefore the costs need to be estimated. Chen and Wang (2006) recognize the issue and continue that the resource usage is not known before the product is manufactured, which emphasizes the important role of cost estimation especially with new and previously unmanufactured products. Therefore, cost estimation offers a solution to determine the costs of those products that have not been previously designed or manufactured.

Niazi et al. (2006) present techniques that are used for estimating product costs. These techniques are divided hierarchically into groups of qualitative and quantitative techniques. Foremost, qualitative cost estimation utilizes previous cost information to determine costs of new products based on the similarities and characteristics of the new product. Whereas quantitative techniques base their cost estimation on analysis of the design characteristics and manufacturing processes. To calculate the costs in quantitative models, analytical functions with variable parameters are used for describing resource using in the operations. Furthermore, Hooshmand et al. (2016) present that each technique has their best suited applicability in different types of product costing situations depending on the design phase of the product. The characteristics, differences, and suitability of each cost estimation technique and occasion are presented in the figure 5.

Product cost estimation techniques				Key advantages	Limitations	Best suited product design phase
Qualitative Cost Estimation Techniques	Intuitive cost estimation techniques		Case-based systems	Innovative design approach	Dependency on previous cases	Preliminary design phase with accuracy of -30 % to +50 %
		Decision support systems	Rule-based systems	Optimzed results	Time-consuming	
			Fuzzy logic systems	Handles uncertainty, reliable estimates	Estimating complex feature costs is monotonous	
			Expert systems	Faster, consistent, and reliable	Complex programming required	
	Analogical cost estimation techniques		Regression model analysis	Simpler method	Limited to solve linearity issues	Conceptual design phase with accuracy of -14 % to +30 %
			Back Propagation neural network model	Operates with uncertain and non-linear problems	Completely dependent on data, high establishment costs	
Quantitative Cost Estimation Techniques	Parametric cost estimation techniques			Utilizes cost-drivers effectively	Ineffective when cost drivers can not be identified	
	Analytical cost estimation techniques		Operation-based cost models	Evaluation of alternative process plans for optimized results	Time-consuming, requires detailed design and process	Detailed design phase with accuracy of -5 % to +15 %
			Break-down cost models	Easier method	Detailed cost information of resource using is required	
			Cost tolerance models	Identifies cost effective design tolerances	Details of design information is required	
			Feature-based cost models	Features with higher costs can be identified	Difficulty to identify costs for small and complex features	
			Activity-based cost models	Easy and effective method using unit activity costs	Requires lead-time information in the early design phases	

Figure 5. Cost estimation techniques (Niazi et al., 2006; Hooshmand et al., 2016)

Hooshmand et al. (2016) present a generic cost estimation model for ETO manufacturing organizations based on parametric approach which estimates costs by utilizing reference structures. Within the model, the costs of new products are determined by comparing new product variants to previously produced or basic products based on their characteristic and cost elements. The presented cost estimation model includes four different equations, where the first two equations include defining costs for structure elements and estimating the total costs for the new product variant based on the costs of structure elements. More specifically, in the first step, weighting factor is used for determining the costs of new product variants based on the differences and similarities in the product characteristic and comparing those to the standard product. In the third and fourth step, the costs of new products are re-estimated if the customer changes have been added during the product development phase. Therefore, the model enables companies to estimate the total costs of new products including the costs of product development with transparent and accurate measures. However, it must be noted that even though the presented model is presented as easily applicable, it is only suitable if the costs are determined for the previous products so that the comparison with the weighting factor can be done. Therefore, a suitable costing system must be implemented before this estimation for new products can be used.

Additionally, Afonso et al. (2021) present and define stochastic approach for costing models as a set of random variables in a mathematical set that operates through a projection model which enables estimating probability distributions and analyzing the costs of products in manufacturing environment. In comparison to traditional deterministic costing models, stochastic approach takes variability of cycle-times into consideration in the costing process, and therefore provides a range of different results of the total product costs depending on the risks, variability, and uncertainties. In addition to the data modeling framework, a new costing model is presented, even though the stochastic method is also applicable in ABC model. Therefore, cost estimation models can be also included as a part of other costing systems for creating a hybrid model to seek improved performance for the accuracy of the costing process, as Bhimani et al. (2015) suggested.

These reviewed costing methodologies, including ABC, TDABC, and cost estimation models, enable calculating, determining, and estimating total costs of cost objects in manufacturing environment with large variety of products that have distinct product features and multifaceted operations with repetitive or completely new products or product variants. As stated earlier, all costing systems trace direct costs and allocate indirect costs to cost objects, but merely the practices are different. However, traditional costing systems were seen to result in inaccurate costing results in MC manufacturing environment with highly customized products due to systematic volume error which has resulted in improvement of costing systems. The key characteristics of the reviewed systems and their suitability in MC environment are summarized in the table 3. below.

Table 3. Applicable costing systems in MC with fully customized products

Costing method	Advantages	Limitations	References
ABC	Accurate product costing results, can include product variation and complex manufacturing processes, efficient and precise cost allocation of indirect costs	Data collected through surveys can be subjective causing costing errors, the implementation, maintenance, and managing are difficult and costly	(Quesado & Silva, 2021; Laith Akram et al., 2017; Järvenpää et al., 2017, p. 147–150)
TDABC	Easier to implement, maintain, and manage than common ABC, applicable in complex environments with large variety of products and manufacturing operations, provides accurate costing results	Can be only used in operations where time can be used as an only cost-driver, only few examples of implementation in industrial environment, is seen to be more suitable for service industry	(Barros & Ferreira, 2017; Namazi, 2016; Öker and Adigüzel, 2016, Soufhwee et al., 2019; Hoozée & Hansen, 2018; Stout & Popri, 2011)
Cost estimation models	Large variety of tools for different situations, also suitable for products that have not been manufactured before and therefore applicable especially for ETO products	Requires previous cost information as estimations rely on previous cost data, not specifically costing systems but offer possibilities to estimate product costs in overall	(Niazi et al, 2006 & Hooshmand et al., 2016)

2.2.4 The most suitable costing system within MC

As discovered, customization increases the complexity of the company operations as product variation grows. To describe the issues induced by the complexity, Cicconi et al. (2020) state that estimating costs and providing accurate quotations is a significant problem in especially ETO performing companies. It is important for manufacturing companies to provide competitive bid as fast as possible with high level of accuracy on cost estimation to provide fast response time for customers and avoid financially poor decisions, even though time and accuracy are seen to be contrary to each other. Løkkegaard et al. (2022) add that process complexity induces cost complexity within the whole product lifecycle. In order to manage the complexity costs and product offerings, unprofitable products must be discontinued, which is especially difficult in ETO companies, as the products may not have been created yet. Therefore, cost estimation of new products based on similar but previously produced products has an important role in product estimation, but they rely on previously calculated product costs which initially require using a costing system to discover those earlier costs, thereby decreasing the role of cost estimation models.

Applicability of TDABC as suitable costing system is promoted in complex operating environment with large product variety with reasonably easy implementation process to calculate the total product costs of products and their variants also in manufacturing environment (Barros & Ferreira, 2017; Öker & Adigüzel, 2016; Namazi, 2016). Furthermore, Fisher and Krumwiede (2015) state that perfect costing system is nonexistent, and that those different systems must be evaluated within different environments through the measures of convenience, costing accuracy, and costs sunk in the implementation phase. Therefore, from the reviewed costing systems, TDABC can be seen to have such features that enables efficient product costing in manufacturing environment with large product variety and diverse operations. ABC implementation was seen to include several barriers in implementation and updating the system, whereas traditional costing systems are not sophisticated enough to include large customization level. Furthermore, cost estimation models are more applicable in situations where products are not yet produced or designed, but other data modelling possibilities could be implemented together with TDABC as well. Additionally, as Persson and Lantz (2022) stated, product modules can be treated and managed as separate products. As modular and configurable products are seen to have similar features in their architectural product structure, they can therefore be seen to enable determining total product costs for those modules and configurations separated from the main product as well. When reviewing ETO performing mass customizers, TDABC is particularly suitable in environments of repeatable and basic ETO that were presented earlier in the figure 2., as the production quantity is larger, and products are simpler in engineer-wise, thus making the production and costing more repeatable.

As previously presented, Barros and Ferreira (2017) note that capacity cost rate, which is introduced in the equation (1), is used for allocating resource costs directly to cost centers based on the time spent on performing the activity on each department. The time spent can be discovered through staff and management questionnaires, in addition straight or historical data-based observations. Balakrishnan et al. (2012) add that in the costing process, time equations are developed for each cost object that determine the quantity of how much of the particular resource is used to complete the transaction within the resource department. Therefore, total product costs can be determined by multiplying the capacity cost rates with the amount of resource used. Furthermore, to describe the TDABC implementation process, Ganorkar et al. (2018) present a two-step framework that enables manufacturing companies to easily implement TDABC in their operations. The presented framework includes the capacity cost rate defined as cost driver rate, and the time equation as a cost of an activity. The implementation process is presented in the figure 6. below.

Step 1: Assign overhead costs to an activity and calculate capacity rate of activity

- Identify various activities
- Identify various overheads to an activity
- Determination of cost driver and practical capacity of overheads
- Calculate cost driver rate for overheads
- Assignment of overhead costs to an activity and calculate cost of activities
- Estimate practical capacity of activities
- Calculate the cost driver date of activities

Step 2: Assign activity cost to product cost

- Determine the practical capacity of activity consumed by the product
- Determine cost of activities consumed by the product
- Final cost calculation

Figure 6. TDABC implementation procedure (Ganorkar et al., 2018)

As a conclusion, TDABC offers an efficient way to allocate indirect costs to cost objects based on the actual time spent on activity execution which directly determines the amount of resources used. It is seen to result in accurate cost estimation calculations for large variety of different or customized products also in manufacturing environment that has multifaceted operations. Whereas traditional costing systems enable more easier implementation and simplified product cost calculations, their accuracy is seen to be lower due to systematic volume error with customized products. In addition, implementation and maintenance of TDABC were seen to be moderately easy when comparing to conventional ABC. However, TDABC is only applicable if time can be used as an only cost driver which also exposes it to costing errors due to subjective or inaccurately calculated time estimations. As an answer to the first research question, ABC, TDABC, and cost estimation models can be presented as such suitable methods that enable determining total product costs in MC manufacturing. In addition, because of the functional benefits of TDABC, it can be presented as the most suitable costing system within such MC manufacturing environment that has a large variety of products including those products that require engineering in the delivery process with the condition that those products are repetitive with low engineering complexity level.

2.3 Product profitability

According to Drury and Tayles (2006), recent management accounting research suggests that product profitability analysis is regarded as one of the most important activities in management accounting practices, since it enables identifying those products that are unprofitable for the company. Therefore, product profitability and its analysis have essential roles in managing the economic performance of the company. In this subchapter, the subject of product profitability and its analysis are overviewed. This section of the literature review connects mass customization with highly customized products and the importance of suitable costing system implementation within such environment to enable the evaluation of accurate product level profitability. Therefore, product level profitability can be seen to tie these presented topics to a comprehensive entity that is built on MC and valid costing method, as it indicates the additional value created by the customization of products.

2.3.1 Financial performance and product profitability

According to Abdul Manaf et al. (2021), profitability has a significant role in ensuring the survival of the company in the long run, and it is often described through measures of revenue, profits, and stock valuation. Järvenpää et al. (2017, 101–102) present that cost-volume-profit (CVP) analysis is used for evaluating profitability of products, services, business units and sectors, and overall profitability of organizations. Based on the CVP analysis, companies can determine contribution margin of their products by subtracting variable costs from the revenues. To proceed with the calculations, total profits are calculated by subtracting fixed costs from the contribution margin. By examining profitability of their products, organizations can recognize their most profitable products and increase understanding of related costs behind certain products. Furthermore, CVP analysis assumes that the costs can be divided into variable and fixed costs, and that they react correspondingly if the sales or operations grow or diminish. However, the analysis does not take economy of scales into consideration, but it nevertheless provides an estimate of the total profitability of the cost object in a reasonable manner. CVP analysis method is presented in the figure 7. below.

Revenues
- Variable costs

= Contribution Margin
- Fixed costs

= Total profit

Figure 7. CVP analysis framework (Järvenpää et al., 2017, p. 101)

To further describe product profitability analysis, Brierley (2016) divide it into two main categories including product profitability analysis (PPA) and customer profitability analysis (CPA). Whereas CPA is used for determining revenues, costs, and profits of distinct customers of an organization, PPA focuses on products instead. The role of precise cost information for profitability analysis is recognized by Drury and Tayles (2006), who emphasize the interconnectivity of costing systems and PPA, as product costing enables companies to generate such cost information that allows measuring profitability of cost objects periodically and in hierarchical levels from product level to business unit level. Therefore, cost information generated by costing systems has an emphasized role in the profitability analysis. As a result, ABC is suggested as a suitable costing system for determining product cost information in profitability analysis due to inaccurate costing results of traditional costing systems. In a study conducted by Öker & Adigüzel (2016), TDABC is used for product profitability analysis together with CVP framework to determine profitability levels of varying products. The benefits of using TDABC utilization in profitability analysis include accurate cost allocation of fixed overhead costs to cost objects. By evaluating the results of the product profitability analysis, TDABC found differing results when compared to standard costing method. The standard costing was seen to underestimate the total costs of the products, and the total gross margin percentage of 10 individual products dropped 11 percentage points when analyzing profitability through TDABC. The usage of TDABC as a tool for profitability analysis is also supported by Namazi (2016), who present previous studies that discovered TDABC to improve the understanding of profitability formation when comparing it also to common ABC. Thus, accuracy of product level profitability analysis can be seen to be dependent on costing systems, as they determine the total costs for products, in addition to other cost objects as well, such as separate customers in CPA. Therefore, connectivity between CPA and PPA can be seen analogous as they both evaluate the profitability of a certain cost object. Furthermore, it can be concluded that the performance of costing systems directly affects the accuracy of profitability analysis as they are based on those product cost calculations.

When evaluating product level profitability in ETO context, Løkkegaard et al. (2022) note that profitability analysis is inevitably more difficult as complexity increases in R&D, manufacturing, supply chains, and professional skills. In addition, ETO products face large amount of cost uncertainty as the costs of materials and labor, in addition to required engineering hours may vary greatly. Furthermore, Järvenpää et al. (2017, p. 148), note that traditional costing systems often result in too low total product costs in customized products because overhead cost allocation do not sufficiently detect differences between company operations. Therefore, it is essential for companies to seek and establish accurate costing systems for fully customized and ETO products in MC manufacturing to accurately examine their product cost structures and profitability.

According to Abdul Manaf et al. (2021), profitability analysis has a significant role both in practice and research, where special focus is targeted on variable factors that affect the profitability. As already presented in the introduction of this research, Fisher and Krumwiede (2015) describe an example of a manufacturing company that was able to perform more detailed product profitability analysis by implementing a more suitable costing system. Eventually, the company discovered that 30 % of their 130 000 products were reducing the profitability of the company. However, Drury and Tayles (2006) acknowledge that previous literature lacks empirical analysis of product profitability, whereas more research is available regarding company-level profitability. To further emphasize the role of PPA in management accounting practices, their questionnaire-based research shows that profitability analysis for cost objects is a used as a management accounting tool at least once a year in 91 % of the responding UK based companies. In addition, Brierley (2016) studied standard and high-customized product manufacturing companies and discovered that 86,5 % of the respondents perform product profitability analysis within their organization and consider it to be very important. However, the largest barriers not to perform profitability analysis is the lack of adequate accounting software, and possibilities to invest in such applications. Furthermore, the study shows that PPA is done to improve the product profitability by making corrective actions to low profit products. As a conclusion, it can be noted that even though PPA has a major role within management accounting practices, previous literature lacks examples of management accounting practices, methods, and related empirical research.

In contradiction to PPA and CPA that can be determined by using CVP analysis on product or customer level, Järvenpää et al. (2017, p. 316–318) present profitability analysis measures that can be calculated based on financial statements. Commonly used profitability measures include gross margin, earnings before interest, taxes, depreciations, and amortization (EBITDA), earnings before interest, and taxes (EBIT), net operating profit after taxes (NOPAT), return on investments (ROI), return on assets (ROA), and return on capital employed (ROCE) which are calculated based on generally accepted equations. Furthermore, Abdul Manaf et al. (2021) describe such measures suitable for corporate level profitability analysis. Thus, these presented profitability measures demonstrate only the profitability of the whole organization at company level based on the financial statement, and do not therefore enable evaluation of product profitability on more detailed level.

