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BUSINESS INTELLIGENCE IMPLEMENTATION FOR OPTIMIZING THE TIMBER SUPPLY CHAIN OF A FINNISH SAWMILL CORPORATION

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ABSTRACT

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The subject of this thesis was business intelligence (BI) implementation and the optimization possibilities it enables in the context of the timber supply chain. Research questions were "What to consider when designing and implementing a BI system for optimizing the timber supply chain?" and "Did the implemented BI system improve the data management of the timber supply chain?". Of the timber supply chain activities, purchasing, timber harvesting, transport, and sorting, were researched. Previous research on optimization possibilities, BI competence, and data warehouse implementation were examined. The case study was conducted following an action design research framework. The thesis was commissioned by the case company, a Finnish sawmill, with 15 units and nearly 900 employees. The results were summarized in two conclusions. Instead of suboptimization efforts, supply chain optimization requires collaboration through the whole supply chain towards a shared objective to provide value for the end customer. A solution including a scalable BI system with a centralized EDW and adequate processes to support decision-making at both strategic and operational levels supports the optimization of a supply chain. Sufficient storage and compute capacity, source data quality, in-house resources and skills, and end-user training are key factors in BI implementation and maintenance. The BI system containing data warehouse and visualization achieved 14 of 16 data management demands, and nine reports were created for end-users.

Keywords: business intelligence, forest industry, supply chains, optimisation, data warehouses

TIIVISTELMÄ

Nousiainen, Sanna
Liiketoimintatiedon hyödyntämisen käyttöönotto puun toimitusketjun optimointiin suomalaisessa sahayhtiössä
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Tutkimuksessa tarkasteltiin liiketoimintatiedon hyödyntämisen käyttöönottoa puun toimitusketjun optimoinnissa. Tutkimuskysymykset olivat "Mitä ottaa huomioon suunniteltaessa ja toteutettaessa business intelligence (BI)-järjestelmää puun toimitusketjun optimoimiseksi?" ja "Paransiko BI-järjestelmän käyttöönotto datan hallintaa puun toimitusketjussa?". Tutkimuksessa selvitettiin puunhankinnan toiminnoista ostoa, korjuuta, kuljetusta ja lajittelua. Lisäksi tarkasteltiin aiempaa tutkimusta optimointimahdollisuuksista, BI-kompetenssista ja tietovaraston käyttöönotosta. Tapaustutkimus noudatti suunnittelutoimintatutkimuksen viitekehystä. Tutkimuksen toimeksiantaja oli suomalainen sahayhtiö, jolla on 15 yksikköä ja lähes 900 työntekijää. Tutkimuksen tuloksena oli, että osittaisten optimointien sijaan toimitusketjun optimointi edellyttää yhteistyötä koko toimitusketjun läpi kohti yhteistä tavoitetta tuottaa lisäarvoa loppuasiakkaalle. Lisäksi BI-ratkaisu, joka sisältää skaalautuvan BI-järjestelmän keskitetyllä tietovarastolla sekä asianmukaiset prosessit päätöksenteon tueksi strategisella ja operatiivisella tasolla, tukee toimitusketjun optimointia. BI-järjestelmän käyttöönotossa ja ylläpidossa on huomioitava riittävä tallennustila ja laskentakapasiteetti, lähdedatan laatu, sisäiset resurssit ja taidot sekä loppukäyttäjien koulutus. Tietovaraston ja visualisointityökalun sisältävä BI-järjestelmä täytti 16 datan hallinnan vaatimuksesta 14, ja yhdeksän raporttia luotiin loppukäyttäjille.

Asiasanat: business intelligence, metsäteollisuus, toimitusketjut, optimointi, tietovarasto

FIGURES

TABLES

TABLE OF CONTENTS

1 INTRODUCTION

Sawn timber is one of the five products most exported from Finland with a value of 2,6 billion euros in 2022 (Sahateollisuus Ry, 2024). In total, the industrial value of wood products reaches nearly 7 billion per year (Tilastokeskus, 2023a). The global market and digitalization provide possibilities for the wood product industry, where the strengths lie in the quality and renewability of the product and the reliability of the domestic supply chain (Kiiskinen & Innovaatiot ja yritysrahoitus, 2021).

The increased quality and flexibility requirements of the timber supply chain demand developing tools and methods for planning the flow of raw materials (Rönnqvist, 2003). In this thesis, a timber supply chain refers to wood procurement as purchasing, felling, transporting, and sorting of roundwood. The scope ranges from the forest to the sawmill reception and contains several opportunities for optimization. This thesis does not engage with forest management and silviculture activities, mill processes, or sales to resellers or end customers. The research is limited to the supply chain of roundwood as it is the preferred material for sawmills.

While optimization is a common concept in industry as a tool to find the best or near-best solution, business intelligence is the main paradigm for decision-making in business management and the financial sector. It refers to collecting and analyzing data to facilitate decision-making. The subject of this thesis is business intelligence implementation and the optimization possibilities it enables in the context of the timber supply chain of the case company.

Overlapping fields often offer interesting research subjects. The concepts such as "storage", "landing", and "log" carry different meanings whether used in the forest or in front of a computer. While timber is the raw material for sawmills to produce sawn timber, business intelligence system ingests raw data and processes it to provide information. These refined products represent forestry and information systems, the research fields in this study that are complemented with business management regarding the literature of supply chain and business intelligence adoption and competence. Data warehouse presents a more technical approach to business intelligence, although the terms are occasionally used synonymously in the research.

Ain et al. (2019) conducted a literature review of 111 peer-reviewed studies about business intelligence adoption, utilization, and success published 2000—2019 concluding the research gap especially related to the impact on marketing and sales, impact on management and internal operations, and impact on procurement. Consequently, business intelligence adoption in the context of a supply chain is a subject worth studying. 56 % of the research was quantitative, and the paper does not mention design research approaches in the research models (Ain et al., 2019). The research method in this thesis is action design research, and the framework by Sein et al. (2011) is used in the case study commissioned by a large Finnish sawmill corporation.

The research questions are:

1) What to consider when designing and implementing a BI system for optimizing the timber supply chain?
2) Did the implemented BI system improve the data management of the timber supply chain?

The first question is researched based on previous literature regarding supply chain, optimization, business intelligence, and data warehouses. The second question is examined by building a design artifact and examining the artifact following the action design research method. This includes utilizing, analyzing, and selecting related findings from the previous literature.

The literature search was conducted mostly in the JYKDOK database by Jyväskylä University Library. Several papers were found in Google Scholar search but then searched by the title from JYKDOK for better availability. The literature available online and published after 2015 was preferred, but older, distinguished papers were researched as well. Regarding forestry research, the search was conducted to find papers related to supply chain and optimization. The quality and systems manager of the case company recommended several forestry sources relevant to the case study.

In the next chapter, the concepts of supply chain and timber supply chain are defined and examined. Four timber supply chain activities are introduced: purchasing, timber harvesting, transport, and sorting. Then the optimization and optimization possibilities for each activity are explored.

In the third chapter, the concepts of business intelligence, business intelligence evolution, and business intelligence competence are studied. The fourth chapter examines data warehouse implementation and elements. First, the planning and selection of data warehouse reference architectures are explained briefly, then source data, data vault, data marts, and finally visualization and analytics.

The fifth chapter introduces the research method, the research process, and the case company. The case study and the results are presented in the sixth chapter. The study follows the action design research framework consisting of four stages: 1) problem formulation, 2) building, intervention, and evaluation, 3) reflection and learning, and 4) formalization of learning. In the last chapter, the research is summarized and conclusions to the research questions are presented.

2 TIMBER SUPPLY CHAIN OPTIMIZATION

A common feature related to both data and raw material is flow. The flow has an objective to bring value to the customer. In between, the number of contributors and the complexity of the process varies significantly. Mentzer et al. (2001, p. 4) summarize a supply chain as "a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer", where upstream refers to the supply and downstream to the distribution.

An integrated network describes the nature of the shared effort for supplying, producing, storing, and distributing raw materials and products (Garcia & You, 2015). The network structure of a supply chain means the entities can have several different roles and belong to several supply chains simultaneously (Mentzer et al., 2001). For example, sawmill companies can trade timber with other companies to avoid long-distance transport and act as both the supplier and the customer. In addition, these companies are competitors responsible for their core supply chains.

The simplified version of a supply chain consists of the intermediate company that provides a product or a service from the supplier to the customer. A more complex supply chain includes the supplier of the original supplier and the customer of the original customer. The former is defined as a direct supply chain (figure 1), the latter as an extended supply chain, and the most complex including all the entities engaging in upstream and downstream flows is called an ultimate supply chain (Mentzer et al., 2001).

To comprehend the case study for the BI system implementation, the timber supply chain from the forest to the sawmill reception is introduced in the next chapter. A BI system supports the data collection and functions related to the optimization of the timber supply chain. The possibilities for optimization are presented after the timber supply chain activities.