In addition, to describe a separate approach for analyzing financial information, Stock and Watson (2020, p. 43) note that econometric models can be applied for evaluating and forecasting values of economic variables, such as sales, growth, or stock prices through numerical values obtained from statistical methods. To put it briefly, econometrics enable utilizing mathematical and economic models together for analyzing financial data based on real-life measures, and its methods are commonly applied both in microeconomics and macroeconomics, marketing, and finance. Furthermore, applying such econometric models provide quantitative answers based on quantitative data. However, direct applications of econometric methods in management accounting were identified not to be common in previous literature. Nevertheless, Burja (2011) present a multi variable regression model for forecasting profitability of industrial companies based on their financial measures obtained from financial statements. The presented results show statistically significant relationship between the performance level of the company and capability to manage resources. In addition, van Triest et al. (2009) studied how customer-specific marketing affected customer profitability through multiple variable regression models which is fundamentally implementing econometric models in management accounting practices. Furthermore, Hada et al. (2018) also presented a multiple regression model for forecasting net profits of furniture manufacturing companies based on independent variables of value added, employee expenses, liability structure, turnover, and inventory levels. These examples present an additional and more detailed methods for evaluating and forecasting profitability levels based on statistical analysis.

As previously noted, a simple CVP analysis can be applied to discover the profitability of certain products, customers, or other defined cost objects. Similar to CPA and PPA, CVP analysis is also dependent on accurate product costing since it has a direct role in the accuracy of the total profit calculations. By reviewing statistical methods in previous profitability analysis research in manufacturing environment, most research focus on industry, company or organizational level profitability measurements based on profit to sales, ROA, and ROE through correlation and regression analysis (Yang & Tsou, 2017; Dalci, 2018). However, Čermák (2015) present a quantitative customer profitability analysis model that measures customer profitability based on weighted average contribution margin ratio, in addition to profitability ratio. The data used in the analysis was based on the cost information obtained from the costing system of the case company, which was evaluated to be detailed enough regardless of its limitations. Regardless of scarce empirical studies of implementing such econometric or general statistical models in management accounting practices, they nevertheless present viable and applicable methods to be implemented inside of a company to support managerial decision making based on the available profitability data.

2.3.2 Profitability improvement in manufacturing environment

According to Drury and Tayles (2006), after profitability levels of products are identified, their profitability can be improved by targeting attention on redesigning the product and outsourcing related activities to seek lower product costs. Ultimately, cost reductions could result in discontinuing recognized unprofitable products. As discovered earlier, in MC environment, profitability and economic performance can be improved by applying configurable products and product modules to strive for automated operations, and to achieve economies of scale, shorter lead times, and improved quality in the manufacturing operations, by improving the customer value creation at the same time (Thyssen et al., 2006; Zhang et al., 2015; Persson & Lanz, 2022; Deshpande, 2018; Willner et al., 2016). In addition, implementation of ABC, was seen to improve financial performance of manufacturing companies in case studies conducted by Pham et al. (2021) and Charaf et al. (2022), even though Laith Akram et al. (2017) did not discover it to have any significant difference in profitability.

To further describe the impact of product design, Guo (2010) conducted quantitative research on how product design affect company level profitability based on financial information from annual reports. Firstly, product design was defined as a conception that optimizes the functionality, value, and external look of the product that both the customer and the manufacturer benefits from. Therefore, design aspect also affects the manufacturing operations by how easy the manufacturing processes are to execute, and how materials are used. The research concluded through statistical analysis that product design has a significant role in improving the financial performance within different industries, by increasing sales and cutting down costs. Furthermore, Liu and Tyagi (2017) note that outsourcing enables companies to transform fixed costs into variable costs and suggest that it allows companies to maintain higher pricing in addition to more centralized focus on focal business transactions optimally resulting in improved profits. Therefore, these observations can be seen to support the view of improved product profitability by setting product design and outsourcing of related activities as targets of attention presented by Drury and Tayles (2006).

Järvenpää et al. (2017, p. 212–213, 230) present an additional perspective to the profitability discussion, and emphasize the effects of pricing on profitability, as sold product is only profitable if its selling price exceeds the costs required to produce it. However, pricing do not merely affect the profitability of the company, but it has a direct impact on the number of sales, and therefore it is seen to require precise analysis to maintain a beneficial ratio between sales and profitability. Different pricing strategies can be divided into five main categories including cost-, market-, target-, value-, and agreed price -based pricing strategies which are presented in the table 4. To describe pricing strategies within different industries, Mikulskienė and Moskvina, (2020) state that value-based pricing is seen to be the most profitable pricing method in most industries. In addition, it is seen to be best suited pricing method in MC environment as products are continuously developed for improved value creation, and market-based pricing is less relevant for those MC manufacturers. The recommended suitability of value-based pricing in mass customized products can be seen to have a certain continuity with previously presented view by Shao (2020), who acknowledged the added customer value and higher pricing in customized, customer-specific, products, as customization is done explicitly to increase the value experienced by the customer.

Table 4. Different pricing strategies (Järvenpää et al., 2017, p. 213–225)

Pricing method	Characteristics
Cost-based	Pricing is based on the actual costs of the product, which emphasizes the role of accurate costing system and sufficiently allocated indirect costs. Required contribution margin and/or total profit are defined and added to the total product costs to determine the final sales price.
Market-based	The price of a product is received directly from the competed markets that define the sales price. It forces companies to cut down their costs and adapt to the received prices within highly competed environments.
Target-based	Prices are set based on the strategic targets of the company. These targets could include ambitions in larger market shares or certain profitability levels. However, contradictory targets could result in trade-off situations between growth and profitability.
Value-based	In value-based pricing, the price is determined based on the value created to the customer. Each customer may value different features making value-based pricing difficult. Quality, exceptional product features, reliable on-time-deliveries, well-known supplier, and locality are such features that are seen bring additional value to increase the sales price.
Agreed price-based	Agreed prices are based on mutual negotiations between the seller and buyer. Products within this group are often complicated such as construction contracts

As a conclusion, it can be stated that product profitability analysis is essential within management accounting practices, and it is recognized in previous research to some extent. However, previous research lacks empirical studies of how product profitability analysis is performed inside different companies and organizations. In addition to CVP analysis, no other detailed practices for periodical product profitability analysis are presented in empirical studies. One suggestion for the lack of related research, could be that the product cost and profitability information is produced by internal management accounting practices for internal usage, and that information is not publicly available, such as company annual reports are public to be used for company or industry-wide profitability analysis. However, profitability of products eventually creates the profitability of the whole company, and its significance cannot be underestimated in planning and evaluating the current and future situation of a company.

2.4 Identified research gaps

As discovered, MC has been studied within the frameworks of configurable products and modularization, and their effect on organizational efficiency which can be seen to be directly associated with profitability of the company (Persson and Lanz, 2022; Deshpande, 2018). Even though improved value creation of customized products is seen to be evident, Wiengarten et al. (2017) state that those economic advantages of MC are not studied well enough through consistent empirical studies. On the other hand, Hvam et al. (2020) noted that previous literature lacks research that identify those attributes in MC that increase complexity induced costs in products and manufacturing operations. To continue with missing related research, Barbosa and Azevedo (2018) noted that previous literature in mass customization focuses on organizational arrangement research instead on performance evaluation. Furthermore, no related research on how optional extras or additional product features on industrial products impact product level profitability was identified. Therefore, a research gap in the evaluation of profitability in mass customization research can be distinctly recognized.

Even though, there is small amount of existing research in product costing and product profitability in mass customization context, such as Myrodia et al. (2017) who studied configurable effect of product configuration on costing accuracy and product profitability, related research is still limited. In addition, Öker and Adigüzel (2017) state there is an evident research gap in implementation studies for TDABC in manufacturing environment even though its benefits are recognized, but most studies regarding implementation of TDABC focus on service-industries. Furthermore, Brierley (2016) add that product profitability analysis is performed internally in organizations based on management accounting reports and acknowledges that it lacks related research. Therefore, available product related cost information can be unreachable for scientific purposes, which can be thought to limit the available empirical results in PPA research. However, it does not explicitly mean that statistical, econometric, or otherwise quantitative analysis is not performed within management accounting practices even though related research is scarce, but it demonstrates the identified research gap within such context. Therefore, this research aims to contribute to identified research gap by producing statistical profitability analysis of products of which customization levels vary between different products based on customer-selected and optional product features, in addition to differing engineering categories and characteristics.

3 Methodology

This chapter presents the methodological approach to the empirical part of this research. The aim is to describe the scientific approach and define the applied research strategy and empirical method. Furthermore, data collection, structuring, and applied statistical analysis methods are described in detail. Finally, the quality of this research is evaluated based on the concepts of validity and reliability.

3.1 Methodological approach

The empirical section of this study is conducted by applying single-case study research design with quantitative research method as an empirical approach thereby generating the research strategy. Single-case study research design was selected to evaluate how well statistical methods can be used for evaluating the impacts of mass customization on profitability, as such techniques have not been performed before within the case company. Therefore, to see the applicability of the statistical method first, no other cases such as other motor types or size categories were selected to be included in the research. According to Bryman and Bell (2011, p. 59–62), case studies can be described to focus the attention of research explicitly on certain cases, that consist of real-life situations, conditions, or structures that are present in predefined organizations, locations, persons, or events. Furthermore, case studies are conducted to study of an existing phenomenon within predefined and delimited context to learn more from and increase understanding of those cases instead of providing generalizable results. The writers continue that case studies are commonly associated with qualitative research, even though quantitative case studies are also suitable within such research design context. Therefore, analysis of profitability of one selected product type in a particular company can be seen to represent such real-life phenomenon where case study research design is applicable with quantitative approach.

According to Creswell and Creswell (2018, p. 4, 138), in quantitative research, statistical analysis is used for determining relationships between different variables to test theories through data. In addition, Mills et al. (2010) continue that quantitative data can be derived from multiple sources including documentation, historical data, and direct observations. Furthermore, the derived data must present significant events that effect the phenomena within the studied case. As a result, the aim is to produce analytical generalization that could result in generating a wider theory. In addition, Bryman and Bell (2011, p. 163–164) support the idea that quantitative research is often thought to result in generalizable results. However, as this research is conducted as a case study for predetermined product in certain company, the results cannot be seen to depict the profitability of other product types or size categories in the organization of the case company or in any other company. As the results are only applicable in the case company's certain product type and size category, it ultimately decreases the generalizability of this case study regardless of its quantitative analysis.

Furthermore, Creswell and Creswell (2018, p. 138) continue that in quantitative research, directional hypothesis can be set to test the actual statistical results against predictions made beforehand. To adapt similar approach, five directional hypotheses are determined together with the case company to see if they hold as predicted based on quantitative data and statistical analysis. The aim of the statistical analysis and testing of directional hypotheses is to describe and explore how customer selected variant codes and customization based on engineering characteristics have affected profitability of those statistical units. Therefore, this research can be seen to have features of both descriptive and analytical research types in quantitative studies. The process of the empirical research is depicted in the figure 8. below.

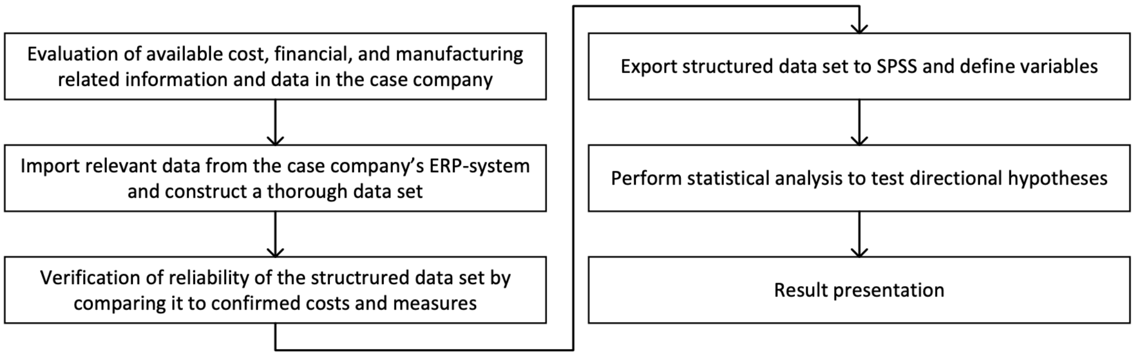

Figure 8. Empirical research process

3.2 Data collection and delimitation

Data for the statistical analysis is collected and imported from the case company's ERP-system and financial reports. The complete data set is structured by combining two different types of data including operative data together with financial information. In the data collection and analysis, [redacted] constitutes a single statistical unit. However, the measure of such unit is not disclosed in the public version of the research. Subsequently, the expression of 'statistical unit', 'individual unit', or simply 'unit' is applied to describe separate statistical units in the sample throughout this research.

Furthermore, both information types of operative and financial data are required for analyzing the effects of product characteristics and customization on product profitability. Operative data consists of customer related information, manufacturing and engineering data, in addition to characteristic features based on the customer-selected variant codes of each statistical unit. The applied financial data includes all the relevant revenue and cost information required to perform profitability analysis. During the research process, these previously separate data sets are combined into unified data set to evaluate profitability based on the existing product attributes of each unit.

As every manufactured motor in the factory of the case company are included in the population, only one product type in certain size category is selected to represent the sample of this analysis, as it is seen as a common type of motor that is manufactured in the case company's factory with varying level of customization. Even though the selected sample consists of motor sizes 1 and 2, they are nevertheless assembled at the same assembly line, and they are otherwise similar regardless of their size. At the moment, for this motor type and size category, the case company offers [redacted] of different variant codes that the customers can choose from to customize the motors to suit their needs. As an example, variant code characteristics could include performance and efficiency related features, changes in the outlook, specific type of testing, or other optional extras or accessories. Therefore, they are all additional to the base product, but enable manufacturing customer specific and customized products. The amount of these selected variant codes varies from 1 to 29 on every statistical unit even though the basic product remains the same. To limit the scope of the analysis, 54 most ordered variant codes and their effect on product profitability receive the closest attention in this research. Variant codes included in this group are labelled as category A. Therefore, the amount of excluded variant codes is constructed to a separate variable of category B, that has a smaller emphasis in the analysis. Furthermore, the amount of 54 variants codes was selected as they depict [redacted] % of the sold variant codes quantitatively measured in the sample. Every unit that had no variant codes were rejected from the sample, as they were seen to depict such fixed code units that are manufactured according to ATO delivery process with predetermined variant codes included in them.

In addition, units that had revenue less than [redacted] € were excluded from the data set, as they were seen to be related to prototypes, samples, and R&D projects, in addition to accounting transfers and adjustments resulted from cancelled units or other related transactions. Therefore, they did not represent a unit that should be included in the sample of actual deliveries. However, units that had warranty costs or other related costs added or reduced later, and they were still manufactured and delivered to the customer, the costs and revenues were presented as the total sum to depict the actual revenue and cost situation of those units. Therefore, based on the selected statistical units of observations, the combined data set can be described as a representative sample, as it depicts general situation of such motor type within the sample.

Finally, the profitability measure of [redacted] is selected to depict product level profitability as it is strategically the most important for the case company. The description of what the profitability measure is, and how it is exactly calculated in this analysis, is left out from this public version of the research. Furthermore, the data was structured based on previously mentioned details to depict and represent actual motors manufactured and sold to customers within the case company in this selected motor type and size category. As a result, the sample consists of 3900 units of observations without any missing values. In detail, the data set includes 92 variables of which 55 were dummy variables to depict the existence of certain variant codes on statistical units or belonging to a certain engineering group. All these variables and their characteristics and statistical scales are presented in the appendix 1. The collected data set can be seen as an independent sample, as the units are separate from each other, and their observed values do not have a relationship between them. The process of data collection and delimitation is depicted in the figure 9 below.