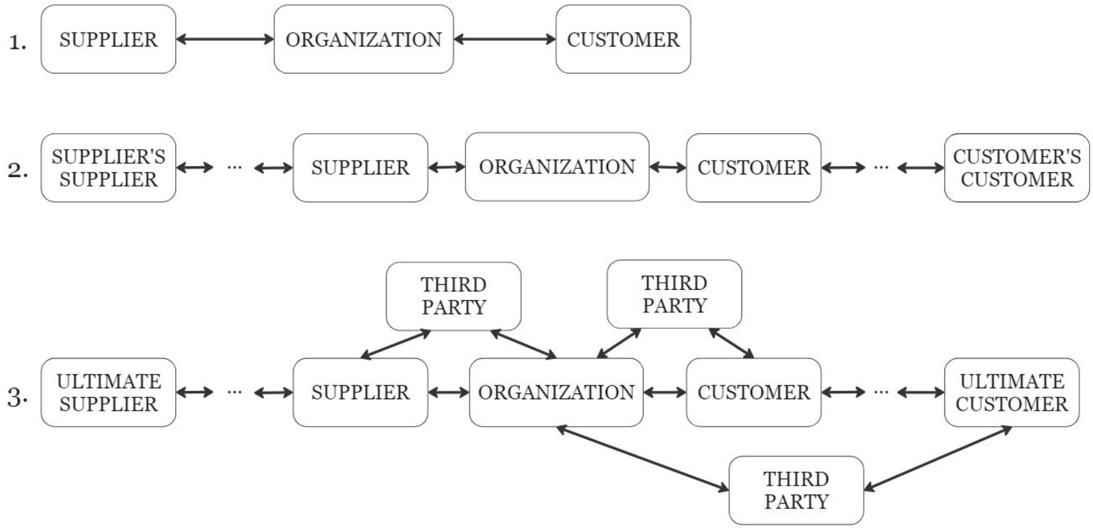

FIGURE 1 The complexity of supply chains: 1. Direct supply chain, 2. Extended supply chain, 3. Ultimate supply chain. Adapted from Mentzer et al. (2001, p. 5), subheadings removed and partners in 3. supply chain replaced with "third party".

2.1 Timber supply chain

The holistic definition of a timber supply chain refers to procurement as a general concept including silvicultural planning, demand planning, acquisition, harvesting, and transport, preceding the mill production, distribution, and sales of the finished product (Carlsson & Rönnqvist, 2005; D'Amours et al., 2008). A more concise definition of a timber supply chain focuses on the manipulation of the trees by felling and forwarding to the landing or terminal and hauling to the mill (Kaulen et al., 2023; K. Väätäinen et al., 2021). Additionally, forest management planning, lots preparation, and harvest auctions can be included (Rauch & Borz, 2020).

The stakeholders engaging in the wood procurement process include forest owners selling timber to the forest experts and operation experts coordinating the timber harvesting and transport with the subcontractors. In addition, there are several resources responsible for silvicultural activities, strategic planning, cooperation with supply chain partners, finance, and development.

Considering the multiple flows between several agents in the process, the timber supply chain can be described as an ultimate supply chain. Notably, the procurement serves the sawmill company, the actual center of the supply chain preceding the downstream flow of the logistics of the processed product to resellers and finally to the end customers. The timber supply chain is thus a supplier for the sawmill supply chain, and the end customer demand directs the procurement (figure 2).

As mentioned in the introduction, this thesis does not engage with forest management and silviculture activities, mill processes, or sales to resellers or end customers. Based on the definitions of timber supply chain and the scope of the business intelligence system introduced in this thesis, four basic operations of the timber supply chain have been examined. The basic operations are purchasing from forest owners, timber harvesting, truck transport from the felling sites, and timber sorting at the sawmill reception.

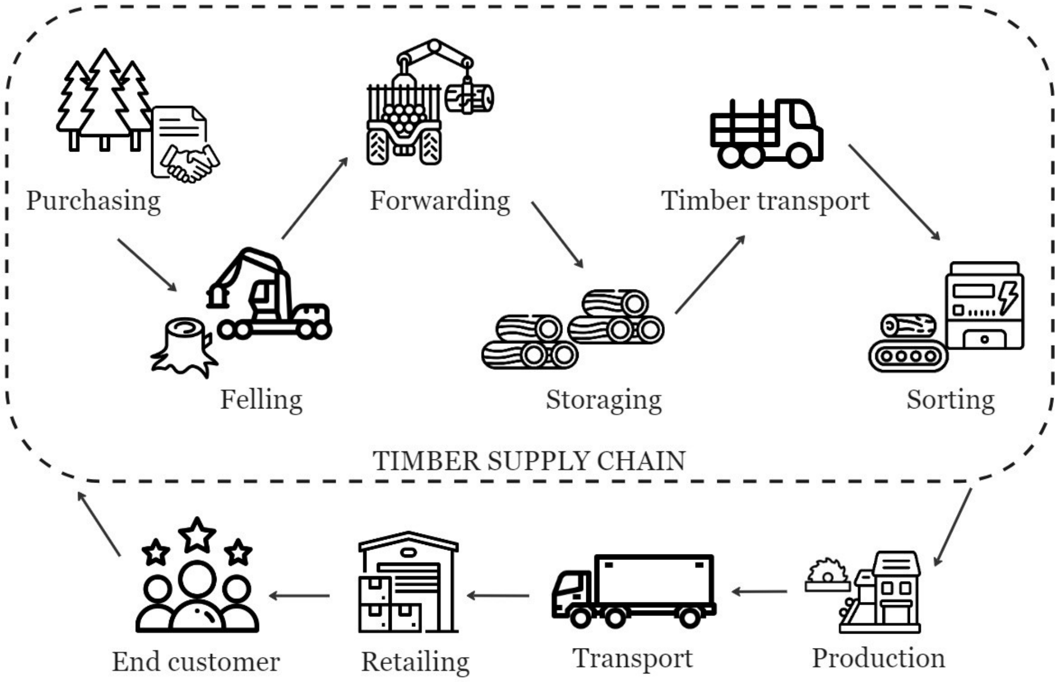

FIGURE 2 Timber supply chain as a supplier for the sawmill supply chain. The figure created by the author based on Kaulen et al. (2023), K. Väätäinen et al. (2021), D'Amours et al. (2008), and Carlsson & Rönnqvist (2005). Silviculture and planning activities excluded, log sorting added as a separate activity. Icons from Flaticon (n.d.).

It is highly important to define the customer included in the timber supply chain. For a forestry expert, the forest owner is the customer when negotiating the timber sales contract and entering information in a customer relationship management (CRM) system. However, timber sellers are suppliers of the main supplier which is the timber supply chain acquiring raw material for the sawmill. The end customer that buys the product from the sawmill or a reseller, is the actual customer.

Customer orientation means that the required sort of timber is available adapting to the demanded amount and schedule, and in high quality (Carlsson & Rönnqvist, 2005). This sets a high objective for the supply chain to provide the raw material as adaptably and accordingly. The processes must also adapt to changing weather conditions, wildfires, and damages caused by insects (K. Väätäinen et al., 2021).

In this chapter, the four timber supply chain activities, and the data related to each, are examined. The most essential functional unit in the timber supply chain is 1 cubic meter (m^3) over bark (Klein et al., 2015). This unit is used to measure the timber from the purchasing to the harvesting, in logistics complemented with weight, and lastly in the timber measurement at the sawmill reception. A timber supply chain is generally coordinated with an enterprise resource planning (ERP) system, which supports and connects the operations and operators.

The timber supply chain consists of numerous independent actors as collaborative processes are not general in the wood sector (François & Bourrières, 2021). Actors include entities with forest assets like independent forest owners, forest owner associations, and large forest industry enterprises both running their pulp- and sawmills, independent sawmills without notable forest assets, and the workers responsible for felling, forwarding, and transporting (Rönnqvist, 2003). The loggers and truckers mainly work in subcontractor companies.

Next, the four activities in the timber supply chain are introduced along with the specific data collected in each phase. The possibilities for optimization of each phase are examined in chapter 2.2.

2.1.1 Purchasing

Private forest owners own approximately 60 % of the Finnish forest land while 26 % belongs to the state (Luonnonvarakeskus, 2019). Open data on the Finnish forest resources is provided by The Finnish Forest Centre operating under the Ministry of Agriculture and Forestry of Finland. The information about the resources is collected using sample plot measurements, laser scanning from an altitude of 1,5—2 kilometers, and aerial photography from an altitude of 7—8 kilometers (Finnish Forest Centre, 2024).

The open dataset of Finnish forest resources includes forest compartment data and grid data (Digi- ja väestötietovirasto, n.d.). A forest compartment, or a stand (fin: kuvio), refers to an area consisting of a specific kind of tree stand, habitat, and requirements. In the open data, the average compartment size is 1,4 hectares (Suomen metsäkeskus, 2023b). A standard grid (fin: hila) used in the grid dataset is a square of 16 x 16 meters (Suomen metsäkeskus, 2023a). Both datasets are represented in vector data (polygon) distributed in OGC GeoPackage and XML formats (Suomen metsäkeskus, 2023a, 2023b).