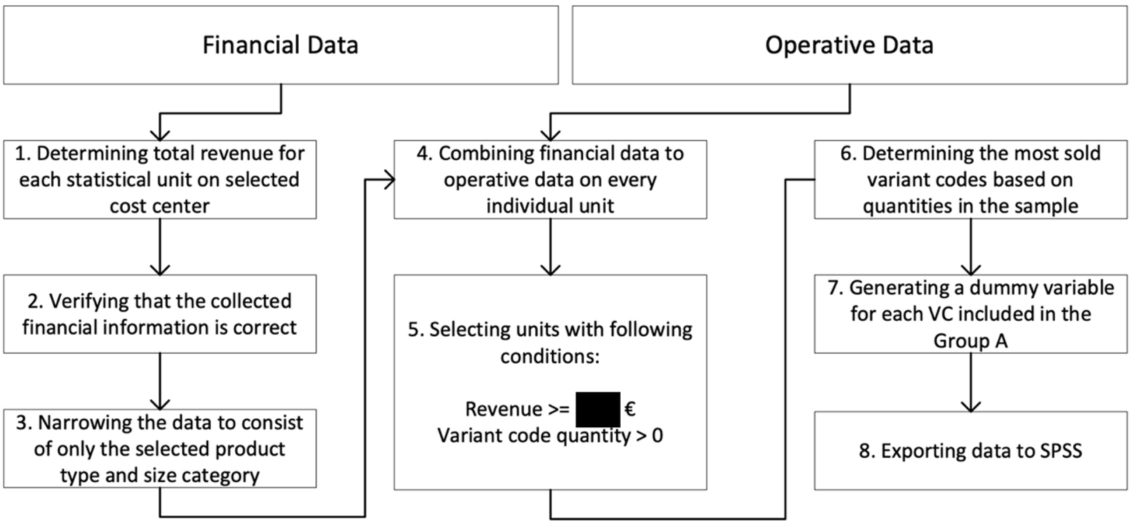

Figure 9. Data collection and delimitation process

3.3 Data analysis methods

After data collection, delimitation, and verification, the statistical analysis is performed by using IBM SPSS statistics software version 28. As the empirical part of this research aims to describe and detect differences, in addition to observing significant dependencies between variables within the representative sample, the applied statistical methods include analysis of correlation coefficients and constructing regression models. Additionally, differences between the means of two samples are examined. According to Quantitative Methods Guidebook (n.d.a) statistical significance testing is often performed against 5 % significance level, which is seen as a common risk level in statistical analysis. Therefore, the applied significance level of 5 % is applied throughout this research.

To estimate the impact of variant codes on product profitability, both simple and multiple linear regression analysis are applied. According to Aczel (2012, p. 378–382), regression analysis is used for describing linear relationship between independent and dependent variables. It is widely applied in business and economics context, as it can be used for generating result estimates based on variation of the independent variables. Furthermore, regression models assume that the relationship between the variables is linear, values of the independent variable are not random, and the errors terms of the model are normally distributed with constant variance and mean value of zero. In addition, Kaakinen and Ellonen (n.d.a; n.d.b) note that the variables must be independent and at least on interval scale or converted into dummy variables. The assumptions of the regression model also include that the variance is not zero for any of the variables. In addition, in multiple regression models, the variables must not be too correlated to each other due to possible multicollinearity issues. The assumptions related to the error terms can be evaluated by examining the model residuals after the model is generated. Multicollinearity can be examined through the value of variance inflation factor, which should receive smaller value than 5 to show evidence against multicollinearity. However, the fulfillment of all assumptions is unlikely, and the regression model tolerates deviation from the assumptions especially if the sample size is large. However, deviations from the assumptions are seen to decrease the reliability of the model. To further evaluate the strength of the obtained estimation model, the measure of coefficient of determination can be examined. It is described through the value of R square which obtains value between 0 and 1. It is used for evaluating how much the variation of dependent variable can explained through the values of the independent variables, thus describing the effectiveness of the model.

As this research aims to increase understanding of the connection between customization and profitability, correlation is evaluated between the level of customization and selected profitability measure. According to Aczel (2012, p. 398), correlation coefficient is applied for examining the relationship between the values of two random variables. As a result, the correlation coefficient obtains value between -1 to 1 representing the direction and relative strength of the detected correlation. Furthermore, Kestilä-Kekkonen (n.d.) continue that Pearson's correlation coefficient can be applied for such variables that are at least interval scaled and normally distributed to determine their linear connectivity. If the conditions are not fulfilled, nonparametric option of Spearman's rank correlation coefficient can be applied for determining monotonous relationship between the two variables. In addition, the measurement of Kendall's tau is an applicable nonparametric correlation measurement in addition to Spearman's rho (Aczel, 2012, p. 609).

In addition to the presented statistical methods that review the relationship between two variables, profitability levels between two groups in the same sample are evaluated through testing of means. Aczel (2012, p. 280, 290) notes that the means between two groups can be examined to see if they statistically differ from each other by applying the test of t-statistics. To further describe the testing of means, (Quantitative Methods Guidebook, n.d.b) continue that the two independent sample t-testing is applicable for variables that are interval or ratio scaled with normal distribution. However, the t-test is not seen to be sensitive if the distribution does not fulfill the requirements of normality, and the sample size is large. To test the normality of the distribution, test measure of Kolmogorov-Smirnov can be applied if the sample size is equal or more than 50. However, if the sample size is large, even small deviation from normality can lead into rejection of normality, and the histograms can be used for evaluating the proximity to normal distribution in addition to the testing.

3.4 Quality of research design

The quality of this research is evaluated through reliability and validity. According to Bryman and Bell (2011, p. 41, 157), reliability refers to the evaluation of consistency of the measures and repeatability of the research. Furthermore, Mills et al. (2010) continue that the concept of reliability generally consists of stability and consistency. Stability describes the evaluation of how the results would be similar and stable if the research would be replicated later. In contrast, consistency describes if the results would be the same if the research would be performed again. As the data used for the analysis consists of only from the fiscal year of [redacted], and it is imported from the case company's ERP system and financial reports, they can be recollected from there again, and repeat the same analysis with repeatable and consistent results, thereby ensuring the consistency and stability. However, annual differences in profitability can be expected if another fiscal year is targeted in repeated research. In addition, the reliability of the results is ensured by describing the data collection, data delimitation, applied variables, and analysis methods with high level of details. Therefore, as the data used for this analysis can be seen to be stable, and it can be retrieved subsequently, they are seen to increase the reliability of the results of this research.

Furthermore, Bryman and Bell (2011, p. 42, 159) define validity as the capability to measure the correct concept that is wanted to be measured. Therefore, validity describes how the results are connected to the intended concept of the research. According to Mills et al. (2010), there are several measures to estimate the validity of the measures and results. Bryman and Bell (2011, p. 160) continue that the concept of validity can be seen to begin from the concept of face validity which depicts how relevant the used measures are to depict the phenomenon based on experienced judges that are familiar with such research field. To increase the validity of this research, collected data is delimited to focus on data based on transactions that are seen to affect the costs and revenues and thus the profitability formation. In addition, the uniformity of the structured data is evaluated against audited financial report. The variables and their characteristics from the collected data set are presented in the appendix 1. Furthermore, those units that are not seen to present an actual delivery to customers are excluded from the data to construct a sample to depict general situation of a manufactured and customized product in the case company. However, the case company utilizes a costing system that is close to job-costing with standardized cost proportions, which can be seen to be prone to systematic volume errors. It can be expected to result in too low costs on orders that have large customization level. However, as Hoozée and Hansen (2018) suggest, previous research assume that at least direct costs are traced effectively without errors on different products. The same assumption is also effectual in this research, and it is assumed that direct costs are precisely traced to cost objects, and they depict actual direct resource using of those products. Furthermore, the cost allocation of indirect costs is also estimated to be precise enough, so that the cost information can be used as such for obtaining reliable results from the analysis. In addition, the selected profitability measure can be seen as commonly used measure in management accounting field to measure product profitability, thereby improving the face validity of this research, even though it is not disclosed in the public version. Furthermore, the selected statistical methods can be seen as regular tools in statistics and econometrics thereby demonstrating their applicability in analyzing financial information. In addition, risk level of 5 % is accepted in the statistical significance testing, which is seen as a standard risk level in statistical analysis. Ultimately, these mentioned measures can be seen to improve the validity of the results. However, it is acknowledged during the research process that deficiencies in the case company's costing system could lead into incorrect results.

4 Results

In this chapter, results of the empirical research are presented. The chapter is divided into four subchapters. The first subchapter outlines assumed directional hypotheses that this section addresses to answer and presents descriptive statistics of the collected data. In the subchapters of two and three, related measures and figures of statistical analysis are presented that show evidence against the assumed directional hypotheses. Finally, in the last subchapter, a summary of the results, answer to the second research question, and accepted and rejected hypotheses are presented together.

4.1 Directional hypotheses and descriptive statistics

The case company has an increasing need to understand how mass customization through variant codes (VCs) and engineering process category affects product level profitability in their electrical motor manufacturing and assembly. As they offer several hundreds of possible VCs to different motor types, and the interconnectivity between individual VCs and their resource using is not always linear, it is too complicated to determine how much single VC generates profits within the scope of this research. Additionally, almost every manufactured motor is different from each other, which makes detailed costing complicated. Therefore, statistical analysis is performed to recognize how different VCs affect profitability based on the existing cost information, and to demonstrate what is the impact of customization on profitability increase on individual units in general. The applied approach can be described as recognizing profitable product attributes through statistical analysis. In addition, regression models that are commonly used in econometrics are applied. Therefore, this statistical method can be seen to combine management accounting practices together with econometric methods. Furthermore, data collection and delimitation are described in detail in the previous chapter. As a result of the data structuring, the gathered sample consists of 92 variables and 3900 statistical units. Therefore, [redacted] presented as a single statistical unit, and the variables consist of characteristics related to their operative, financial, and design features.

Based on prevalent assumptions, five directional hypotheses were set to together with the case company to guide the research process and data analysis. Therefore, this chapter of the research aims to confirm or reject the presented hypotheses through the evidence obtained from statistical analysis. The directional hypotheses are divided into two main categories that consists of reviewing separately the impact of VCs and differing engineering group on profitability. To begin with, higher customization level can be seen to increase both resource using and pricing at the same time, as further customization consumes more resources and more customized products can be seen as more fitting to customer requirements resulting in higher pricing. Therefore, it is reasonable to evaluate the relationship between the degree of customization based on the number of VCs against increased profitability level. Furthermore, as the case company offers large selection of possible VCs for the selected product type, and the most sold VC1 is sold nearly twice the amount of the second most sold VC2, as shown in the appendix 2. Thus, it is important to understand its influence on profitability estimates. At the same time, as the impact of every VC on profitability is estimated, it reveals such VCs of which existence estimate the highest or lowest profitability level on individual units. Furthermore, as VCs are often included several on every unit, their interconnectivity on profitability is evaluated through categorizing VCs into 7 groups, from where VCs included in the Category 3 are assumed to be the most profitable. Therefore, the first directional hypothesis includes total of three sub-hypotheses that are described below.

$$H1a\text{: } Higher\ number\ of\ VCs\ is\ connected\ with\ higher\ profitability\ level$$
$$H1b\text{: } The\ most\ sold\ single\ VC\ has\ the\ largest\ positive\ impact\ on\ profitability$$
$$H1c\text{: } VCs\ included\ in\ category\ 3\ estimate\ higher\ profitability\ than\ other\ categories$$

Electric motors in this product and size category have varying level of customization from small adjustments to fully customized and large amount of engineering requiring products. Furthermore, units are categorized in two separate groups of 1 and 2 based on their operative characteristics related to engineering. The amount of engineering work can also be seen to propose how divergent the specific design is from more common configurations, which is a signal of a more customized product. Therefore, its connectivity to profitability is reasonable to evaluate. These considerations lead into the second directional hypothesis which is divided into two subtypes shown below.

$$H2a: Profitability\ level\ is\ different\ between\ engineering\ group\ 1\ and\ group\ 2$$
$$H2b: Increased\ engineering\ work\ is\ connected\ with\ higher\ profitability\ level$$

Based on descriptive statistics, statistical units in this motor type and size category are generally profitable with the mean profitability level value of 71,109 points. It must be mentioned that the presented profitability level does not depict actual figures in the case company, and it is made unrecognizable. Furthermore, the total revenue and amount VCs sold is hidden from this public version. To describe applied customization of individual units based on the quantity of VCs, the total number of VCs vary from 1 to 29 with the average value of [redacted]. In addition, VC QTY: Group A and VC QTY: Group B depict how many VCs are included in every unit in the sample in terms of quantity within such VC group. As described earlier, group A consists of the most sold VCs whereas the group B of the least sold VCs. Their distributions or other details are not nevertheless revealed. These descriptive statistics are presented in the table 5. below.

Table 5. Descriptive statistics of the whole sample

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Revenue EUR	3900	[redacted]				
Profitability level	3900	-87,776	148,692		71,109	31,347
VC QTY: Group A	3900	0	19	[redacted]		
VC QTY: Group B	3900	0	15			
VC total QTY	3900	1	29			

To describe the statistical units in general, it can be noted that most of the units can be included in the engineering category 2 in both selected size categories. To be more specific, the total of 79,79 % of all orders are included in the second category. The count of individual statistical units separated by size and engineering category is presented in the figure 10. below.

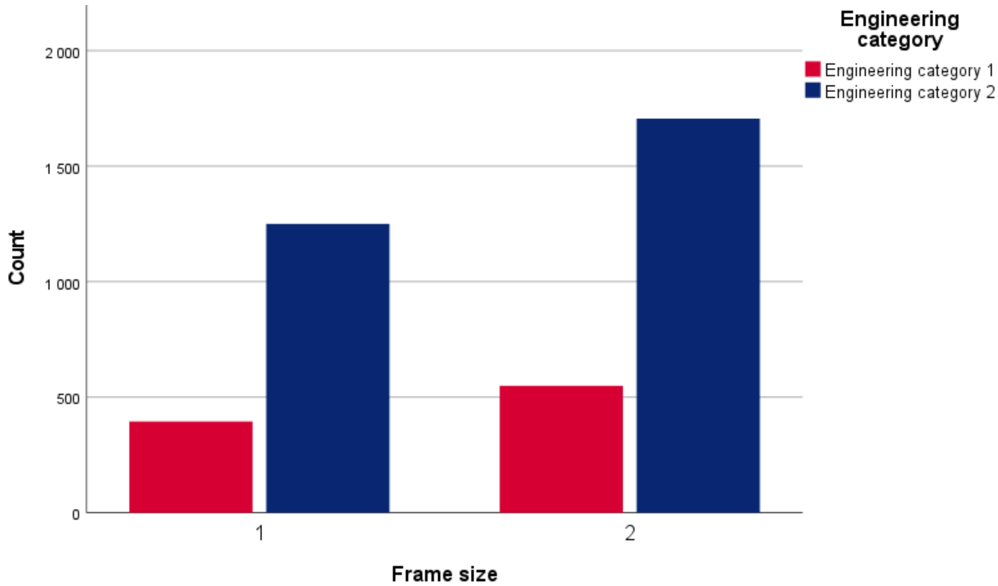

Figure 10. Distribution of units based on engineering category and size

To further describe both size categories separately, a difference between their profitability level is recognized and presented in the figure 11. Based on the boxplot figure, the size category 2 units have a higher profitability level on average. In addition, it is observed to have smaller deviation between the profitability values. As this research aims to provide an overall picture of the effects of customization on profitability within the same product type and size category, the differences between the two size categories are given less emphasis. Therefore, profitability is mainly reviewed from the perspective of the total sample even though the size category would have a significant effect on the results.

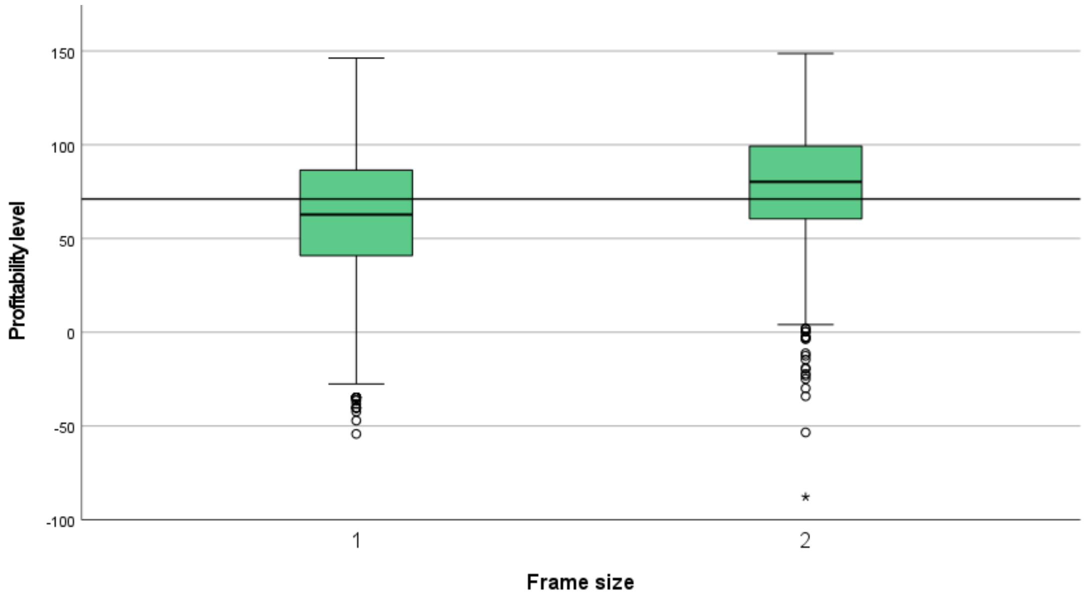

Figure 11. The difference between size categories and profitability levels

4.2 Relationship between profitability and variant codes

The first directional sub-hypothesis suggests that higher number of VCs on a statistical unit has a relationship with higher level of profitability. To test the first hypothesis of $H1a$, relationship between the quantity of VCs and profitability level are evaluated through correlation analysis. Commonly used correlation measure of Pearson correlation coefficient r_{xy} can be applied for evaluating linear correlation between variables that are normally distributed. Therefore, normality of both distributions is confirmed before selecting the applicable correlation coefficient measure. If the normality assumption does not hold, nonparametric correlation measures are applied. To proceed with the testing, variables of Profitability level and both groups of VC QTY: Group A and VC QTY: Group B are selected in the analysis to see if divergent results can be found in between the VC groups. Firstly, the tests of normality and related histograms are presented in the figure 12. below.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
VC QTY: Group A	,133	3900	<,001	,929	3900	<,001
VC QTY: Group B	,254	3900	,000	,748	3900	<,001
Profitability level	,038	3900	<,001	,983	3900	<,001

a. Lilliefors Significance Correction

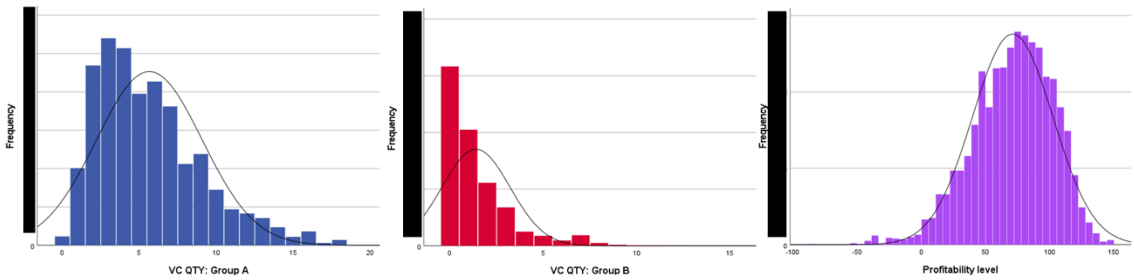

Figure 12. Normality test statistics and related distribution histograms

The null hypothesis of Kolmogorov-Smirnov test suggest that the distribution is equal to a normal distribution. Based on the test results, none of the presented distributions follow normal distribution, and null hypothesis can be rejected for all the selected variables. This is also visible from the included histograms, from where the distribution of Profitability level is the closest approximate to a normal distribution. Therefore, to analyze the correlation between the variables, nonparametric rank correlation coefficient tests of Spearman's ρ and Kendall's τ are applied. The test results are presented in table 6. below.

Table 6. Rank correlation coefficient of VC QTY and profitability

Correlations

			VC QTY: Group A	VC QTY: Group B	Profitability level
Kendall's tau_b	VC QTY: Group A	Correlation Coefficient	1,000	,290**	,163**
		Sig. (2-tailed)	.	<,001	<,001
		N	3900	3900	3900
	VC QTY: Group B	Correlation Coefficient	,290**	1,000	,191**
		Sig. (2-tailed)	<,001	.	<,001
		N	3900	3900	3900
	Profitability level	Correlation Coefficient	,163**	,191**	1,000
		Sig. (2-tailed)	<,001	<,001	.
		N	3900	3900	3900
Spearman's rho	VC QTY: Group A	Correlation Coefficient	1,000	,367**	,232**
		Sig. (2-tailed)	.	<,001	<,001
		N	3900	3900	3900
	VC QTY: Group B	Correlation Coefficient	,367**	1,000	,256**
		Sig. (2-tailed)	<,001	.	<,001
		N	3900	3900	3900
	Profitability level	Correlation Coefficient	,232**	,256**	1,000
		Sig. (2-tailed)	<,001	<,001	.
		N	3900	3900	3900

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

Based on results of the Spearman's ρ and Kendall's τ rank correlation coefficients, profitability level and VC QTY: Group A obtained correlation coefficient values of $\rho = 0{,}232, p < 0{,}001 \; and \; \tau = 0{,}163, p < 0{,}001$ whereas profitability level and VC QTY: Group B obtained values of $\rho = 0{,}256, p < 0{,}001 \; and \; \tau = 0{,}191, p < 0{,}001$. Hypotheses for testing the statistical significance for both Spearman's ρ and Kendall's τ are shown below.

$$H_0: \; x \; and \; y \; are \; statistically \; independent$$
$$H_1: \; x \; and \; y \; are \; statistically \; dependent$$

The evaluation of the results of Spearman's ρ and Kendall's τ nonparametric correlation coefficient analysis indicates that there is a statistically significant but otherwise weak and positive correlation between the profitability level and quantity of VCs in both categories of A and B. Based on the detected results, H_0 can be rejected with the significance level of 0,1 % in both VC categories on both measures of Spearman's ρ and Kendall's τ. Thus, the number of VCs in both categories are positively but nevertheless weakly correlated with improved profitability level. The correlations are presented in the scatter plot figures shown below in figure 13., which demonstrates the rising but gradual direction of profitability when VC quantity increases. Large dispersions between profitability and VC quantity in both categories are visible in the scatter plot figures, which ultimately impair the accuracy of the obtained correlation coefficient values. However, the directions of the relationships between profitability and VC group variables are still visibly positive.

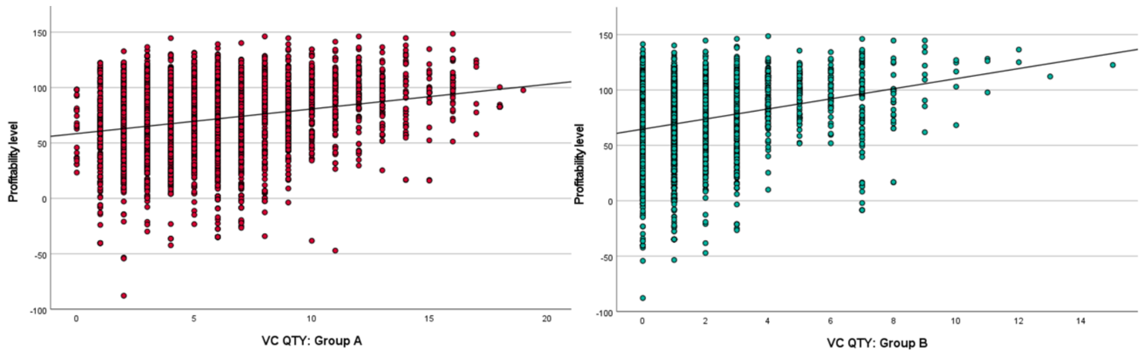

Figure 13. Scatter plot figures for both VC groups and profitability levels

As an answer to the first directional sub-hypothesis, $H1a$ can be accepted. Based on the results, it can be confirmed that the quantity of variant codes on a statistical unit have a positive and statistically significant correlation to the profitability level in both VC categories. Therefore, units with more VCs in either VC group tend to have an improved profitability level. Interestingly, the group B of VCs show stronger correlation to higher profitability level when compared to the group A. Even though the dispersion is notable in the scatter plot figures, statistical units with large VC quantities and low profitability levels can be seen as less common, which is an indicate of the correctness of the obtained correlation coefficient results.

To test the second sub-hypothesis of $H2b$, which assumes that the most sold single VC is the most profitable, a simple linear regression model is performed for every 54 VCs that are included in the VC QTY: Group A in the selected product and size category. The existence of a certain VC on an individual statistical unit is constructed by generating a separate dummy variable with the value of 0 or 1 to depict if certain VC is included in such unit. This is performed to make the data suitable for performing regression analysis that estimates the differences in expected profitability levels based on VC existence. Furthermore, as the sample size is large, the fulfilment of all regression model assumptions is given less emphasis. Statistical significance testing of the models and coefficients are nevertheless performed. Therefore, to seek evidence to confirm or reject $H2b$, the effect of every VC in the group A on profitability level are estimated through simple regression models where each VC is set separately as an independent variable and profitability level as a dependent variable. The null hypothesis for significance testing of the regression model F-test suggest that the model does not exist as the values for the coefficients are zero. Similar null and alternative hypotheses for the coefficient's t-test are presented below, where the alternative hypothesis of H_1 suggest that there is a statistically significant relationship between the variables.

$$H_0\colon \beta_\iota = 0\ (regression\ coefficients\ are\ zero)$$
$$H_1\colon \beta_\iota \neq 0\ (regression\ coefficients\ are\ not\ zero)$$

It must be noted that these presented regression models are separate models instead of multiple variable regression model to avoid multicollinearity issues that would arise in between of highly correlated variables in multiple regression model. Therefore, the presented separate models provide estimates of the relationships between profitability and individual VCs impact on profitability one by one. In addition, this analysis is restricted to cover only those VCs that belong in the group A of the most sold VCs to centralize the analysis to the most popular product options. The sample consists of both size categories together to depict the overall situation in this product type. The objective is to search for evidence of which VC's existence estimates the highest profitability level. The results of each regression model are presented in the table 7 below, and they are listed in the order of the VC popularity within the sample. In addition, to evaluate both size categories separately, the same analysis is performed, but the sample is divided according to the size category. These additional results are presented in the appendix 3 and 4 for the use of the case company but eliminated from the public version of this research. As the main emphasis on this research is on both size categories together, their results are not further described nor evaluated.

Table 7. Linear regression model results for profitability estimates

Explanatory Variable	Constant	Constant t-test p-value	Coefficient	R Square	ANOVA F-value	ANOVA F-test p-value	Anova F-test H1 Acceptance	Intercept t-value	Intercept p-value	Coefficient t-test H1 acceptance
1	68,111	0,000	5,135	0,70 %	25,588	< 0,001	Accepted	5,058	< 0,001	Accepted
2	68,994	0,000	7,253	1,10 %	43,591	< 0,001	Accepted	6,062	< 0,001	Accepted
3	67,007	0,000	14,921	4,50 %	184,41	< 0,001	Accepted	13,58	< 0,001	Accepted
4	69,453	0,000	6,439	0,80 %	31,682	< 0,001	Accepted	5,629	< 0,001	Accepted
5	73,352	0,000	-8,845	1,50 %	59,662	< 0,001	Accepted	-7,724	< 0,001	Accepted
6	72,308	0,000	-4,877	0,40 %	17,582	< 0,001	Accepted	-4,193	< 0,001	Accepted
7	70,88	0,000	0,963	0,00 %	0,667	0,414	Rejected	0,817	0,414	Rejected
8	66,576	0,000	20,995	7,60 %	320,43	< 0,001	Accepted	17,9	< 0,001	Accepted
9	70,848	0,000	1,309	0,00 %	1,086	0,298	Rejected	1,042	0,298	Rejected
10	71,909	0,000	-4,807	0,30 %	12,76	< 0,001	Accepted	-3,572	< 0,001	Accepted
11	72,102	0,000	-6,167	0,50 %	20,496	< 0,001	Accepted	-4,527	< 0,001	Accepted
12	70,553	0,000	3,641	0,20 %	6,814	0,009	Accepted	2,61	0,009	Accepted
13	68,152	0,000	21,083	5,50 %	224,94	< 0,001	Accepted	14,998	< 0,001	Accepted
14	69,757	0,000	11,147	1,30 %	54,258	< 0,001	Accepted	7,298	< 0,001	Accepted
15	71,816	0,000	-6,077	0,40 %	15,132	< 0,001	Accepted	-3,89	< 0,001	Accepted
16	70,509	0,000	5,229	0,30 %	11,042	< 0,001	Accepted	3,323	< 0,001	Accepted
17	69,925	0,000	10,465	1,10 %	44,075	< 0,001	Accepted	6,639	< 0,001	Accepted
18	69,014	0,000	19,452	3,70 %	149,82	< 0,001	Accepted	12,24	< 0,001	Accepted
19	70,321	0,000	7,833	0,60 %	22,135	< 0,001	Accepted	4,705	< 0,001	Accepted
20	71,098	0,000	0,109	0,00 %	0,004	0,949	Rejected	0,064	0,949	Rejected
21	71,09	0,000	0,221	0,00 %	0,015	0,902	Rejected	0,123	0,902	Rejected
22	69,48	0,000	21,028	3,20 %	129,51	< 0,001	Accepted	11,38	< 0,001	Accepted
23	69,305	0,000	25,576	4,30 %	177,88	< 0,001	Accepted	13,337	< 0,001	Accepted
24	70,343	0,000	10,974	0,80 %	31,249	< 0,001	Accepted	5,59	< 0,001	Accepted
25	70,446	0,000	9,506	0,60 %	23,404	< 0,001	Accepted	4,838	< 0,001	Accepted
26	70,241	0,000	12,582	1,00 %	40,756	< 0,001	Accepted	6,384	< 0,001	Accepted
27	71,826	0,000	-10,677	0,70 %	28,555	< 0,001	Accepted	-5,344	< 0,001	Accepted
28	70,638	0,000	7,029	0,30 %	12,281	< 0,001	Accepted	3,504	< 0,001	Accepted
29	72,183	0,000	-17,172	1,80 %	69,855	< 0,001	Accepted	-8,358	< 0,001	Accepted
30	70,111	0,000	18,016	1,70 %	68,565	< 0,001	Accepted	8,28	< 0,001	Accepted
31	70,264	0,000	15,610	1,30 %	50,114	< 0,001	Accepted	7,079	< 0,001	Accepted
32	70,007	0,000	20,361	2,20 %	86,038	< 0,001	Accepted	9,276	< 0,001	Accepted
33	71,105	0,000	0,072	0,00 %	0,001	0,974	Rejected	0,032	0,974	Rejected
34	69,886	0,000	23,158	2,70 %	109,45	< 0,001	Accepted	10,462	< 0,001	Accepted
35	71,246	0,000	-2,719	0,00 %	1,405	0,236	Rejected	-1,185	0,236	Rejected
36	70,359	0,000	15,067	1,10 %	43,052	< 0,001	Accepted	6,561	< 0,001	Accepted
37	70,498	0,000	12,350	0,70 %	28,679	< 0,001	Accepted	5,355	< 0,001	Accepted
38	70,14	0,000	20,102	1,90 %	74,981	< 0,001	Accepted	8,659	< 0,001	Accepted
39	71,452	0,000	-7,395	0,20 %	9,627	0,002	Accepted	-3,103	0,002	Accepted
40	71,829	0,000	-15,610	1,10 %	43,033	< 0,001	Accepted	-6,56	< 0,001	Accepted
41	71,449	0,000	-7,579	0,30 %	9,792	0,002	Accepted	-3,129	0,002	Accepted
42	70,065	0,000	24,816	2,50 %	100,99	< 0,001	Accepted	10,049	< 0,001	Accepted
43	70,617	0,000	12,293	0,60 %	23,164	< 0,001	Accepted	4,813	< 0,001	Accepted
44	70,855	0,000	6,457	0,20 %	6,245	0,012	Accepted	2,499	0,012	Accepted
45	71,525	0,000	-10,820	0,40 %	17,255	< 0,001	Accepted	-4,154	< 0,001	Accepted
46	71,023	0,000	2,281	1,40 %	0,749	0,387	Rejected	0,865	0,387	Rejected
47	71,315	0,000	-5,668	0,10 %	4,477	0,034	Accepted	-2,116	0,034	Accepted
48	71,625	0,000	-14,280	0,70 %	28,4	< 0,001	Accepted	-5,329	< 0,001	Accepted
49	70,673	0,000	12,879	0,60 %	21,641	< 0,001	Accepted	4,652	< 0,001	Accepted
50	70,28	0,000	25,055	2,00 %	81,324	< 0,001	Accepted	9,018	< 0,001	Accepted
51	70,254	0,000	26,259	2,20 %	88,141	< 0,001	Accepted	9,388	< 0,001	Accepted
52	70,848	0,000	8,069	0,20 %	8,094	0,004	Accepted	2,845	0,004	Accepted
53	70,429	0,000	21,215	1,40 %	56,201	< 0,001	Accepted	7,497	< 0,001	Accepted
54	71,922	0,000	-25,369	2,00 %	80,866	< 0,001	Accepted	-8,993	< 0,001	Accepted