The largest timber purchasers are sawmills and the forest industry integrate companies that operate in both areas of mechanical and chemical forest industries. The mechanical forest industry (wood products industry) consists of sawmills, plywood, chipboard, fiberboard, wood construction products, and construction industries while the chemical forest industry refers to pulp and paper production (Finnish Forest Association, n.d.). Roughly 43 % of the raw wood is used in the wood products industry, mostly to produce sawn timber made of spruce and pine (Luonnonvarakeskus, 2024).

The buyer can acquire timber directly from the forest owner or via an intermediary like a forestry management association. The majority of the timber buyers, forestry management associations, and forestry service businesses in Finland engage in the digital timber marketplace Kuutio, the service where forest owners can send calls for offers to several timber buyers (Suomen Puukauppa Oy, 2019).

The pricing and the use of timber are based on the species, the diameter, the length, and the quality of the trees. According to the Finnish Forest Association (n.d.), roundwood timber of every tree species can be sorted into two grades, pulpwood or logs. Kaulen et al. (2023) and D'Amours et al. (2008) use the term "assortment" instead of "grade". Because grading can also refer to the strength and quality of sawn timber (Fredriksson, 2024), timber assortment (fin: puutavaralaji) describes stems of a certain tree species and characteristics more distinctly.

Stems with a small diameter, thin upper parts of the trees, and trees of inferior quality qualify as pulpwood used to produce pulp. Coniferous logs have a straight stem of at least four meters and a 15-centimeter minimum top diameter, and small-diameter logs have a minimum of 3,7 meters height and 11 cm top diameter (Piira et al., 2007). In addition to pulpwood and logs, timber assortments include spars, poles, billets, blocks, Egyptian balks, battens, and forest energy timber (Finnish Forest Association, n.d.).

The timber sales contract can include the felling, or the seller can independently deliver the logs to the roadside storage for the timber truck. The former practice, referred to as standing sales, dominates the field (Melkas, 2022), as harvesting requires time, skills, and equipment. The timber can be delivered directly to the mill, but these contracts are mainly signed between forest companies.

2.1.2 Timber harvesting

Timber harvesting refers to the felling of the trees and carrying them from the stump to the road-side storage. The unique Finnish-Swedish felling terms like "leimikko" (swe: stämplingspost, eng: stand (of timber) marked for cutting) and "apteeraus" (swe: aptering, avmätning, eng: marking for cross-cutting) (Sanastokeskus Ry, n.d.-a, n.d.-b) reflect the long-standing tradition, practices, and research concerning Nordic forestry.

The felling preparation consists of matching the felling volume and qualities to the contractually agreed provision of specific assortments along with coordinating the forestry operations, workers, machines, and important harvesting information (Kaulen et al., 2023). Harvesting is often planned simultaneously with transportation (D'Amours et al., 2008).

A block (fin: lohko) usually contains several forest compartments. In general, the same type of felling is applied to the whole block. After the first thinning of the forest followed by one or several thinning cycles, the final felling takes place. The final felling is mainly performed as clear felling, but there are alternative practices like clear felling in strips of 20-50 meters (Latokartano, 2023).

In Finland, most of the timber is measured by the harvester (Melkas, 2022). The harvester head cuts the tree at the base, then delimbs and cuts the stem to logs according to the bucking instructions sent to the machine by the forest company (figure 3). Bucking patterns vary with many length and diameter combinations to produce a set of output products (D'Amours et al., 2008). In future visions, harvesters are seen as unmanned vehicles utilizing machine vision, sensors, robotics, and AI (Rautio et al., 2023).

FIGURE 3 A harvester cutting a stem according to the bucking instructions. The figure by Versowood Group (2016). The color altered by the author.

A forwarder, i.e. a forest tractor, collects the logs and carries them to the roadside landing, also referred to as road-side storage or intermediate storage. Secondly, intermediate storage can be associated with terminals (D'Amours et al., 2008). Terminals store timber from several felling sites. Since customers value fresh wood, the optimal duration of roundwood storage is relatively short in the forest like at the landings and terminals, except for in the winter (K. Väätäinen et al., 2021).

Standard for Forest machine Data and Communication (StanForD) is an XML-based standard for communication between computers in forest machines used in several countries developed and maintained by Skogforsk, the Forestry Research Institute of Sweden (Sahateollisuus Ry, 2024; Skogforsk, 2023). Files under the StanForD standard include data from each tree like diameter at breast height, volume, log classification, timestamp of cutting, and operator identification (Rossit et al., 2019).

2.1.3 Transport

In this context, transport refers to the hauling of timber by a timber truck from the roadside storage or terminal to the place of delivery like a sawmill or a paper mill. The carrying of the logs to the storage by a forwarder is part of the timber harvesting. In the common free forest method, the hauling company or mill organizes the timber logistics (Kaulen et al., 2023). One or several transport companies are in charge of the transport (D'Amours et al., 2008).

Since transportation may take up to 40% of the operational costs (D'Amours et al., 2008), it is unexpected that the efforts to improve the logistics in the wood sector have emerged later compared to other industries (François & Bourrières, 2021). The weather conditions affect the transportability especially on forest roads compared to the main road infrastructure. Other reasons may be related to the abundance of wood resources and lower level of transport and storage costs in the past (François & Bourrières, 2021).

Väätäinen et al. (2021) stated several drivers to develop roundwood logistics such as fast technology development, amendments related to road transport, and increasing environmental concerns. The forestry sector strives to decrease logistics costs (K. Väätäinen et al., 2021). The considerable measures include maximizing payloads within legal limits, minimizing hauling distances, improving road infrastructure, and considering higher gross vehicle weight limits (Kärhä et al., 2024).

Similarly to the data on Finnish forest resources, road infrastructure data is openly available in Digiroad dataset which consists of the center line geometry and the road and street network of Finland (Finnish Transport Infrastructure Agency, 2023). Data is published in ESRI Shapefile and Geopackage along with R and K package formats (Väylävirasto, 2022).

While StanForD standard is merely related to harvesting, papiNET standard has a wider application. It is an industry-founded and maintained standard in XML format for digital data exchange in almost all areas of the timber supply chain (Kaulen et al., 2023). IT company Tietoevry has developed an open-source platform Forest Hub which leverages papiNet and B2B-integration service Business Information Exchange (BIX) to provide a message standard between the systems of organizations involved in the timber supply chain (Tietoevry, 2017). For example, the delivery message from the timber truck reaches sawmill reception via Forest Hub decreasing manual tasks.

2.1.4 Sorting

Since the scope of this thesis is limited to the timber supply chain from the forest to the timber sorting in the mill, the focus in this chapter is on the data related to the reception of timber. Further mill processes and sales of sawn timber are not researched.

While pulpwood is treated in bundles, each sawlog delivered to the mill can be examined with laser scanning and X-ray imaging. These technologies show the quality and mechanical properties of the timber presenting the fracture behavior and possible failures formed at different stages of growth (Toumpanaki et al., 2021). Fredriksson (2024) has claimed that 3D scanning requires additional X-ray data for reliably presorting logs for strength.

Tracking the timber refers to the direction from the supplier to the customer, whereas tracing is identifying the supplier and origin of the sawn timber (Kaulen et al., 2023). Traceability can be utilized to improve timber quality because the growing locations affect the properties of wood (Toumpanaki et al., 2021). Sustainability issues and high-level customer service are also notable drivers for traceability. Mentzer et al. (2001) include information as one element in the supply chain flow, and the origin of the timber can be a valuable piece of information for the customer of the sawn product.

Tracing can be divided as active or passive depending on whether there is technology attached to timber (active) or is the tracing accomplished by tracing the properties of the timber itself (passive) (Kaulen et al., 2023). Modern methods of timber measurement can serve traceability. Kaulen et al. (2023) concluded their research in favor of passive optical biometric tracing like X-ray tomography where the structure of the log functions as its identifier. Naturally, the data quantity collected in the scanning of logs is extensive.

2.2 Optimization possibilities

Defined strictly, optimization is a quantitative method for measuring minimum and maximum value under defined constraints (Waller & Fawcett, 2013). A more practical definition is that optimization refers to finding the best possible solution for the group of options produced by simulation (Niemi et al., 2020). In this thesis, optimization is a wide concept related to finding the optimal solution or solutions for the example cases of timber supply chain. In a broad sense, optimization is a tool for decision-making. Different optimization models or functions are beyond the scope of this research.

Contrary to the idea of optimization as a universal, infallible function, the optimal solution should be evaluated and implemented compared to solutions almost as optimal (Waller & Fawcett, 2013). The level of the optimization must be assimilated to the reached benefit, and a considerable method is to focus on the sources of error that have the most significant impact on the optimization results (Niemi et al., 2020). Optimization is serving a purpose, in this case offering possibilities to improve the timber supply chain.

The time frame regarding forests spans decades, but at the same time, there are decisions to be made quickly for example when the transport conditions change. In the timber supply chain, four levels of planning are recognized with different periods (table 1).

TABLE 1 Planning level time frames in the timber supply chain. Adapted from Rönnqvist (2003, p. 271). Presenting the first column of the original table.