Based on the obtained results, it can be noted that 7 of the regression models did not show statistically significant evidence to support the H_1 which indicates that the there is a connection between the values of the variables. Therefore, VCs including 7, 9, 20, 21, 33, 35, and 46 cannot be seen not explain the variation of the profitability level on 5 % significance level. On the other hand, the remaining 47 regression models showed statistically significant support that they explain such variation. The general estimation model for Profitability level with obtained values is expressed as below:

$$Profit\widehat{abilit}y\ Level = Constant + Coefficient_{VC} * X \qquad (2)$$

Furthermore, by examining the values of the coefficients that were statistically significant, it can be noted that the existence of VC51 on a unit is seen to estimate the highest profitability level by increasing it by 26,259 points. In contradiction, VC54 is seen to predict to decrease profitability from the constant value by 25,369 points when it is included on an individual unit. The strengths of the presented estimates are evaluated through the coefficient of determination measure of R square, which indicates how much the independent variable explains the value of the dependent variable. Its value varies between 0 and 1, and higher value indicates higher degree of explanation to the variation of the dependent variable. Based on the results, single VCs seem to have small R square values, which indicate that individual VCs do not widely explain the profitability of a unit. However, small R square values can be seen as reasonable results, as most units include varying quantity of different VCs and other cost or price effecting features, which can be seen together construct the totality of profitability. Thus, the effect of individual VCs on profitability can be agreed to be small. However, VC that explains profitability the most, is VC8 with R square value of 7,6 %. Regardless of the small R square values in general, all the 47 statistically significant regression models still show evidence that the existence of certain VCs estimate higher or lower profitability levels on such units. However, the presented models do not take into consideration what other VCs are include in those statistical units. Therefore, it is acknowledged that large correlations to other VCs can affect the coefficient values of the presented regression models. To evaluate the highest and lowest values of statistically significant regression models, the 10 highest and lowest profitability level coefficients for those VCs are listed and presented in table 8. below.

Table 8. Ten VCs estimating the highest and lowest profitability levels

Explanatory Variable	Description	Constant	Profitability estimate Coefficient	R Square
51		70,254	26,259	2,20 %
23		69,305	25,576	4,30 %
50		70,28	25,055	2,00 %
42		70,065	24,816	2,50 %
34		69,886	23,158	2,70 %
53		70,429	21,215	1,40 %
13		68,152	21,083	5,50 %
22		69,48	21,028	3,20 %
8		66,576	20,995	7,60 %
32		70,007	20,361	2,20 %
11		72,102	-6,167	0,50 %
39		71,452	-7,395	0,20 %
41		71,449	-7,579	0,30 %
5		73,352	-8,845	1,50 %
27		71,826	-10,677	0,70 %
45		71,525	-10,820	0,40 %
48		71,625	-14,280	0,70 %
40		71,829	-15,610	1,10 %
29		72,183	-17,172	1,80 %
54		71,922	-25,369	2,00 %

Based on the results shown in table 7, it can be confirmed that the existence of most sold VC1 do not estimate the highest profitability on individual units. The regression coefficient on VC1 obtains value of $\beta_1 = 5{,}135\ (p < 0{,}001)$ which is 21,124 points smaller than the VC51 that has the highest coefficient value of $\beta_{51} = 26{,}259\ (p < 0{,}001)$. Therefore, it presents evidence against $H2b$, which can be hence rejected.

Interestingly, VC4 that can be seen to enable the broadest level of customization and is always manufactured according to specific customer requirements, that are not standardized in the case company, receives coefficient value of 6,439. By ranking the coefficient values from the highest to smallest, VC4 ranks thirty. Therefore, it can be proposed that regardless of its broad possibilities to offer high customization level and adaptation to customer requirements, it does not estimate exceptional value creation for the case company in terms of profitability in general. However, VC4 can be expected to have high deviation in its expected estimate on profitability level in between different individual units as it can include nearly anything from small adjustments to demanding requirements on motor performance level. Therefore, the impact of VC4 on profitability as an unstandardized customization in detail would be a relevant research area for further studies.

Finally, the third sub-hypothesis of $H1c$ suggest that the VCs included in VC category of 3 estimate higher profitability level than other categories. The categorization of VCs is based on how they affect motor characteristics, manufacturing, or its related support functions if such VC is included in the unit. Therefore, VCs are separated into 7 different categories of 1, 2, 3, 4, 5, 6, and 7, but the descriptions and other details of these categories are left unknown in this public version. The categories of each VC are presented in the appendix 2. for the use of the case company. This presented categorization is simplified version from the original categorization that the case company uses. It is done to narrow the number of variables in the proposed multiple regression model. In addition, previously mentioned VC4 is not included in these categories as it could represent any of those categories in different statistical units, and it cannot be simply categorized. Furthermore, only the VCs included in the category A of most sold VCs are counted in these mentioned 7 categories. This is done to direct the focus of this research to the most sold VCs. Therefore, new variables are introduced for each category to present how many VCs in such category each unit has from the group A of most sold VCs. The distribution and quantity of each VC category is shown below in table 9.

Table 9. Descriptive statistics of categorized VCs

	Mean	Std. Deviation	N
Profitability level	71,1088	31,3470	3900
Category 1 VC QTY	1,4000	1,3042	3900
Category 2 VC QTY	,1218	,3677	3900
Category 3 VC QTY	,0741	,2620	3900
Category 4 VC QTY	,6521	,5825	3900
Category 5 VC QTY	2,4587	1,5906	3900
Category 6 VC QTY	,4187	,7214	3900
Category 7 VC QTY	,2749	,4465	3900

Based on the categorization of VCs, multiple regression analysis is performed to see the effect of each VC category on profitability level by setting those categories as independent variables, and profitability level as a dependent variable. As a result, the impact of every category on profitability can be estimated and compared to each other. Additionally, it enables to evaluate the interconnectivity between the selected VC categories and estimated profitability levels. To continue with constructing the regression model, correlations between different variables are evaluated to avoid issues that could arise from multicollinearity. As the distributions of the VC categories were visibly and through Kolmogorov-Smirnov tests not seen to present normal distributions, nonparametric correlation coefficient measure Kendall's τ was introduced to evaluate the correlations between the variables. The results are shown in table 10.

Table 10. Kendall's tau correlation coefficients between VC categories

			Category 1 VC QTY	Category 2 VC QTY	Category 3 VC QTY	Category 4 VC QTY	Category 5 VC QTY	Category 6 VC QTY	Category 7 VC QTY
Kendall's tau_b	Category 1 VC QTY	Correlation Coefficient	--						
		Sig. (2-tailed)	.						
		N	3900						
	Category 2 VC QTY	Correlation Coefficient	-,037**	--					
		Sig. (2-tailed)	,009	.					
		N	3900	3900					
	Category 3 VC QTY	Correlation Coefficient	,198**	,006	--				
		Sig. (2-tailed)	<,001	,701	.				
		N	3900	3900	3900				
	Category 4 VC QTY	Correlation Coefficient	,300**	-,025	,118**	--			
		Sig. (2-tailed)	<,001	,114	<,001	.			
		N	3900	3900	3900	3900			
	Category 5 VC QTY	Correlation Coefficient	,275**	-,012	,148**	,190**	--		
		Sig. (2-tailed)	<,001	,403	<,001	<,001	.		
		N	3900	3900	3900	3900	3900		
	Category 6 VC QTY	Correlation Coefficient	,097**	-,042**	,166**	,036*	,126**	--	
		Sig. (2-tailed)	<,001	,007	<,001	,017	<,001	.	
		N	3900	3900	3900	3900	3900	3900	
	Category 7 VC QTY	Correlation Coefficient	,444**	-,109**	,295**	,258**	,176**	,206**	--
		Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001	<,001	.
		N	3900	3900	3900	3900	3900	3900	3900

Based on the results of Kendall's tau correlation coefficients, statistically significant correlation can be found in between most variables. However, multicollinearity issues are seen to arise if the correlation is more than 0,9. In the obtained coefficient results, the highest observed correlation measure is 0,444. Therefore, the multiple regression model can be constructed with using all the 7 categories together without high risks of multicollinearity. The model results are shown in the figure 14. below.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,3616[a]	,1307	,1292	29,252

a. Predictors: (Constant), Category 7 VC QTY, Category 2 VC QTY, Category 5 VC QTY, Category 6 VC QTY, Category 4 VC QTY, Category 3 VC QTY, Category 1 VC QTY

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	500883,268	7	71554,753	83,621	<,001[b]
	Residual	3330410,604	3892	855,707		
	Total	3831293,872	3899			

a. Dependent Variable: Profitability level

b. Predictors: (Constant), Category 7 VC QTY, Category 2 VC QTY, Category 5 VC QTY, Category 6 VC QTY, Category 4 VC QTY, Category 3 VC QTY, Category 1 VC QTY

Figure 14. Multiple regression model summary and ANOVA

Based on the results of the ANOVA, obtained values of $F(7, 3892) = 83{,}621, p < 0{,}001$ suggest that at least some of the independent variables explain the variation of the profitability level. In addition, the coefficient of determination receives value of $R^2 = 0{,}1307$, which can be interpreted that the constructed regression model represents 13,1 % of the variation of the profitability level. Furthermore, the values of the coefficients are shown in figure 15.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	63,830	,976		65,374	,000		
	Category 1 VC QTY	6,616	,451	,275	14,682	<,001	,635	1,574
	Category 2 VC QTY	-7,759	1,282	-,091	-6,051	<,001	,987	1,013
	Category 3 VC QTY	14,966	1,911	,125	7,831	<,001	,876	1,142
	Category 4 VC QTY	-2,620	,866	-,049	-3,025	,003	,863	1,159
	Category 5 VC QTY	-,927	,324	-,047	-2,865	,004	,828	1,207
	Category 6 VC QTY	2,999	,691	,069	4,341	<,001	,884	1,132
	Category 7 VC QTY	2,127	1,274	,030	1,670	,095	,678	1,475

a. Dependent Variable: Profitability level

Figure 15. Multiple regression model coefficients for VC categories

The results of the t-tests for coefficients show that 6 of the 7 VC category coefficients estimate the variation of the profitability on a level that is statistically significant, and only $H_0\colon \beta_{Category\ 7\ VC\ QTY} = 0$ can be accepted with 5 % significance level. Thus, the coefficient value of Category 7 VC QTY can be expressed as zero, whereas the remaining coefficients can be accepted to be significant at 5 %. However, the coefficient of Category 7 VC QTY would be significant at 10 % level, but it is still discarded from the model. To evaluate the measures of collinearity statistics, the obtained value for variance inflation factors (VIF) can be described to be low, which indicate that the risks are low for multicollinearity, as the values for VIF are smaller than 5. Therefore, the correlation can be described to be small in between the variables, which was also visible in the previously presented table 10. Small risks for multicollinearity can be seen to increase the reliability of the obtained model to explain the dependent variable of profitability level.

Based on the values of the obtained coefficients, the results show that VCs in the category of 3 show evidence to positively affect profitability the most with the highest coefficient value of 14,966. In addition to VC codes included in the category 3, VCs in categories of 1 and 6 were also seen to have positive connection to higher profitability level of an individual unit. Therefore, profitability level can be seen to be improved on such units that include VCs from these categories with positive coefficients. On the contrary, categories of 2, 4, and 5 were seen to have negative impact on profitability. Therefore, higher number of VCs in these categories on an individual unit estimates lower profitability level.

To estimate the total profitability level based on the VC quantities in each category, the constructed multiple regression model can be presented as a formula (3) shown below. The coefficient term of category 7 is left out from the model because of the statistical insignificance to explain the variation of the profitability level.

$$\widehat{Profitability} = 63{,}83 + 6{,}62 * X_1 - 7{,}76 * X_2 + 14{,}97 * X_3 - 2{,}62 * X_4 - 0{,}93 * X_5 + 3{,}0 * X_6 \quad (3)$$

To answer the directional hypothesis of $H1c$, it can be stated that the multiple regression model shows evidence to support the view that the VCs in the category 3 have the largest positive impact on profitability level. Therefore, based on the highest positive coefficient value of category 3 in the obtained model, the presented directional hypothesis of $H1c$ can be accepted.

4.3 The effect of engineering on profitability

The second directional hypothesis assumes that engineering has an impact on the profitability level of an individual unit. Products that require engineering can be described as highly customized as their characteristics and other features cannot be determined automatically with existing configurations. Therefore, to fulfill the requirements set by customers, these products must go through engineering. The distribution of statistical units included in the engineering groups of 1 and 2 were presented earlier in the figure 10. It can be noted that nearly 80 % of the units belong in the engineering category of 2 when both size categories are evaluated together. Furthermore, $H2a$ suggest that the profitability level is different in between of groups of 1 and 2. To test the presented hypothesis, independent-samples t-test is performed to compare the means between the profitability levels and engineering groups separately in both size categories. The test enables to examine if there is statistically significant difference in the means of different groups, with the following statistical hypothesis testing of $H_0\colon \mu_1 = \mu_2$ and $H_1\colon \mu_1 \neq \mu_2$. First, the assumption of normal distribution is examined for size category 1, and obtained results are presented in figure 16. below.

Tests of Normality

		Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Engineering category	Statistic	df	Sig.	Statistic	df	Sig.
Profitability level	Engineering category 1	,037	395	,200*	,989	395	,005
	Engineering category 2	,048	1250	<,001	,983	1250	<,001

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

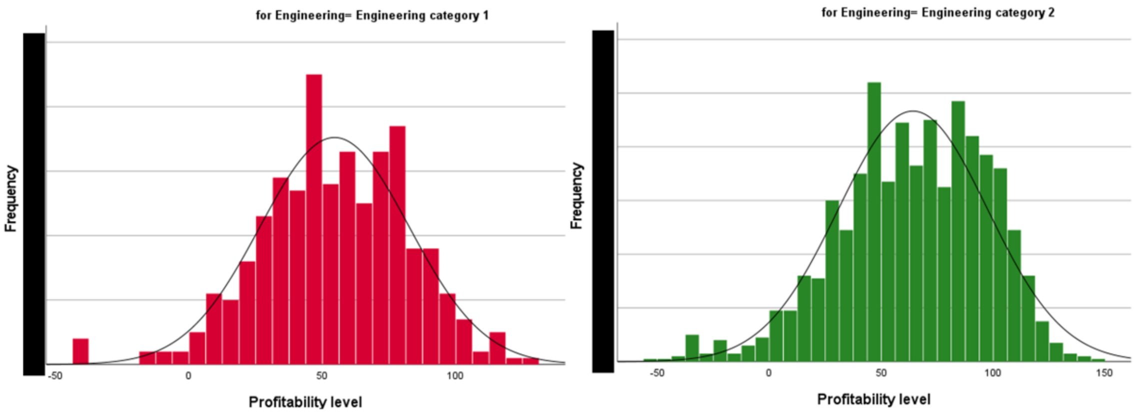

Figure 16. Distribution evaluation for profitability level in size category 1

To examine the shapes of the distributions, Kolmogorov-Smirnov normality test is applied, where null hypothesis posit that the distribution follows normal distribution. Firstly, in the size category 1, the observed distribution of Engineering category 1 fulfills the requirements of normal distribution with significance level of 5 % as $p = 0{,}200$, and thus null hypothesis is accepted. In contradiction, the test results do not show evidence that the distribution of Engineering category 2 is normally distributed as $p < 0{,}001$, which leads to rejection of the null hypothesis. To continue with the testing of normality, the test results for the size category 2 are shown in the figure 17 below. After evaluating the normality of the distributions, the results of the applied statistical testing are presented.

Tests of Normality

	Engineering category	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Profitability level	Engineering category 1	,050	549	,003	,972	549	<,001
	Engineering category 2	,035	1706	<,001	,981	1706	<,001

a. Lilliefors Significance Correction

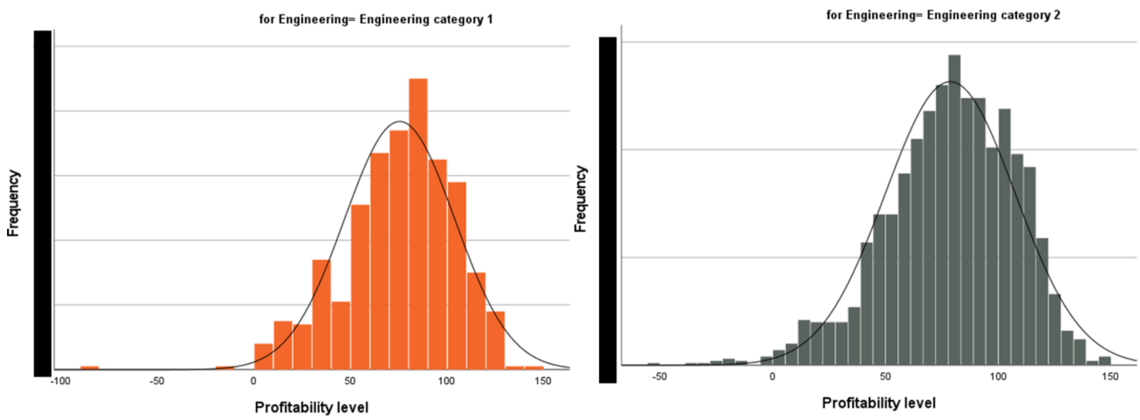

Figure 17. Distribution evaluation for profitability level in size category 2

In the size category 2, the Kolmogorov-Smirnov normality test do not show support for normal distributions in either of the engineering categories with 5 % significance level, and null hypotheses are rejected for both variables. However, due to a large sample size and proximities to normal distributions observed from the histograms, the shapes of the distributions enable these samples to be used in the analysis of t-test for equal means. The t-test is not seen to be sensitive for not fulfilling the normality assumption, if the sample size is large and the distributions are not extremely skewed, which are both true in this occasion. Therefore, the testing of means is applicable to be done with the independent samples t-test. First, the test results for size category 1 are presented in the figure 18.

Group Statistics

	Engineering category	N	Mean	Std. Deviation	Std. Error Mean
Profitability level	Engineering category 1	395	54,551723735	27,960655925	1,4068532800
	Engineering category 2	1250	64,140701636	33,396583063	,94459801408

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Profitability level	Equal variances assumed	19,059	<,001	-5,163	1643	<,001	<,001	-9,588977901	1,8572600416	-13,23182427	-5,946131532
	Equal variances not assumed			-5,659	779,350	<,001	<,001	-9,588977901	1,6945505479	-12,91540189	-6,262553914

Figure 18. Independent samples t-test for size category 1

Based on the results of the Levene's test ($F = 19{,}059,\ p < 0{,}001$), the evidence shows that the variances are not equal between the groups, as hypotheses for Levene's test propose that $H_0\colon \sigma_i^1 = \sigma_i^2$ against $H_1\colon \sigma_i^1 \neq \sigma_i^2$. Thus, the results applied from the t-test is $t(779) = -5{,}659,\ p < 0{,}001$, which indicates that the null hypothesis of the t-test can be rejected. Therefore, it can be stated that there is a statistically significant difference between the means of profitability levels in the engineering categories of 1 and 2 in the size category 1 with the significance level of 0,1 %. To continue with the testing, the test results for size category 2 are shown in the figure 19.

Group Statistics

	Engineering category	N	Mean	Std. Deviation	Std. Error Mean
Profitability level	Engineering category 1	549	75,366179273	28,532470040	1,2177361469
	Engineering category 2	1706	78,677790596	28,730972614	,69560198837

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Profitability level	Equal variances assumed	,122	,727	-2,353	2253	,009	,019	-3,311611323	1,4074059730	-6,071559037	-,5516636094
	Equal variances not assumed			-2,361	932,073	,009	,018	-3,311611323	1,4024063069	-6,063851079	-,5593715675

Figure 19. Independent samples t-test for size category 2

Levene's test results ($F = 0{,}122,\ p = 0{,}727$) indicate that the variances between the categories are equal with 5 % significance level. Therefore, the applied measure for the t-test obtains values of $t(2253) = -2{,}353,\ p = 0{,}019$, which implies that the null hypothesis can be rejected with 5 % significance level. Therefore, there is a statistically significant difference between the means of engineering categories of 1 and 2 also in the second size category of statistical units. However, the results would not be significant with 1 % significance level, but with the chosen risk level of 5 %, the results can be nevertheless accepted. By evaluating the numeric values of the means between both groups, the differences can be observed to be small. However, the difference is visibly larger in the size category 1 than it is in category 2. The differences between the means of both groups are depicted in the boxplot figure 20. below, which also shows the expected higher mean values for profitability in the engineering category 2.

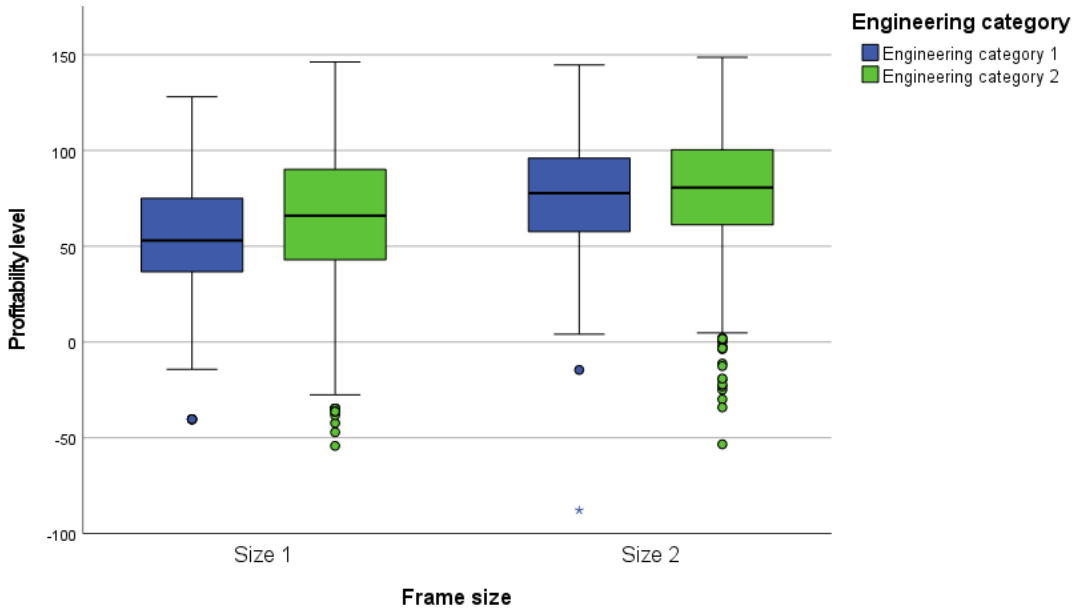

Figure 20. Profitability evaluation between engineering categories

As a result of the two separate testing of equal means, the second directional sub-hypothesis of $H2a$ can be accepted with significance level of 5 % obtained from the t-test of two independent variables. Therefore, it can be stated that the profitability level between engineering categories is different in both size categories. By evaluating the results more closely, the statistical units in the engineering category of 2 indicate improved profitability level in both size categories on average. In the size category 1, the difference between observed means of profitability was visibly larger and measured to be 9,589 points, whereas in category of 2, observed difference was only 3,312 points. Therefore, the difference between profitability levels in the size category 2 is very small in practice, even though the difference was accepted to be statistically significant at 5 %.

As discovered, statistical units in the engineering category 2 were seen to have higher profitability level on average. To further examine the effects of differing engineering groups on profitability, $H2b$ suggest that increased engineering work is connected with higher profitability level. This assumption is based on the idea that increased amount of engineering work extends the customization of the product, thus improves the value received by the customers. The amount of engineering work is determined based on type of the motor, in addition to the quantity of certain VCs and their characteristics, but the exact measure and description of what the presented engineering work number depicts is not exposed. To evaluate the relationship between quantity of engineering work and profitability level, appropriate correlation coefficient measure is applied. Before performing the analysis, the sample is delimited to include only such units that require engineering. Therefore, such statistical units that do not require engineering work at all are left out from this analysis, as the amount of engineering work for those units would be zero. Furthermore, the number of applied sample size in this specific testing is not revealed. To begin with, results for the normality test and related histograms are presented in the figure 21. below.

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
Profitability level	[redacted]	100,0%	0	0,0%	[redacted]	100,0%
Engineering work	[redacted]	100,0%	0	0,0%	[redacted]	100,0%

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Profitability level	,044	[redacted]	<,001	,979	[redacted]	<,001
Engineering work	,342	[redacted]	,000	,748	[redacted]	<,001

a. Lilliefors Significance Correction

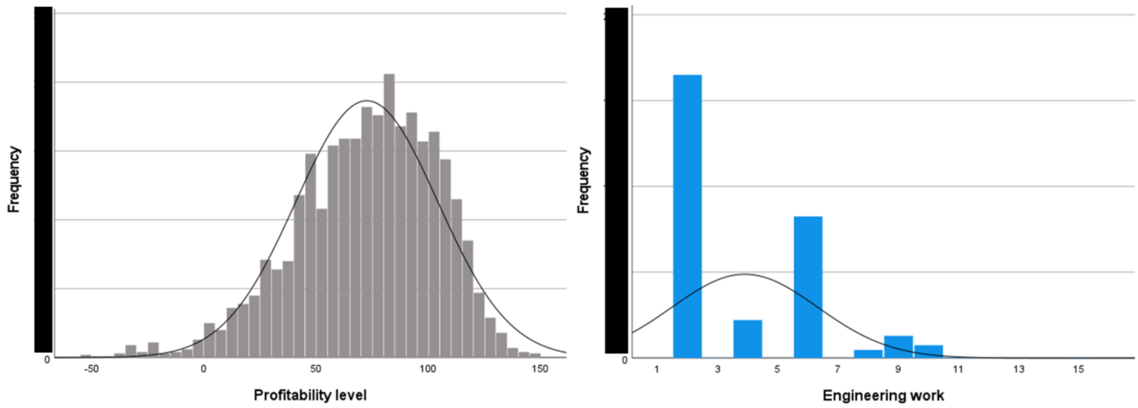

Figure 21. Normality tests and distribution histogram for engineering work

Based on results of the Kolmogorov-Smirnov normality tests, neither of the distributions follow normal distribution, and both null hypotheses can be rejected. As the assumption of normal distributions is not fulfilled, the applied measures for correlation measure are Spearman's rank correlation coefficient ρ and Kendall's τ. The results for correlation measures are shown in the table 11. below.

Table 11. Correlation between engineering work and profitability

Correlations

			Profitability level	Engineering work
Kendall's tau_b	Profitability level	Correlation Coefficient	--	
		Sig. (2-tailed)	.	
		N	[redacted]	
	Engineering work	Correlation Coefficient	,051**	--
		Sig. (2-tailed)	<,001	.
		N	[redacted]	[redacted]
Spearman's rho	Profitability level	Correlation Coefficient	--	
		Sig. (2-tailed)	.	
		N	[redacted]	
	Engineering work	Correlation Coefficient	,066**	--
		Sig. (2-tailed)	<,001	.
		N	[redacted]	[redacted]

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

Descriptive Statistics

	Mean	Std. Deviation	N
Profitability level	72,530510082	31,611687373	[redacted]
Engineering work	3,90	2,416	[redacted]

The test results present that the correlation coefficients obtain values of $\rho = 0{,}066, p < 0{,}001$ and $\tau = 0{,}051, p < 0{,}001$. As the null hypothesis for significance testing of correlation coefficients suggest that the variables are statistically independent, the test results show evidence for rejecting the null hypothesis with 0,1 % significance level. Therefore, statistically significant positive correlation can be found between profitability and the amount of engineering work. However, as both coefficient values of $\rho = 0{,}066$ and $\tau = 0{,}051$ are very close to zero, they indicate virtually nonexistent correlation between the amount of engineering work and profitability level regardless of the statistical significance. Thus, the connection between engineering duration and profitability cannot be seen to have connection in practice. Further examination of the correlation is presented in the scatter plot figure 22. Based on the scatter plot, it is visible that connectivity between the two variables is not apparent as the correlation coefficients also suggest.

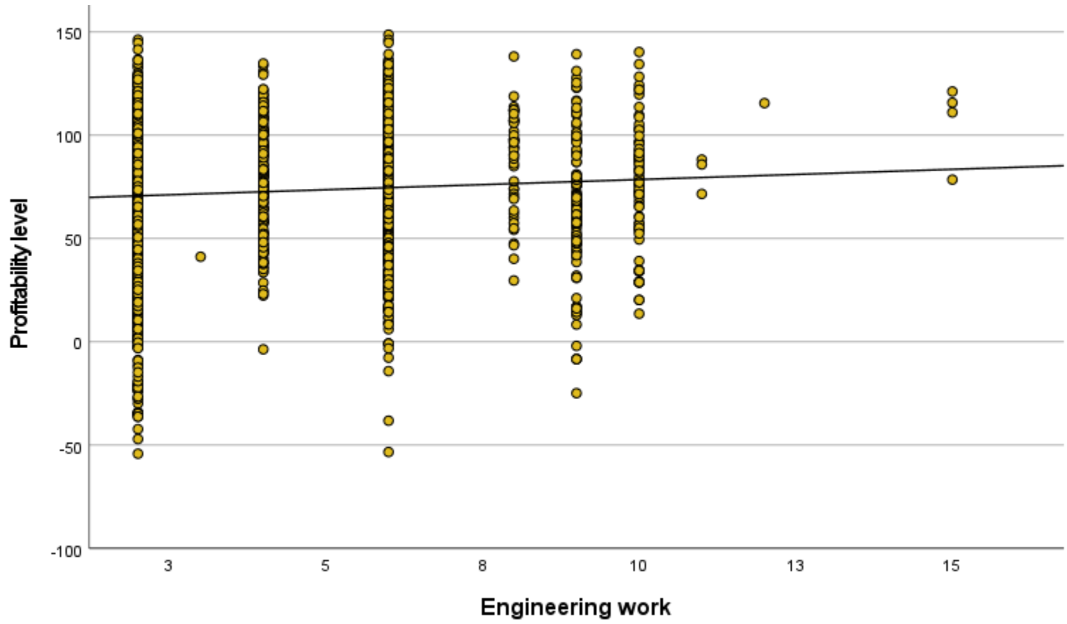

Figure 22. Scatter plot of profitability level and amount of engineering work

As an answer to the sub-hypothesis of $H2b$, the amount of engineering work and profitability were not seen to have relationship in between the two variables. Based on the obtained correlation coefficient values, the relationship is virtually nonexistent in practice, even though the obtained correlation coefficient values were seen to be statistically significant. Regardless of the statistical significance of the correlation coefficient values, but as the coefficient values are nearly zero, $H2b$ can be rejected, which indicates that the amount of engineering work cannot be seen to have connection with the profitability level of a statistical unit.

4.4 Summary of results

As a summary of the obtained results from the statistical analysis, it can be noted that the quantity of different VCs on an individual unit is seen to have a weak but nevertheless positive impact on improved profitability level in both VC groups of A and B. However, as an interesting observation, it was noted the VCs in the group B were seen to have stronger correlation to higher profitability. Based on the results of the correlation coefficients, $H1a$ was accepted. By evaluating each VC included in the group A separately and reviewing their impact on profitability estimate, it was discovered that 7 VCs in total did not explain the variation of the profitability level when both size categories were examined together. From the 47 statistically significant regression models, 14 of the VCs estimated decreasing profitability on those units where such VCs were included. Nonetheless, totality of 33 VCs estimated higher profitability on those presented regression models. Additionally, existence of VC51 estimated the highest profitability increase with the coefficient value of 26,259 points. However, as the most sold VC1 estimated to increase the profitability only 5,135 points, it led to rejection of $H1b$. Therefore, the most sold VC was proved not to be the most profitable product option. Finally, $H1c$ assumed that VCs included in the category 3 estimated the highest positive connection with profitability. The analysis was constructed by creating a multiple regression model, which indicated that VCs included in the category 3 had indeed the highest impact on profitability level based on the coefficient value of the regression model, thereby providing evidence to accept $H1c$. Furthermore, the presented model discovered that categorized VCs included in the VC Group A explained 13,1 % of the profitability variation based on the value of coefficient of determination.