Planning level	**Time frame**
Strategic planning	over five years
Tactical planning	0,5 – 5 years
Operative planning	one day to six months
Online planning	less than 24 hours

Optimization is already leveraged in strategic planning, where the felling target and forest management methods for the forest holding are decided based on the action plan included in the open forest resource data (Niemi et al., 2020). According to Rönnqvist (2003), when optimization starts with strategic planning, the strategic level solution presents a constraint for the optimization in the tactical planning, and so on downward the planning levels. Niemi et al. (2020) present a similar planning process where the values and demands of the decision-maker influence the optimization which then guides the tactical and operative planning (figure 4).

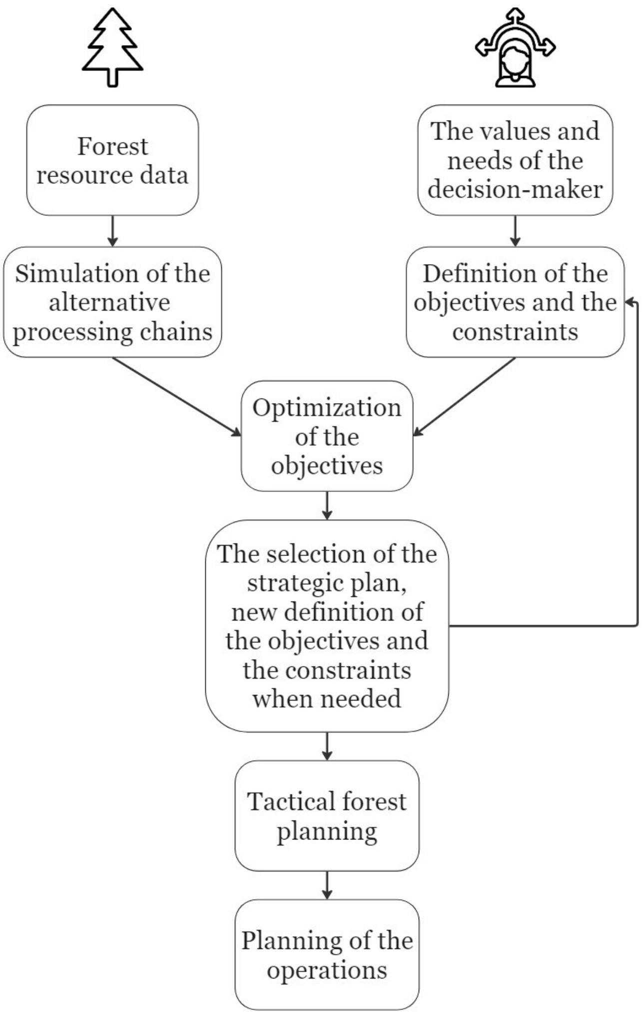

FIGURE 4 The forest planning process. Adapted from Niemi et al. (2020, p. 13). Translated from Finnish. Icons from Flaticon (n.d.).

The open forest resource data can also direct the procurement to optimal locations based on the required timber assortments. Since it is challenging to match the available standing timber according to the demand (Finnish Forest Association, 2024), the tools to optimize the purchasing are profitable. Timber marketplace Kuutio is also supported by the Finnish forest resource data (Kauppi, 2017), and classifying the calls for offers from forest owners presents an optimization opportunity.

The forest compartments near each other are felled at the same time to minimize the costs of harvester-forwarder transit and timber transport. This is an example of a complex spatial optimization problem at the tactical level as the price increases in correlation with the hectares and the pursued solution is often sufficient, not universally best (Niemi et al., 2020).

When it comes to the traceability of the sawn timber, the potential of the data a harvester collects combined with coordinates is significant (Kaulen et al., 2023). The detailed measurements of a tree stem are delivered in harvest product (HPR) files that comply with the StanforD standard. Since StanforD2010 location data has been included in the file. When the information about the quality of logs provided by X-ray imaging is combined with harvesting data on the characteristics, it is possible to predict the quality of logs and create bucking instructions based on the prediction (Raatevaara, 2019)

At the operative level, the harvester semi-independently optimizes the bucking according to the value and distribution matrices that determine the number of logs cut to a certain length depending on the log diameter (Riikilä, 2020). Optimal bucking instructions match the demanded dimensions of sawn timber for the end customer but should simultaneously meet the expectations of the forest owner. Supply chain management emphasizes the collaborative effort to serve customers, but also the fostering of long-term partnerships (Mentzer et al., 2001). Forest owners as the suppliers of the raw material hold a key role in the process.

Regarding transport, the means to decrease costs, improve energy efficiency, and reduce greenhouse gas emissions include scheduling and routing of timber trucks (Kärhä et al., 2024). This requires computing and storage capacity because optimization requires calculating the distance for every possible storage-to-destination option (Carlsson & Rönnqvist, 2005). An example system from Sweden combining geographic information system (GIS) and road data with a linear programming model has been tested to decrease costs by 5-20 percent compared to manual solutions (D'Amours et al., 2008).

Increasing the backhaulage tours to minimize unloaded driving would improve the efficiency of timber logistics even further with a decrease of 2,0—4,5 %, in occasional cases even 7 %, in unit costs (Carlsson & Rönnqvist, 2005; J. Väätäinen et al., 2002).

Because the number of cubic meters the timber supply chain feeds to the sawmill is impressive, even small changes in the processes can have a significant influence (Waller & Fawcett, 2013). The complexity of the timber supply chain and the uncontrollable factors related to weather conditions and the global market situation make optimizing challenging. This creates a demand for a tool that enables optimization and analytics to support decision-making.

The BI system must adapt to the extensive amount of data collected throughout the timber supply chain. Digitalization and automation in the data collection would decrease the loss of data in the supply chain (Kaulen et al., 2023). A modern data warehouse infrastructure is supporting this objective.

3 BUSINESS INTELLIGENCE

Business intelligence (BI) refers to the abstract solution for management to improve decision-making, and to the tools and technologies enabling it (Rouhani et al., 2018). Trieu (2017) named "business analytics", "big data", "data mining", and "data warehousing" as synonyms for BI. In this thesis, the main concept is business intelligence since its general use in the business environment. Data warehouse as a BI tool is introduced in the fourth chapter, along with data-related topics and analytics.

In this chapter, the concept of BI is defined, and the evolution of BI is examined. Finally, the BI competence in organizations is researched to build the basis for the design in the case study.

3.1 Business intelligence definition

In addition to the basic meaning of capacity to understand, intelligence refers to communication and exchanging information like in the context of military intelligence (Oxford English Dictionary, 2023). Regarding the research on artificial intelligence, the term "intelligence" dates back to the 1950s (Chen et al., 2012).

The concept of business intelligence is closely related to both business management and information technology. Business analytics (BA) is often used as a synonym for BI (Siau & Chen, 2020; Trieu, 2017) and also the combination term BI&A (Chen et al., 2012), but it can be claimed that these concepts are distinguishable.

Mashingaidze and Backhouse (2017, p. 488) summarized the relations of BI, BA, and big data (BD): "BD is data with high volume, variety of sources and high velocity. BI is a set of tools and techniques to use data for decision-making. BA is an advanced form of BI. BD is data that can be used in both BI and BA."

Wieder and Ossimitz (2015) disagree with the definition of BI as merely a set of technical tools but also a process to support managerial decision-making, outlining four distinct layers of BI (table 2).

TABLE 2 The layers of business intelligence (Wieder & Ossimitz, 2015).

BI layer	**Definition**
BI software	Standard products (e.g. data warehouse software, data mining software, digital dashboards software)
BI tools or BI applications	BI software products installed, configured and usable in an organization for a specific purpose (e. g. supply chain planning)
BI solution	A collection of BI tools, IT infrastructure (e. g. servers, operating systems, integration platforms, networks), and processes supporting BI objectives
BI scope	A broad construct including the previous and the diffusion across business units, the level of functionality varies between organizations

3.2 Business intelligence evolution

Business intelligence derives from the decision support system (DSS), the 1970s invention of sourcing operational data to independent repositories companies developed to support decision-making (Watson, 2005). BI was popularized in the 1980s in business and information technology sectors (Chen et al., 2012). The first to use the term was Howard Dresner of the Gartner Group in 1989 (Müller et al., 2010). At the same time in the late 1980s, traditional data warehousing emerged as the solution for managing a large mass of data especially in the sectors of telecommunication, financial services, and retailing for customer orientation (Watson, 2005).

According to Chen et al. (2012), the first of the three phases of BI&A included statistical methods and data mining based on relational database management systems (RDBMS) handling well-structured data in the 1990s. Since 2000, partly unstructured and customer-created web content emerged in addition to traditional data management systems generating a demand for text and web analytics, and in the 2010s BI expanded further to mobile and sensor-based content (Chen et al., 2012). In forestry, these technologies that were modern and emerging in the research of 2012 are now used for example in the timber sorting X-ray sensors and cross-cutting sensors embedded in the harvester head.

Since the beginning of the 2000s, vendor technologies enabled real-time data warehousing that was not dependent on the refresh cycles like traditional data warehouses (Watson, 2005). Cloud storage and computing, the Internet of Things (IoT) along with big data analytics are some of the most significant technologies of the last 20 years (Delen & Ram, 2018).

3.3 Business intelligence competence

BI can be leveraged in organizations to transform business processes and develop new or improved products or services (Trieu, 2017). In the timber supply chain, this could mean providing tracing data for the sawmill product or enhancing the felling and transport process. Poor data availability along with delayed or incorrect facts leading to similarly biased decisions, and increased costs due to building and maintaining non-integrated data sources and siloed applications are key organizational drivers of BI adoption (Manglik, 2006).

Naturally, companies aim for increased revenue, but several studies present that the BI effect on financial success is complex and consists of important non-financial factors. The research by Hou (2016) examined the impact of BI system usage on organizational performance in 139 companies in the semiconductor industry in Taiwan. The study showed that frequent and endurable system usage leads indirectly to improved financial performance, because of the improved non-financial performance including streamlined internal processes and performance towards the customers (Hou, 2016). Financial profit is merely a fragment, or the result, of the multiple effects BI has on the company. Rouhani et al. (2018) stated that long-term intangible benefits, such as support in strategy formation and planning, process improvement, and enhancing employee satisfaction appeared more beneficial for organizations and valued by the executives than immediate tangible benefits such as cutting time and costs or new ways of revenue creation for stakeholders.

One non-financial factor in BI system usage also supporting financial performance is the learning and growth perspective (Hou, 2016), which Hou adopted from Kaplan and Norton (2001). Learning and growth is a base for reaching the organizational strategy as it concerns employee capabilities and required technologies along with the general organizational climate (Kaplan & Norton, 2001).

Trieu (2017, p. 118) validated the firm factor: "Several papers have shown or described how a deeply analytical, evidence-based decision-making culture positively affects the use of information in business processes to generate BI impacts" ultimately affecting the organizational performance. Sangari and Razmi (2015) recognized the cultural dimension of BI competence, and expanded it to include external factors in the context of supply chain BI:

> Then, by supply chain BI competence we mean the ability to provide the supply chain-related information and knowledge that supports supply chain decision-making at different levels, ranging from strategic network planning, outsourcing, and procurement to detailed scheduling and lot sizing. It incorporates information on both the entire supply chain, including upstream and downstream supply chain partners, as well as the general business environment. (Sangari & Razmi, 2015, p. 359).

Managerial competence concerning internal BI processes and technical competence referring to BI technologies create a foundation for cultural competence defined as the product of the first two dimensions (figure 5) (Sangari & Razmi, 2015).

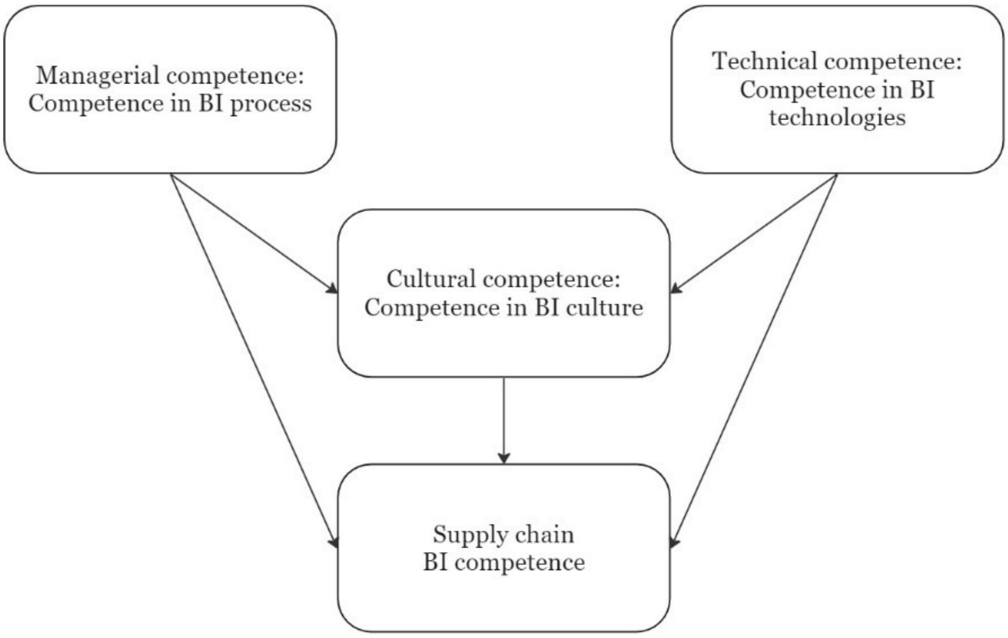

FIGURE 5 The dimensions of supply chain BI competence. The figure created by the author based on Sangari and Razmi (2015).

Wieder and Ossimitz (2015) examined the BI-related factors in an organization influencing the quality of decision-making (figure 6). Two main paths occurred between successful BI management leading to successful decision-making: first through high data quality ensuring high information quality, and second via greater BI scope with more functionality and diffusion across several business units (Wieder & Ossimitz, 2015).

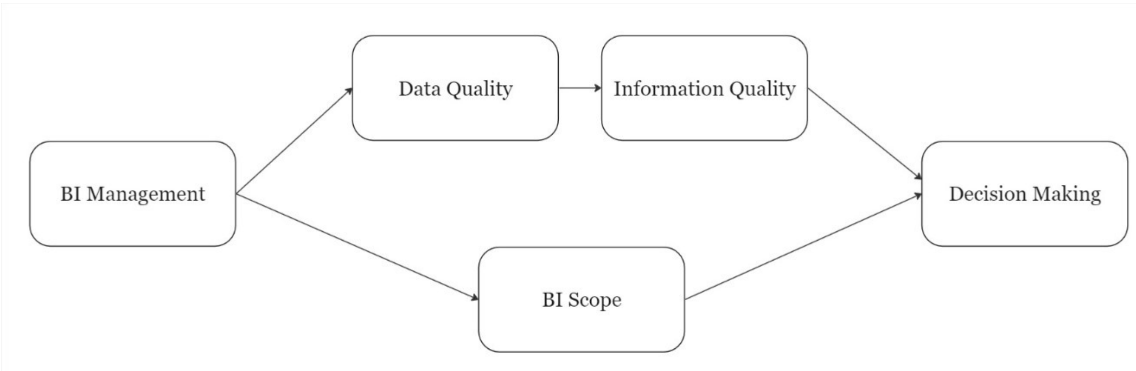

FIGURE 6 The BI impact factors on decision-making. Adapted from Wieder and Ossimitz (2015, p. 1168). Simplified presentation of the original relationship map.

The use of a BI system often requires companies to invest in more flexible IT infrastructure (Siau & Chen, 2020). Effective use is a key factor in a successful BI process (Trieu, 2017), but challenged by difficulties like lack of user knowledge, data and reporting problems, and system errors (Ain et al., 2019; Deng & Chi, 2012). Latency refers to the response time at several levels: data latency influences analysis latency which then determines how quickly the organization can make decisions (Trieu, 2017). Effective use of a BI system combined to a flexible IT infrastructure leads to an organization that is agile to detect threats and possibilities and respond accordingly (Siau & Chen, 2020).

4 DATA WAREHOUSE IMPLEMENTATION

As mentioned in the previous chapter, big data, data mining, and data warehousing are often synonymous with BI (Trieu, 2017), because they are so crucial methods for providing the information that the business needs. These concepts are analyzed and defined in this chapter.

Data warehouse (DW) planning starts with the forward-looking requirement analysis that determines the information needs and further the data requirements; the implementation process takes the same steps backward (Wieder & Ossimitz, 2015). This chapter presents the theoretical base for the IT artifact which is built and evaluated in the case study described in the sixth chapter. First, different DW architectures are presented. Then source data, data vault, and data marts as elements of DW are examined. Finally, the visualization and analytics are studied.

4.1 Data warehouse definition

It can be argued that big data, data mining, and data warehousing concepts have distinct meanings. Big data is related to the size (terabytes to exabytes) and complexity of the data which sets a demand for advanced technologies for storing, processing, and visualization (Chen et al., 2012). Data mining as a method means the search for patterns and relationships in a large dataset (Waller & Fawcett, 2013).

A BI system can be divided into data warehouse and data analytics. The two stages consist of processing and visualizing the data:

> Data is extracted from data sources, transformed, and loaded - - into data stores. The data is then made available for end user access and decision support applications. It can be considered as decision support data infrastructure that is used for multiple, varied decision support purposes (Ariyachandra & Watson, 2010, p. 201).

Consequently, the tasks in the first stage of DW are the identification, collection, storage, and maintenance of data, and in the second retrieving, processing, and communicating data for the decision-maker (Wieder & Ossimitz, 2015).

4.2 Reference architectures

Key factors concerning DW architecture selection are the existing systems and business environment, and deciding whether the DW is built for the whole organization or only for smaller units. Excluding the legacy solutions, three reference architectures are presented, with the notion that the term “reference” points to the multiple variations when implemented in different business environments (Ariyachandra & Watson, 2010). These architectures include federated, data mart bus, and enterprise data warehouse architectures.

Federated architecture with separate data marts integrates data from several systems and is the option for companies that already have complex environments (Ariyachandra & Watson, 2010). If the company starts building DW without significant constraints, this might not be selected as the reference architecture. In data mart bus architecture by Ralph Kimball, the conformed dimensions are created when designing the first data mart, and the following data marts are linked to the first (Ariyachandra & Watson, 2010).