The second directional hypotheses assumed that differing engineering category and amount of engineering work had an impact on profitability. By reviewing the means of profitability levels in between of engineering groups 1 and 2 separately in both size categories, it was discovered that the mean values were different in both engineering categories, and $H2a$ was accepted. The observed differences between the profitability levels of different engineering groups were nevertheless seen to be small. However, the difference between profitability levels of the groups was notably larger in the size category of 1 with the difference of 9,589 points, whereas in category 2, it was only 3,312 points. Furthermore, the relationship between the amount of engineering work and profitability level was evaluated through the values of correlation coefficients. Based on the results, statistically significant dependency between the variables was found, but as the coefficient values were very close to zero, it indicated that the connection was virtually nonexistent. Therefore $H2b$ was rejected. The results of all directional hypotheses are presented in the table 12. below.

Table 12. Directional hypotheses result summary

Directional hypotheses	**Results**
H1a: Higher number of VCs is connected with higher profitability level	Accepted
H1b: The most sold single VC has the largest positive impact on profitability	Rejected
H1c: VCs included in the category 3 estimate higher profitability than other categories	Accepted
H2a: Profitability level is different between engineering group 1 and group 2	Accepted
H2b: Increased engineering work is connected with higher profitability level	Rejected

Based on the obtained results from the statistical tests, and as an answer to the second research question of this study, it can be stated that mass customization of electric motors is a profitable operating strategy for the case company in the reviewed product line and size category. This view is supported by the results that indicate that the number of VCs is positively connected with the profitability level in both variant code groups of A and B. Thus, higher number of VCs on a statistical unit can be thought to result in more customized products, which is ultimately positively connected with profitability level. In addition, 33 individual VCs in the group A were seen to estimate improved profitability level in those units where they were included in. Therefore, it indicates that the profitability level would be lower without the customization. However, 14 of those reviewed VCs were seen to estimate lower profitability level in those units where they were included, but they nevertheless presented the minority of the VCs included in the analysis. Furthermore, by dividing VCs into 7 different categories, 3 of them were seen to have positive impact on profitability, and at the same time 3 of them estimated lower profitability, as the last category did not show statistically significant evidence against affecting the variation of the profitability level. Furthermore, VCs in the category 3 were seen to estimate the largest positive impact on profitability level. In addition, the constructed multiple regression model with VC categories as independent variables were seen to explain the variation of the profitability level by 13,1 %, thereby indicating that the impact of customization through VCs have a recognizable effect on profitability.

Furthermore, the difference between the mean values of profitability levels in separated engineering groups were discovered to be different with 5 % statistical significance level in both size categories. Even though the profitability levels were higher in the engineering group 2 on average in both size categories, the observed differences can be described as recognizable but otherwise small, which is visible in the figure 20. In contradiction, the amount of engineering work was seen to have near zero correlation to profitability level in practice. Therefore, increased amount of engineering work did not show neither improved nor impaired profitability level on individual statistical units.

Based on the presented results, mass customization can be stated to improve the profitability of electric motor manufacturing in the case company when it is evaluated through the measures of VC quantities and engineering categories of 1 and 2. As a conclusion, these presented results in this whole subchapter show strong and statistically significant evidence that mass customization indeed improves the profitability of electric motor manufacturing in general in the case company, thereby supporting the answer to the second research question. As a conclusion, it can be stated that statistical units with more variant codes and belonging to engineering group 2 can be described as such customized units that are more profitable than other units with less VCs and that are included in the engineering category of 1.

However, as recognized in the literature review, costing systems and their accuracy to trace and allocate costs to cost objects with precision were seen to have a highlighted role in product profitability analysis. As this research assumes that the costing is well performed and the product costs are therefore calculated correctly, the results and their accuracy are nevertheless dependent on the costing results. Therefore, the obtained results can be seen as accurate as the applied costing system is in the case company, which can be though to limit the accuracy of the presented results.

5 Conclusions

This final chapter of the research presents main findings and results of this research and recognizes their theoretical contribution to current scientific literature. Furthermore, managerial applications are presented as this research can be seen to have close relations to mass customization and otherwise complex manufacturing industries and their management accounting practices. Finally, limitations of this research are acknowledged and ideas for future research are presented.

5.1 Main findings and results

The aim of this research was to examine how mass customization affects product level profitability in manufacturing companies. Firstly, the literature review presented recent academic advancements and research within the topic areas of mass customization, cost accounting, and product profitability analysis which were all tied together to a single entity to depict the purpose of this research. Mass customization can be presented as an attractive operating strategy for many manufacturers that seek improved value creation and competitive advantage by producing customer-tailored products. In the best-case scenario, mass customization is seen to achieve benefits of both mass production and customization at the same time. However, as products become more complex and variation grows, it also increases the complexity within the manufacturing operations resulting in higher operating costs and challenges to manage the production. Therefore, the value creation of mass customization must exceed the increasing amount of complexity costs to be profitable, which is eventually an indicate of the improved value creation of the customization for the manufacturing company. To manage the complexity induced costs and growing lead times, predetermined and automized product configurations and modules are suggested to be implemented.

However, as product variation becomes extensively large, determination of product costs becomes more difficult, as traditional costing systems can be seen insufficient in such complex environments. These traditional costing systems were seen to lead into costing errors that arise through systematic volume errors in costing results of single products. The recognition of this has led to development of improved costing systems such as ABC, TDABC, and cost estimation models to offer improved costing results in such high variating environment. Implementing an accurate costings system has a highlighted role when product profitability levels are determined for different products, as inaccurate cost information results in incorrect results in profitability analysis. In mass customization, the amount of indirect costs can be seen to grow due to increasing amount of required support functions, and these costs must be then allocated precisely to different products to depict their actual costs based on their resource using. Only accurate cost information can therefore bring value to the managerial accounting practices, as wrong information could lead into wrong decisions. The first research question examined the different available costing systems within such complex manufacturing environment and discovered that TDABC would be the best suited costing system to apply for accurate costing results with relatively easy implementation process. Thereby, the presented literature review tied the concepts of mass customization, product costing systems, and profitability analysis together, and described their close interconnectivity.

Furthermore, the empirical section of this research was carried through quantitative statistical analysis based on data collected from the case company to answer the second research question. The analysis included statistical methods of regression and correlation analysis in addition to comparison of means that were applied to test the predefined directional hypotheses. The effects of mass customization on profitability were analyzed through different variant codes and their quantities on individual statistical units, in addition to differences between engineering groups, which were applied as the measure of customization. Based on the results, and as an answer to the second research question, it was discovered that mass customization of electrical motors is a profitable operations strategy for the case company in the selected motor type and size category. The identified research question was answered by obtaining results to 5 directional hypotheses related customization and its dimensions. These directive hypotheses were chosen together with the case company to direct the statistical analysis. The evidence shows that there is a small but nevertheless positive correlation between the profitability level and the number of variant codes on individual statistical units. In addition, by evaluating variant codes separately, 33 of 47 of the statistically significant regression model-based estimates were seen to improve the profitability level of an individual unit. By categorizing the variant codes into seven categories, 3 of them were seen to estimate improved profitability, 3 negative profitability, and 1 remaining category did not show statistically significant impact on affecting the profitability level at all. However, the total impact of all categories was still seen to be positive. Furthermore, by evaluating the effect of both engineering groups, it was discovered that units in group 2 were seen to have statistically significant higher profitability level in both size categories on average. However, the amount of engineering and profitability level were seen to have practically nonexistent connection. Based on the obtained results from the statistical tests, the second research question regarding the increased profitability of mass customization in electric motor manufacturing in the case company was confirmed based on the statistical evidence.

This research has contributed to the current scientific literature by combining statistical and econometric product profitability analysis within the framework of mass customization manufacturing. As identified research gap remark, current literature lacks empirical studies of how profitability is affected by mass customization, how optional product features impact profitability in industrial environment, and how statistical or econometric methods in profitability analysis can be utilized in management accounting practices. Therefore, this research has a direct contribution to these identified research gaps by providing such empirical evidence, even though the actual financial and other product related measures are made unrecognizable in the public version due to confidentiality reasons.

5.2 Managerial applications

The presented statistical method of regression model, where product characteristics are recognized through dummy variables of their own, enables companies to evaluate the differences between customized products and their impact on selected variables through statistical methods. Furthermore, the presented method can be also used for examining other features than profitability. As an example, it is well applicable for estimating lead times and material or labor costs based on those product features also for products that are not manufactured before, thereby offering large variety of managerial applications and a procedure to utilize it in practice. In addition, the obtained results from analysis offer possibilities for the case company to evaluate how the total profitability or performance of those underperforming variant codes could be improved based on their impact on profitability. Therefore, this research can be seen to have close relations to management accounting, and especially to statistical profitability analysis practices in manufacturing companies that produce large variety of products with distinct product features.

In addition, the presented model and statistical method can be implemented in the case company to include every motor type and size category. It is well applicable in such situation, as the data is already existing, but it is only applied in this research by far. By implementing the same analysis for all products and size categories, it would enable making comparison in between of multiple products and estimating the impacts of other VCs that were not included in this analysis. Further possibilities of applying the presented method can be seen to increase the managerial applications of this research within the case company.

5.3 Limitations and future research

This study and its results are limited to depict strictly the situation within the case company and its selected product type and size category. As already noted in the methodology section, regardless of that quantitative research aim to provide generalizable results, generalization of the results of this study is not justified in any other context than in the case company. In addition, differing results are also expected if different product and size categories would be selected as the target of the analysis. However, the statistical methods and particularly the regression model is well applicable for performing other research related to understanding of how certain product features and other characteristics affect and estimate product level profitability.

The trustworthiness of the obtained results is limited by several causes. From the data quality perspective, the research assumes that the product costing is done precisely, and related costs are thus accurately traced and allocated to cost objects. Therefore, incorrect cost information would lead into wrongful results on profitability analysis, resulting incorrect results in this research. The cost information from the case company was evaluated to be precise enough as such to produce accurate results. However, the results can be described as precise as the costing system in the case company is. In addition, as only selected amount of different variant codes was selected to be included in the closer analysis in the regression models, the results could differ if the excluded variant codes would be included in the analysis. From the statistical method perspective, this research gives less emphasis to some assumptions, especially in the regression models due to large sample size. Large deviations from the regression model assumptions can be seen to result in more imprecise results. Nonetheless, the main assumptions and significance levels of regression model and their coefficients were seen to be fulfilled. In addition, as large amount of varying information is described through one estimated number, it is inevitable that it includes certain impreciseness and deviations.

For the future, interesting research problems could include examining the differences between traditional and more advanced costing systems on recognizing product profitability levels in mass customization manufacturing environment, which would require implementing a new costing system. Furthermore, within the same context of this research, similar analysis could be used for constructing a multiple case study within the case company to include other size categories and motor types as well. This could be seen to result in more generalizable results inside of the case company. In addition, more complex regression models could be implemented to depict the relationship between different variables in more detailed level with smaller errors terms of the estimates. In addition, as already recognized before, from the perspective of the case company, a more detailed evaluation of non-standardized mass customization and its effects on profitability would be an interesting topic area to focus on next.

References

Abdul Manaf, S. M., Bidin, N. F., Salleh, W. A., Idris, A. R., & Mohd Yusoff, Z. Z. (2021). PROFITABILITY PERFORMANCE ANALYSIS: THE EVIDENCE FROM PRIVATE TELECOMMUNICATION FIRMS IN MALAYSIA. Malaysian management journal, 25, 191-212. https://doi.org/10.32890/mmj2021.25.8

Aczel, A. D. (2012). Complete business statistics. Wohl Publishing.

Afonso, P., Vyas, V., Antunes, A., Silva, S., & Bret, B. P. J. (2021). A stochastic approach for product costing in manufacturing processes. Mathematics (Basel), 9(18), 2238. https://doi.org/10.3390/math9182238

Aichner, T., & Gruber, B. (2017). Managing customer touchpoints and customer satisfaction in B2B mass customization: A case study. International Journal of Industrial Engineering and Management, 8(3), 131-140.

Akinc, U., & Meredith, J. R. (2015). Make-to-forecast: Customization with fast delivery. International journal of operations & production management, 35(5), 728-750. https://doi.org/10.1108/IJOPM-12-2012-0567

Atkinson, A. A., Kaplan, R. S., & Young, S. M. (2004). Management accounting (4th, international ed.). Prentice-Hall.

Balakrishnan, R., Labro, E., & Sivaramakrishnan, K. (2012). Product costs as decision aids: An analysis of alternative approaches (Part 1). Accounting horizons, 26(1), 6-20. https://doi.org/10.2308/acch-50086

Barbosa, C., & Azevedo, A. (2018). Hybrid modelling of MTO/ETO manufacturing environments for performance assessment. International journal of production research, 56(15), 5147-5171. https://doi.org/10.1080/00207543.2017.1421788

Barros, R., & Ferreira, A. (2017). Time-driven activity-based costing: Designing a model in a Portuguese production environment. Qualitative Research in Accounting and Management, 14(1), 2-20. https://doi.org/10.1108/QRAM-10-2015-0095 Bhimani, A., Horngren, C. T., Datar, S. M., & Rajan, M. V. (2015). Management and cost accounting (Sixth edition.). Pearson Education Limited.

Bhimani, A., Horngren, C. T., Datar, S. M., & Rajan, M. V. (2015). Management and cost accounting (Sixth edition.). Pearson Education Limited.

Brierley, J. A. (2016). An examination of the use of profitability analysis in manufacturing industry. International journal of accounting, auditing and performance evaluation, 12(1), 85-102. https://doi.org/10.1504/IJAAPE.2016.073896

Bryman, A., & Bell, E. (2011). Business research methods (3rd ed.). Oxford University Press.

Burja, C. (2011). FACTORS INFLUENCING THE COMPANIES' PROFITABILITY. Annales Universitatis Apulensis: Series Oeconomica, 13(2), 215-224. https://www.proquest.com/scholarly-journals/factors-influencing-companies-profitability/docview/922556485/se-2

Burlina, C., & Di Maria, E. (2020). Manufacturing and value-added dynamics in global value chains: The case of Italy. Competitiveness review, 30(4), 457-470. https://doi.org/10.1108/CR-10-2019-0100

Cannas, V. G., Masi, A., Pero, M., & Brunø, T. D. (2022). Implementing configurators to enable mass customization in the Engineer-to-Order industry: A multiple case study research. Production planning & control, 33(9-10), 974-994. https://doi.org/10.1080/09537287.2020.1837941

Čermák, P. (2015). Customer Profitability Analysis and Customer Life Time Value Models: Portfolio Analysis. Procedia economics and finance, 25, 14-25. https://doi.org/10.1016/S2212-5671(15)00708-X

Charaf, K., Rahmounib, A. F., & Sabar, M. (2022). The association between Activity-Based Costing and performance: Empirical evidence from Moroccan companies. Accounting and management information systems, 21(1), 25-45. https://doi.org/10.24818/jamis.2022.01002

Chen, Z., & Wang, L. (2007). A generic activity-dictionary-based method for product costing in mass customization. Journal of manufacturing technology management, 18(6), 678-700. https://doi.org/10.1108/17410380710763859

Chiarini, A., & Vagnoni, E. (2017). Strategies for modern operations management: Answers from European manufacturing companies. Benchmarking: an international journal, 24(4), 1065-1081. https://doi.org/10.1108/BIJ-11-2015-0115

Cicconi, P., Castorani, V., Germani, M., Mandolini, M., & Vita, A. (2020). A multi-objective sequential method for manufacturing cost and structural optimization of modular steel towers. Engineering with computers, 36(2), 475-497. https://doi.org/10.1007/s00366-019-00709-0

Creswell, J. W. & Creswell, J. D., (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. (5th edition). SAGE Publications, Inc.