The enterprise data warehouse (EDW) by Bill Inmon completes the development towards a DW that truly is the single source of data, as the data marts are dependent on the central DW (Inmon & Linstedt, 2014). Although the implementation of EDW architecture requires more time and technical skills, it has the strongest support for the control of the whole organization and information sharing across business departments (Ariyachandra & Watson, 2010).

The layers of EDW are staging, or landing, for ingesting the source data, enterprise data warehouse as the central storage, and data marts for delivering the information (Inmon & Linstedt, 2014). The data vault examined in the next chapter is a key part of the EDW layer. The architecture as a whole is illustrated in chapter 6.2.1 in the case study.

Following the reference architecture selection, the software, hardware, and integrations are selected and configured. Compared to on-premises DW, the benefit of the cloud DW is the computing power and the scalability according to the need. The pay-per-use solutions were first created to the demand of small and medium size companies that needed more data storage space and compute capacity at a reasonable price (Delen & Ram, 2018), but are now general business models. When adopting cloud storage, the location (e.g. West Europe or North Europe) is significant from the cyber security and data protection point of view. Since the selections are highly dependent on the business environment, the examination of these objects is excluded from this research.

4.3 Source data

The source data for DW comes often from operational data sources such as enterprise resource planning (ERP) and customer relationship management (CRM) systems, and the formats of the data vary greatly (Hou, 2016). In Finland, 91 % of the companies with over 100 employees use an ERP system and 76 % a CRM system (Tilastokeskus, 2023b). Data quality is even more essential for BI competence than data quantity (Wieder & Ossimitz, 2015), so the input data requires examination, cleaning, and formatting (Hou, 2016).

Structured data is mostly numeric values or text strings organized in relational tables, unstructured data text contents in heterogeneous formats such as e-mail or answers to open questions, and semi-structured (i.e. schemaless, self-describing) data such as XML or JSON files positions in between the previous in flexibility (Batini et al., 2009). Compared to traditional relational databases, data lake was developed as the solution for ingesting also unstructured data.

According to the review of data quality frameworks by Cichy and Rass (2019), completeness, timeliness, and accuracy are the key dimensions of data quality followed by consistency and accessibility (table 3). DW techniques support the objective of providing high-quality data complying with these dimensions (Al-Okaily et al., 2023).

TABLE 3 The dimensions of data quality based on Cichy and Rass (2019). The definitions based on Wang and Strong (1996).

Dimension	**Meaning**
Completeness	The breadth, depth, and scope of the data
Timeliness	The currency of data
Accuracy	The correctness, precision, and reliability of the data, the easy identification of errors in data
Consistency	The solid organization and formatting of the data
Accessibility	The ease and speed of retrieving the data

The flow of data from the data source to DW requires the often automated process of extract, transform, load (ETL) where the data is fetched from the source system, transformed from the source data to the form of business data that is then stored in DW (Inmon & Linstedt, 2014; Sherman, 2014). The more modern process is ELT, where the raw data is loaded directly to DW and transformed afterward.

4.4 Data vault and data marts

Dan Linstedt is known as the developer of data vault modeling. A data vault model is based on the normalization and separation of classes of data (Inmon & Linstedt, 2014). The idea of normalization is to decrease redundancy in data

(Sherman, 2014). A data vault can combine the data lake with unstructured data and a relational database requiring a more structured approach. The vault in the name refers to the metadata about where and when the data has been transferred to EDW supporting data integrity and auditing (Inmon & Linstedt, 2014).

In data vault modeling, the hub tables contain the business keys based on the critical path of the business process, satellite tables include the attributes, and link tables the relationships between the tables (Inmon & Linstedt, 2014). In the timber supply chain, a contract number of the timber sales contract can be identified as a business key that is included in several processes. The contract numbers are transformed into hash codes, and both the original numbers and the hashed versions are stored in the hub table. Hashing promotes stability and support for parallel loading (Inmon & Linstedt, 2014). The keys for the relationships between the contracts and felling blocks can be fetched from the link table. Satellite tables are the largest since they store all the descriptive data, in this example the contract details such as the name and address of a forest owner.

A key benefit of data vault modeling is the scalability when adapting to the possible changes and increments in the business data (Inmon & Linstedt, 2014). In addition to the data vault, a database schema is another concept that describes the structure of a database. A database schema consists of database objects such as tables, views, and procedures. A view can present data combined from several tables. The metadata about the database is stored in the information schema.

Schema also describes different dimensional models where the data tables are organized to support reporting and analytics. Fact tables with transactional data and dimensional tables with descriptive data are modeled in the form of a star schema or a more normalized snowflake schema (figure 7) (Sherman, 2014). In addition, there are other types of dimensional models like the combination of the previous. If the fact table contains for example the operative data of the felling, the dimensions might contain data on the timber assortments, the harvester, and the felling block.

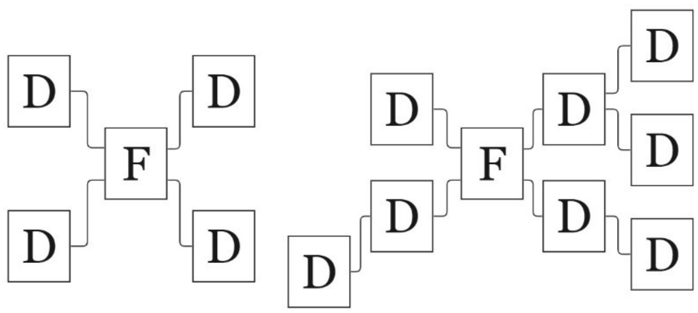

FIGURE 7 Star schema on the left and snowflake schema on the right. The figure created by the author based on Sherman (2014).

After the data vault divides the business data into different classes, a schema gathers the required data into a schema. Data marts are collections of facts and dimensions that provide the information for the visualization. Inmon and Linstedt (2014) state that data marts should be called information marts instead. Data marts can be created based on the requirements of a certain department or function (Hou, 2016). Data marts can be created also based on unit location or other factors depending on the business environment.

4.5 Visualization and analytics

Sangari and Razmi (2015) have mentioned online analytical processing (OLAP), dashboards, and analytic and reporting tools as BI technologies. While online transactional processing (OLTP) systems require fast and reliable writing operations when handling business transactions, OLAP systems supporting BI leverage dimensional modeling to query data sets effectively for analysis (Sherman, 2014). Dashboards are a combination of report visualizations.

To satisfy end users and improve the perceived benefit of the BI system, the reports should be easily available always when needed and contain relevant information (Al-Okaily et al., 2023). Monitoring usage and frequent errors, and sharing knowledge by e.g. the user presentative are tools to support the regular user, as a power user's challenges with role authorization and system errors can be alleviated with consideration for the work environment (Deng & Chi, 2012). Sufficient training for users is crucial to gaining the full potential of the BI system (Al-Okaily et al., 2023).

39 % of Finnish companies have a BI system and 41 % use data analytics (Tilastokeskus, 2023b). Watson (2005) predicted almost 20 years ago that a real-time DW could support current operational decisions related to business processes, in addition to the strategic decisions the traditional DW supports. Real-time requires a robust system that handles the ETL process reliably and with minimal latency.

The possibilities for optimization and advanced analytics are limitless. The evolution of analytics from descriptive to prescriptive can be conceptualized with the questions to be answered in the analysis (Delen & Ram, 2018; Tamym, 2023):

- Descriptive analytics: What happened?
- Diagnostic analytics: Why does it happen?
- Predictive analytics: What will happen?
- Prescriptive analytics: What should I do and why?

According to Lepenioti et al. (2020), both the academic research and industry fields have focused on descriptive and predictive analytics, and prescriptive analytics is yet in its early stages. Delen and Ram (2018) define BI and DW technologies under descriptive analytics, data mining, and machine learning as enablers for predictive analytics, and optimization along with simulation as enablers for prescriptive analytics. Like in BI evolution, the traditional tools continue to support decision-making as new technologies emerge.

5 RESEARCH METHODOLOGY

The purpose of this research is to study the design and implementation of a BI system in a specific organizational context. In addition, the implemented system is evaluated regarding the objectives of the timber supply chain. The research is conducted following the principles of design research, specifically action design research. The focus of action design research is developing a solution for a certain challenge, in this case, the need for a well-managed BI tool to improve decision-making.

First, the action design research is studied with the framework that is used in the case study. Then, the research process and research material are briefly presented. As the research method emphasizes organizational context, the case company is introduced at the end of this chapter.

5.1 Research method

As opposed to natural sciences examining and predicting objects as they are, the objective of design science is to develop a solution, an artifact, for a certain problem domain (Hevner, 2004). In this thesis, this artifact is a BI system. Design science is not merely an artifact or a methodology, but a paradigm where the built artifact is part of the data to be examined (Baskerville, 2008). Design science research (DSR) produces artifacts and researches the building of the artifacts (Iivari, 2015).