Dalci, I. (2018). Impact of financial leverage on profitability of listed manufacturing firms in China. Pacific accounting review, 30(4), 410-432. https://doi.org/10.1108/PAR-01-2018-0008

de Treville, S., Ketokivi, M., & Singhal, V. (2017). Competitive manufacturing in a high-cost environment: Introduction to the special issue. Journal of operations management, 49-51(1), 1-5. https://doi.org/10.1016/j.jom.2017.02.001

Deshpande, A. (2018). Relationships between advanced manufacturing technologies, absorptive capacity, mass customization, time to market and financial and market performance: An empirical investigation. Asia-Pacific journal of business administration, 10(1), 2-20. https://doi.org/10.1108/APJBA-03-2017-0024

Dohale, V., Gunasekaran, A., Akarte, M. M., & Verma, P. (2022). 52 Years of manufacturing strategy: An evolutionary review of literature (1969-2021). International journal of production research, 60(2), 569-594. https://doi.org/10.1080/00207543.2021.1971788

Drury, C., & Tayles, M. (2006). Profitability analysis in UK organizations: An exploratory study. The British accounting review, 38(4), 405-425. https://doi.org/10.1016/j.bar.2006.05.003

Fisher, J. G., & Krumwiede, K. (2015). Product Costing Systems: Finding the Right Approach. The Journal of Corporate Accounting & Finance, 26(4), 13-21. https://doi.org/10.1002/jcaf.22045

Fogliatto, F. S., da Silveira, G. J., & Borenstein, D. (2012). The mass customization decade: An updated review of the literature. International journal of production economics, 138(1), 14-25. https://doi.org/10.1016/j.ijpe.2012.03.002

Franke, N., & Hader, C. (2014). Mass or Only "Niche Customization"? Why We Should Interpret Configuration Toolkits as Learning Instruments. The Journal of product innovation management, 31(6), 1214-1234. https://doi.org/10.1111/jpim.12137

Ganorkar, A. B., Lakhe, R. R., & Agrawal, K. N. (2018). Implementation of TDABC in SME: A Case Study. The Journal of corporate accounting & finance, 29(2), 87-113. https://doi.org/10.1002/jcaf.22327

Guo, L. (2010). Product Design and Financial Performance. Design Management Journal, 5(1), 5-19. https://doi.org/10.1111/j.1948-7177.2010.00010.x

Haag, A., & Haag, L. (2019). Further empowering variant tables for mass customization. International Journal of Industrial Engineering and Management, 10(2), 155-170. https://doi.org/10.24867/IJIEM-2019-2-236

Hada, T., Bărbuţă-Mişu, N., & Mărginean, R. (2018). Forecasting Firm Performance: Evidence from Romanian Furniture Firms. Ekonomika - Vilniaus universitetas, 97(1), 87-104. https://doi.org/10.15388/ekon.2018.1.11781

Haug, A., Shafiee, S., & Hvam, L. (2019). The costs and benefits of product configuration projects in engineer-to-order companies. Computers in industry, 105, 133-142. https://doi.org/10.1016/j.compind.2018.11.005

Hooshmand, Y., Köhler, P., & Korff-Krumm, A. (2016). Cost Estimation in Engineer-to-Order Manufacturing. Open Engineering (Warsaw), 6(1), 22-34. https://doi.org/10.1515/eng-2016-0002

Hoozée, S., & Hansen, S. C. (2018). A comparison of activity-based costing and time-driven activity-based costing. Journal of management accounting research, 30(1), 143-167. https://doi.org/10.2308/jmar-51686

Hvam, L., Hansen, C. L., Forza, C., Mortensen, N. H., & Haug, A. (2020). The reduction of product and process complexity based on the quantification of product complexity costs. International journal of production research, 58(2), 350-366. https://doi.org/10.1080/00207543.2019.1587188

Ikäheimo, S., Malmi, T., & Walden, R. (2019). Yrityksen laskentatoimi (8., uudistettu painos.). Alma Talent Oy.

Jassem, S. (2021). Alternative To Distortions Created By Traditional Cost Accounting: Throughput Accounting. Academy of strategic management journal, 20(2), 1-15.

Järvenpää, M., Länsiluoto, A., Partanen, V., & Pellinen, J. (2017). Talousohjaus ja kustannuslaskenta (2.–4. painos.). Sanoma Pro Oy

Kaakinen, M. & Ellonen, N, (n.d.a). Regressioanalyysi. In Quantitative Methods Guidebook. Finnish Social Science Data Archive. Retrieved 2023-01-30 from https://www.fsd.tuni.fi/fi/palvelut/menetelmaopetus/kvanti/regressio/analyysi/

Kaakinen, M. & Ellonen, N, (n.d.b). Regressiomallin arviointi. In Quantitative Methods Guidebook. Finnish Social Science Data Archive. Retrieved 2023-02-09 from https://www.fsd.tuni.fi/fi/palvelut/menetelmaopetus/kvanti/regressio/arviointi/

Kestilä-Kekkonen, E. (n.d.). Kovarianssi ja korrelaatio. In Quantitative Methods Guidebook. Finnish Social Science Data Archive. Retrieved 2023-01-30 from https://www.fsd.tuni.fi/fi/palvelut/menetelmaopetus/kvanti/korrelaatio/korrelaatio/

Kristianto, Y., Helo, P., & Jiao, R. J. (2013). Mass customization design of engineer-to-order products using Benders' decomposition and bi-level stochastic programming. Journal of intelligent manufacturing, 24(5), 961-975. https://doi.org/10.1007/s10845-012-0692-z

Korneeva, E., Hönigsberg, S., & Piller, F. (2021). Mass Customization Capabilities in Practice – Introducing the Mass into Customized Tech-Textiles in an SME Network. International Journal of Industrial Engineering and Management, 12(2), 115-128. https://doi.org/10.24867/IJIEM-2021-2-281

Laith Akram, M. A., & Yusuf Ali, K. A. (2017). The Implementing Activity-Based Costing Technique (ABC) and Its impact on Profitability: A Study of Listed Manufacturing Companies in Jordan. International Journal of Economics and Financial Issues, 7(2), 271-276. https://www.proquest.com/scholarly-journals/implementing-activity-based-costing-technique-abc/docview/2270076701/se-2

Li, H., Ji, Y., Luo, G., & Mi, S. (2016). A modular structure data modeling method for generalized products. International journal of advanced manufacturing technology, 84(1-4), 197-212. https://doi.org/10.1007/s00170-015-7815-6

Li, Z., Yang, H., & Xu, J. (2022). How to adopt mass customization strategy: Understanding the role of consumers' perceived brand value. Computers & industrial engineering, 173, . https://doi.org/10.1016/j.cie.2022.108666

Liu, Y., & Tyagi, R. K. (2017). Outsourcing to convert fixed costs into variable costs: A competitive analysis. International journal of research in marketing, 34(1), 252-264. https://doi.org/10.1016/j.ijresmar.2016.08.002

Løkkegaard, M., Bertram, C. A., Mortensen, N. H., Hvam, L., & Haug, A. (2022). Identifying profitable reference architectures in an engineer-to-order context. International journal of production research, ahead-of-print(ahead-of-print), 1-15. https://doi.org/10.1080/00207543.2022.2036850

Mazbayeva, K., Barysheva, S., & Saparbayeva, S. S. (2022). The influence of the importance of cost information, product diversity and accountants' participation on the activity-based costing adoption. Journal of accounting & organizational change, 18(2), 346-366. https://doi.org/10.1108/JAOC-01-2021-0013

Mikulskienė, B., & Moskvina, J. (2020). Peculiar properties of the pricing process in customized furniture manufacturing enterprises. Journal of revenue and pricing management, 19(6), 411-420. https://doi.org/10.1057/s41272-020-00242-6

Mills, A. J., Durepos, G., & Wiebe, E. (2010). SAGE Publications, Inc., https://dx.doi.org/10.4135/9781412957397

Myrelid, A., & Olhager, J. (2015). Applying modern accounting techniques in complex manufacturing. Industrial management + data systems, 115(3), 402-418. https://doi.org/10.1108/IMDS-09-2014-0250

Myrelid, A., & Olhager, J. (2019). Hybrid manufacturing accounting in mixed process environments: A methodology and a case study. International journal of production economics, 210, 137-144. https://doi.org/10.1016/j.ijpe.2019.01.024

Myrodia, A., Kristjansdottir, K., & Hvam, L. (2017). Impact of product configuration systems on product profitability and costing accuracy. Computers in industry, 88, 12-18. https://doi.org/10.1016/j.compind.2017.03.001

Myrodia, A., Hvam, L., Sandrin, E., Forza, C., & Haug, A. (2021). Identifying variety-induced complexity cost factors in manufacturing companies and their impact on product profitability. Journal of manufacturing systems, 60, 373-391. https://doi.org/10.1016/j.jmsy.2021.04.017

Namazi, M. (2016). Time-driven activity-based costing: Theory, applications and limitations. Iranian journal of management studies, 9(3), 457. https://doi.org/10.22059/ijms.2016.57481

Niazi, A., Dai, J. S., Balabani, S., & Seneviratne, L. (2006). Product cost estimation: Technique classification and methodology review. Journal of manufacturing science and engineering, 128(2), 563-575. https://doi.org/10.1115/1.2137750

Ning, F., Shi, Y., Cai, M., Xu, W., & Zhang, X. (2020). Manufacturing cost estimation based on a deep-learning method. Journal of manufacturing systems, 54, 186-195. https://doi.org/10.1016/j.jmsy.2019.12.005

Nothhelfer, R. (2017). Financial Accounting. De Gruyter.

Novak, P., Papadaki, Š., Hrabec, D., & Popesko, B. (2016). Comparison of managerial implications for utilization of variable costing and throughput accounting methods. Istrazivanja i projektovanja za privredu, 14(3), 351-360. https://doi.org/10.5937/jaes14-10895

Peeters, K., & van Ooijen, H. (2020). Hybrid make-to-stock and make-to-order systems: A taxonomic review. International journal of production research, 58(15), 4659-4688. https://doi.org/10.1080/00207543.2020.1778204

Pellinen, J. (2019). Kustannuslaskenta ja kannattavuusajattelu. (3., uudistettu painos.). Alma.

Persson, M., & Lantz, B. (2022). Effects of customization and product modularization on financial performance. Journal of engineering and technology management, 65. https://doi.org/10.1016/j.jengtecman.2022.101704

Pham, D. C., Nguyen, L. S., Doan, T. N., Ta, T. T., & Pham, H. L. (2021). The influence of activity-based costing implementation on firm performance: An empirical evidence from Vietnam. Montenegrin journal of economics, 17(4), 167-179. https://doi.org/10.14254/1800-5845/2021.17-4.15

Pietrzak, Z., Wnuk-Pel, T., & Christauskas, C. (2020). Problems with activity-based costing implementation in Polish and Lithuanian companies. Inžinerinė ekonomika, 31(1), 26–38. https://doi.org/10.5755/j01.ee.31.1.2433

Quantitative Methods Handbook. (n.d.a). Hypoteesien testaus. Finnish Social Science Data Archive. Retrieved 2023-4-2 from https://www.fsd.tuni.fi/fi/palvelut/menetelmaopetus/kvanti/hypoteesi/harjoitus1/

Quantitative Methods Handbook. (n.d.a). Hypoteesien testaus – SPSS-Harjoitus 1. Finnish Social Science Data Archive. Retrieved 2023-4-2 from https://www.fsd.tuni.fi/fi/palvelut/menetelmaopetus/kvanti/hypoteesi/harjoitus1/

Quesado, P., & Silva, R. (2021). Activity-based costing (ABC) and its implication for open innovation. Journal of open innovation, 7(1), 1-20. https://doi.org/10.3390/joitmc7010041

Radionova, N., Skrypnyk, M. & Voronkova, T. (2019). DUAL NATURE OF INDUSTRIAL ENTERPRISE COST MANAGEMENT SYSTEM. Baltic Journal of Economic Studies, 5(2), 184-190. https://doi.org/10.30525/2256-0742/2019-5-2-184-190

Ruiz-de-Arbulo-Lopez, P., Fortuny-Santos, J., & Cuatrecasas-Arbós, L. (2013). Lean manufacturing: Costing the value stream. Industrial management + data systems, 113(5), 647-668. https://doi.org/10.1108/02635571311324124

Shamsuzzoha, A., Kekäle, T., & Helo, P. T. (2010). Aligning external varieties to internal varieties for market solutions. International Journal of Innovation and Learning, 8(4), 377-392. https://doi.org/10.1504/IJIL.2010.035748

Shao, X. (2020). What is the right production strategy for horizontally differentiated product: Standardization or mass customization? International journal of production economics, 223, 107527. https://doi.org/10.1016/j.ijpe.2019.107527

Sheng, H., Feng, T., Chen, L., & Chu, D. (2022). Operational coordination and mass customization capability: The double-edged sword effect of customer need diversity. The international journal of logistics management, 33(1), 289-310. https://doi.org/10.1108/IJLM-11-2020-0417

Soufhwee, A., Mohamad, E., & Abdul Rahman, A. A. (2019). Enhancement of time-driven activity–based costing (TDABC) by using simulation in manufacturing process towards industry 4.0. International journal of innovative technology and exploring engineering, 8(10), 1895-1900. https://doi.org/10.35940/ijitee.J9243.0881019

Stock, J. H. & Watson, M. W. (2020). Introduction to Econometrics, Global Edition (4th ed.). Pearson.

Stout, D. E., & Propri, J. M. (2011). Implementing Time-Driven Activity-Based Costing at a Medium-Sized Electronics Company. Management Accounting Quarterly, 12(3), 1-11. https://www.proquest.com/scholarly-journals/implementing-time-driven-activity-based-costing/docview/884349163/se-2

Thyssen, J., Israelsen, P., & Jørgensen, B. (2006). Activity-based costing as a method for assessing the economics of modularization—A case study and beyond. International journal of production economics, 103(1), 252-270. https://doi.org/10.1016/j.ijpe.2005.07.004

van Triest, S., Bun, M. J., G., van Raaij, E., M., Vernooij, M. J., & A. (2009). The impact of customer-specific marketing expenses on customer retention and customer profitability. Marketing Letters, 20(2), 125-138. https://doi.org/10.1007/s11002-008-9061-2

Vedernikova, O., Siguenza-Guzman, L., Pesantez, J., & Arcentales-Carrion, R. (2020). Time-driven activity-based costing in the assembly industry. Australasian accounting, business & finance journal, 14(4), 3-23. https://doi.org/10.14453/aabfj.v14i4.2

Wiengarten, F., Singh, P. J., Fynes, B., & Nazarpour, A. (2017). Impact of mass customization on cost and flexibility performances: The role of social capital. Operations management research, 10(3-4), 137-147. https://doi.org/10.1007/s12063-017-0127-2

Willner, O., Powell, D., Gerschberger, M., & Schönsleben, P. (2016). Exploring the archetypes of engineer-to-order: An empirical analysis. International journal of operations & production management, 36(3), 242-264. https://doi.org/10.1108/IJOPM-07-2014-0339

Yang, C., & Tsou, M. (2017). Does an own-brand produce higher profitability? Evidence from Taiwan's manufacturing firms. The Journal of business & industrial marketing, 32(7), 925-936. https://doi.org/10.1108/JBIM-05-2016-0104

Zhang, M., & Tseng, M. M. (2007). A Product and Process Modeling Based Approach to Study Cost Implications of Product Variety in Mass Customization. IEEE transactions on engineering management, 54(1), 130-144. https://doi.org/10.1109/TEM.2006.889072

Zhang, M., Qi, Y., Zhao, X., & Duray, R. (2015). Mass customisation systems: Complementarities and performance consequences. International journal of logistics, 18(6), 459-475. https://doi.org/10.1080/13675567.2015.1015507

Öker, F. and Adigüzel, H. (2016), Time-Driven Activity-Based Costing: An Implementation in a Manufacturing Company. J. Corp. Acct. Fin, 27: 39-56. https://doi-org.proxy.uwasa.fi/10.1002/jcaf.22144

Appendices

Appendix 1. Variables list

Excluded from the public version.

Appendix 2. Variant code distribution

Variant code	Description	Catgory	Quantity	Percentage of total	Cumulative %
1		5			
2		4			
3		7			
4		Other			
5		5			
6		4			
7		6			
8		1			
9		5			
10		5			
11		1			
12		1			
13		1			
14		1			
15		5			
16		4			
17		1			
18		5			
19		5			
20		5			
21		5			
22		6			
23		5			
24		5			
25		1			
26		1			
27		1			
28		5			
29		5			
30		6			
31		1			
32		5			
33		2			
34		1			
35		1			
36		1			
37		1			
38		6			
39		5			
40		5			
41		5			
42		3			
43		5			
44		5			
45		5			
46		5			
47		5			
48		2			
49		5			
50		1			
51		5			
52		5			
53		3			
54		2			
Other variant codes					100,00 %

Appendix 3. Linear regression models for size category 1

Excluded from the public version.

Appendix 4. Linear regression models for size category 2

Excluded from the public version.