Peffers et al. (2018) have defined five genres of design science research, each with a distinct focus (table 4), processes, and evaluation measures. Because the artifact in this research is designed for a specific organization, the action design research (ADR) methodology appears as the most adequate genre to apply. Design science research methodology (DSRM) separates the building of the artifact and the context (Sein et al., 2011). The other genres are also unsuitable. The objective of IS design theory (ISDT) for a wide theory is out of the scope of this research. The design-oriented IS research (DOIS) includes testing the performance and the benefits of an artifact, while explanatory design theory (EDT) focuses on the effects of design features on the use (Peffers et al., 2018). Instead, this research emphasizes the building phase of the artifact and the intervention to the case organization.

TABLE 4 The genres and focal points of design science research (Peffers et al., 2018).

Genre	**Focus**
IS design theory (ISDT)	Creating generalizable design theories
Design science research methodology (DSRM)	Technical knowledge and the context of the design
Design-oriented IS research (DOIS)	The design of improved IS solutions
Explanatory design theory (EDT)	The effects of the design features
Action design research (ADR)	Organizational context of the design

As the characteristics of the genres are different, the categorization provides a tool when evaluating the quality of the research (Peffers et al., 2018). Since design science research is often related to designing and evaluating a specific artifact in a specific context, the research cannot always be easily reproduced, and conclusions generalized. However, the objectives of ADR include producing design principles, not design theories like in ISDT. While the objective in DOIS is an innovative artifact (Peffers et al., 2018), in ADR the relationship to the context organization is more important. These considerations are necessary when examining the credibility of a design science research paper applying the ADR method.

ADR has complemented design science research with organizational context as one factor that influences the design and the artifact during development and use (Sein et al., 2011). Iivari (2015) links the research by Sein et al. (2011) to the tradition of empirical qualitative research since the problem of the client should guide the research process.

ADR consists of four stages (figure 8), where the last, formalization of learning, generalizes the results from previous stages as a solution for the class of problems defined in the first stage of problem formulation (Sein et al., 2011). The principles and tasks under the stages are studied in the sixth chapter related to the case study.

As evaluation, reflection, and learning are key factors in ADR, it is a valuable framework to use in a situation where an organization is implementing a new system, developing it, and searching the ways to leverage it. The research following the framework by Sein et al. (2011) is not only describing the research context but contributing to it (Iivari, 2015).

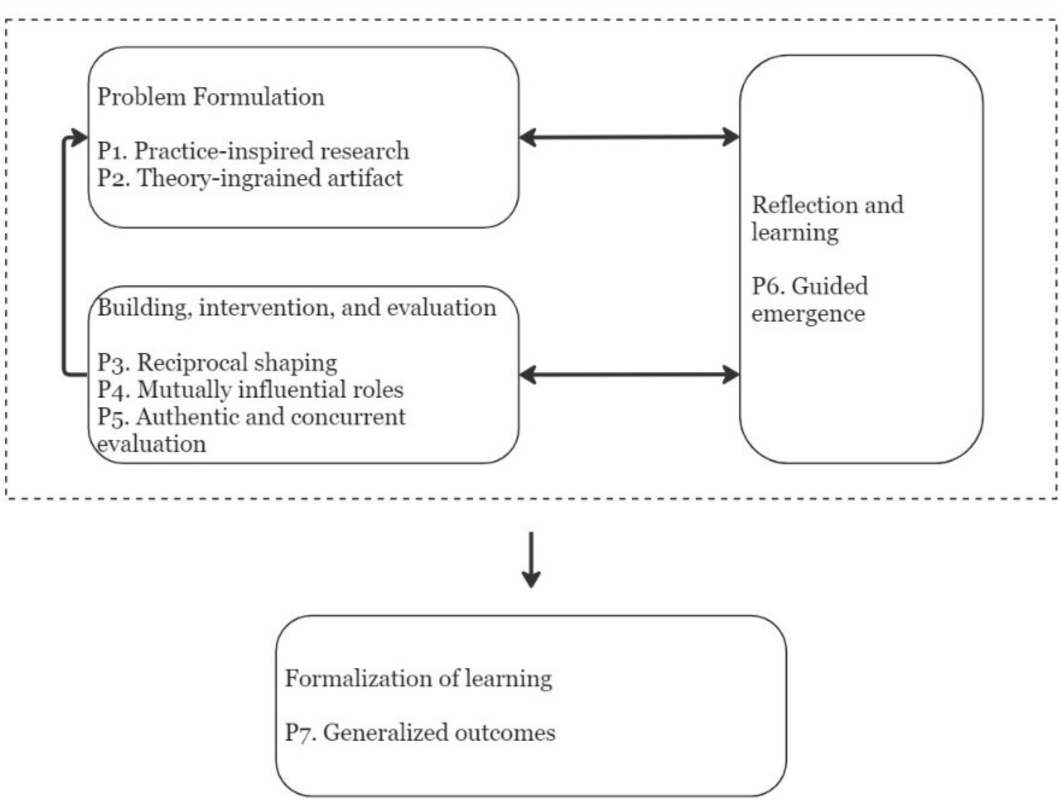

FIGURE 8 Action design research framework (Sein et al., 2011, p. 41).

5.2 Research process

The research was initiated by the case company in November 2022 when the author joined the information technology team and was designated to work mainly on the BI system implementation project. The specification requirement phase for the project was finished, but the written material was available.

The author had tasks related to the timber supply chain as a new operational system was launched in September 2022; the system that later provided the source data for the implemented BI system. Familiarizing with the timber supply chain is valuable since to work with data for supply chain management, the understanding of the domain is crucial (Waller & Fawcett, 2013). Working with the end users of the visualizations is practical for collaboration and feedback.

As the research and simultaneously the BI system project advanced and was completed at the end of 2023, the focus on the work shifted from the timber supply chain to the management of the data warehouse. The project team including members from the case company and a consultant company is introduced in the sixth chapter with the case study. Because the key experts for designing, using, and evaluating the BI system artifact were part of the project team, structured or semi-structured interviews were unnecessary. Instead, discussions and orientation to the timber supply chain and the ICT environment of the case company with the director of development, forestry director, head of ICT, quality and systems manager, and business controller provide the knowledge base for the research. The experts from the consultant company shared knowledge about the BI system in meetings, discussions, and written materials.

The written research material includes the files and communication of six channels in Teams account shared by the project team: the requirement specification material, weekly meeting memos, system documentation (30 pages), and ELT process documentation (21 p.). In addition, there were occasional meetings with the vendor of the operational system and the documentation of source data (57 p.) provided by the vendor.

Before the deployment phase of the BI system project, a training day was organized by the consultant company covering project management, advanced analytics, data architecture, and data visualization. In addition, approximately 10 hours of training for the BI system tasks were provided in 2024 after the project phases were finished. Naturally, the literature review conducted and presented in previous chapters creates a foundation for ADR research.

5.3 Case company

The case company of the research is Versowood, the largest private producer of sawn timber producer and processor in Finland. Versowood has 14 units in Finland and one in Estonia. In addition to sawn timber, the company produces wood packaging products, glulam, cladding panels, gardening and agriculture products, bioenergy products like wood pellets, and earth construction and road-building elements such as bridges. The annual turnover is approximately 508 million euros, and the number of employees is nearly 900. The domestic market brings in 43 % of the turnover while 25 % comes from Europe and 16 % from Asia.

Typically, the sawmill industry is known as a field particularly sensitive to economic fluctuations. Versowood was established in 1946 and has expanded continuously as the latest acquisition of a new unit took place in January 2024. Megatrends like digitalization are part of the strategy as well as the will to reform and innovate toward constant change. In addition to production, company departments include wood procurement, sales, finance, ICT, marketing and communications, and human resources each with department-specific systems, data, and reporting.

In wood procurement, the total amount of purchased timber reaches 4 million cubic meters (m^3), of which 2,85 million is used for own production and the rest delivered to partners. 50 forest experts buy the timber from the forest owners. Harvesting and transport are performed by 60 harvester-forwarder teams and 70 timber trucks employing 70 business owners with 300 employees. Operation experts manage these operations, and three regional managers are each responsible for their area.

In the specification requirements of the BI system, an important notion is the intention to expand the system to the whole organization. Old and new reporting can exist in a hybrid model where older visualizations are replaced gradually with the visualizations of the new system. Currently, there are approximately 80 users of the old reporting system by Qlik, but in the future both the old and new reports could serve 150 employees. A new operational system for production is also under specification.

The operational system for the timber supply chain, the modern forestry ERP system Connected Forest, was launched in September 2022. Versowood experts contributed to the design provided by an external vendor. Like the data from the previous system, the data from Connected Forest was provided to create reporting independently. Consequently, the first scope for BI system implementation was wood procurement. Operation experts and regional managers from the wood procurement form the group of sixteen end users, but there are already visualizations shared with other units and roles. In the case study presented in the next chapter, Versowood is referred as Company.

6 CASE STUDY AND RESULTS

Action design research introduced in the previous chapter is the framework for the case study, where the BI system is implemented in the ICT infrastructure of Company in cooperation with the consultant company and the vendor of the operational system. The first scope for the visualizations provided by the system is the timber supply chain.

Problem formulation resembles the requirement specification phase of an implementation project since it is essential to consider the issues to resolve and design the system accordingly. In the building phase, the implementation cycles are described along with the intervention to Company and evaluation of the whole process. The emergent factors of the building phase are reflected. Finally, the results of learning are formalized as a solution to a class of problems.

6.1 Problem formulation

The reporting of wood procurement before the new ERP system launched in September 2022 was based on daily refresh cycles which in certain cases did not match the demanded frequency. This was a laborious process since it demanded refreshing the whole dataset. The visualizations were created in an older environment by Qlik like the sawmill production reports. Instead of a central data warehouse, there was a separate BI application for every source system.

The first task of the problem formulation stage is identifying and conceptualizing the research opportunity (figure 9) (Sein et al., 2011). The previous BI system is not introduced in detail. Instead, the causes behind this research are summarized as problems of the previous data management and demands for the BI system to be built (table 4). Although the problems and demands in the data management are related to the timber supply chain, they can be generalized to Company as a whole. This emphasizes the scalability of the design artifact.

1. Identify and conceptualize the research opportunity.
2. Formulate initial research questions.
3. Cast the problem as an instance of a class of problems.
4. Identify contributing theoretical bases and prior technology advances.
5. Secure long-term organizational commitment.
6. Set up roles and responsibilities.

FIGURE 9 Tasks in the problem formulation stage of ADR (Sein et al., 2011, p. 41).

TABLE 5 The problems in data management and demands for the BI system defined in Company before the implementation project.

Problems	**Demands**
Dependence of the ERP vendor	Access to own operational data
Low refresh cycle frequency	More frequent refresh cycles
Several sources of data	Single source of data
Data inconsistency	Data consistency
Data redundancy	Data normalization
Lacking data historization	Time travel capabilities
Legacy system with uncertain future support	Modern system with support
Unconnected tools	Comprehensive ecosystem
Lacking one scalable solution	Scalable system for expansion
Greater vulnerabilities by multiple systems and sources	Continuous cyber security improvement
Scattered reporting	Standardized reporting tool
Manual processes	Automated processes
Manual optimization	Advanced tools for optimization
Outdated visual reports	Modern visual reports
Reports and collaboration in separate environments	Collaboration embedded in reports
Lacking infrastructure for data sharing	Data sharing capabilities

The support for the current version of reporting software by Qlik is not guaranteed in the future, and Company has adopted several Microsoft solutions like Teams and Sharepoint environment for communication and collaboration. Cloud platform Azure and business intelligence tool Power BI are also familiar to Company. In many companies, modern shared channels and embedded reports replace customary practices related to Excel files and e-mails, but the feature to export files from the report views is still necessary.

The requirement for automation throughout the system from data to visual reports increases along with the refresh cycles especially approaching real-time reporting. The demands for automation, optimization calculations, and integrated storage must be matched with compatible solutions with sufficient capacity for computing and storage. Naturally, Company is responsible for its cyber security measures, but adopting standardized data warehousing platforms with built-in security features would simplify the implementation and use of the system.

The innovative culture declared in Company values and strategy aligns with the intent to create a stable, comprehensive solution for data-driven decision-making. Initially, it requires access to the data and tools to manage it accordingly. The organizational culture supporting data collection for decision-making is a crucial factor in BI competence (Hou, 2016; Trieu, 2017), and the theory of supply chain BI competence expands the culture to all the stakeholders (Sangari & Razmi, 2015). Data-sharing capabilities support the sharing of information in the supply chain.

The initial question before building a BI system was "What information do we need for facilitating business processes?" These needs define the data requirements. The data source and data quality questions follow and finally influence the choice of technologies and architecture. Detailed specification questions for reporting were:

- What are the current information-sharing channels? Strengths and weaknesses?
- What is the total number of end-users for reports?
- Does Company need more standardized or custom reports, or both?
- Is there a demand for advanced data analytics (forecasting, optimization)?
- Does Company have resources and capabilities for in-house reporting and analysis?
- Is real-time reporting demanded in certain business processes?
- Is the data mostly quantitative, or is there text content e.g. feedback?
- Is there a demand for limited access to certain reports?
- Is there a demand for reports accessible with mobile devices?

The context of the BI system is limited to the operational data from Connected Forest, wood procurement acting as the pioneer of the data warehouse implementation. Summarizing the research problem as BI for optimizing a timber supply chain sets a basis for the definition of the class of problems. As Sein et al. (2011) state, the definition can be tentative. Following the research subject, the initial class of problems is the optimization of a supply chain.

The theoretical base for the research is introduced in the main chapters of this thesis concerning timber supply chain, business intelligence, and data warehouse. Prior advances in data warehouse technology are relevant to the research. As the extent of BI scope correlates positively with the impact on decision-making (Wieder & Ossimitz, 2015), developing a BI system with more functionality aligns with the intent to optimize the timber supply chain.

The stakeholders in the research project are the employees of both Company and the consultant company. From Company, there are six members in the project team: director of development, forestry director, head of ICT, quality and systems manager, the author of the thesis as system specialist, and occasionally business controller. The participation of these central roles of Company and the investment in BI system consultation and technologies reflect the commitment of the organization to the artifact design. From the consultant company, a core team of four persons complemented with extra resources when required contributed to the project.

The main responsibilities of each team member can be identified (table 5), although the collaboration inside Company, inside the consulting company, and between these organizations ensured that members contributed to several responsibility areas. The members of ADR team can act in multiple roles, but identifying the assignments serves the project evaluation later (Sein et al., 2011). For example, the data architect was also building data ingestion automation and the quality and systems manager participated in requirement specification also from the BI system perspective. Also from the practice perspective, it is still beneficial to define clear roles and responsibilities for the team members to facilitate the project effectively.

TABLE 6 The roles and responsibilities of ADR project team members. C = Company, CC = Consultant company.

Role	**C/CC**	**Main responsibility**
Director of development	C	Requirement specification for BI system, agreements
Forestry director	C	Requirement specification for timber supply chain
Head of ICT	C	ICT infrastructure of Company
Quality and systems manager	C	Requirement specification for timber supply chain, development of visualization and analytics
System specialist	C	Project management, data modeling, assistance in visualization and analytics
Business controller	C	Familiarization with data warehouse, development of finance BI reports
Project manager	CC	Coordinating consultant resources according to Company requirements
Data architect	CC	DW infrastructure, data modeling
Data engineer	CC	Data ingestion and data pipeline
BI consultant	CC	BI report visualization and technical implementation

The author of the thesis is the main researcher, but other Company team members contribute to the requirement specification of the timber supply chain and BI system along with practical use cases for BI tools and optimization. The consultant company presents technical choices based on previous cases and expertise that are originally based on DW and BI technology development and advances.

6.2 Building, intervention, and evaluation

The second stage in ADR is based on the field problem and related research theories identified in the first stage, setting an opportunity for knowledge creation (Sein et al., 2011). In this case, the IT artifact to be built is a BI system to support decision-making in the timber supply chain. The tasks in the building, intervention, and evaluation (BIE) stage include selecting the BIE form (figure 10), which means emphasizing either the artifact design as in IT-dominant BIE or the intervention in the organization as in organization-dominant BIE (Sein et al., 2011). This research approaches the IT-dominant end of the continuum, as building an artifact is the focus of this ADR.

1. Discover initial knowledge-creation target.
2. Select or customize BIE form.
3. Execute BIE cycle(s).
4. Assess need for additional cycles, repeat.

FIGURE 10 Tasks in the building, intervention, and evaluation stage of ADR (Sein et al., 2011, p. 43).

The ADR principle of reciprocal shaping describes the intertwined relationship between the organization and the IT artifact influencing each other (Sein et al., 2011). To design a BI system, the demands of Company were carefully considered. Secondly, the BI system demands shaping of the ICT infrastructure and practices in the organization. The requirement specification of the project started in August 2022 and the deployment phase in January 2023. Based on the workshops, 28 reporting needs were identified and 11 of them were defined as priority 1. The emphasis of learning was at first on the processes of Company and the timber supply chain. Starting from the training session in November 2022 the emphasis shifted to the building of the BI system.

In addition to Company and the consultant company, the vendor of the operational system participated in workshops and later in the meetings concerning data exports from the system to the Company's data warehouse. The vendor is an important stakeholder in the BI system project as the supplier of the data but is not a direct member of ADR team.

As the BIE stage is characterized by mutually influential roles and mutual learning (Sein et al., 2011), it can be argued that the vendor contributed to ADR by sharing data with the export documentation. The delivery of the operational data is the prerequisite for building and developing the BI system in this project. The building of the artifact is examined in the next subchapter, and secondly, the intervention and evaluation related to the BIE cycles.

6.2.1 Building the IT artifact

The BI system was built following the enterprise data warehouse (EDW) architecture introduced in the fourth chapter. The reference architecture selection is based on the recommendation by the data architect of the consultant company and the research literature comparing different architecture options. EDW is an organization-wide, mature solution that enables scaling (Ariyachandra & Watson, 2010). A scalable system with separate data marts is essential for the future expansion of the BI system to several business processes. The architecture of the BI system is presented in figure 11.

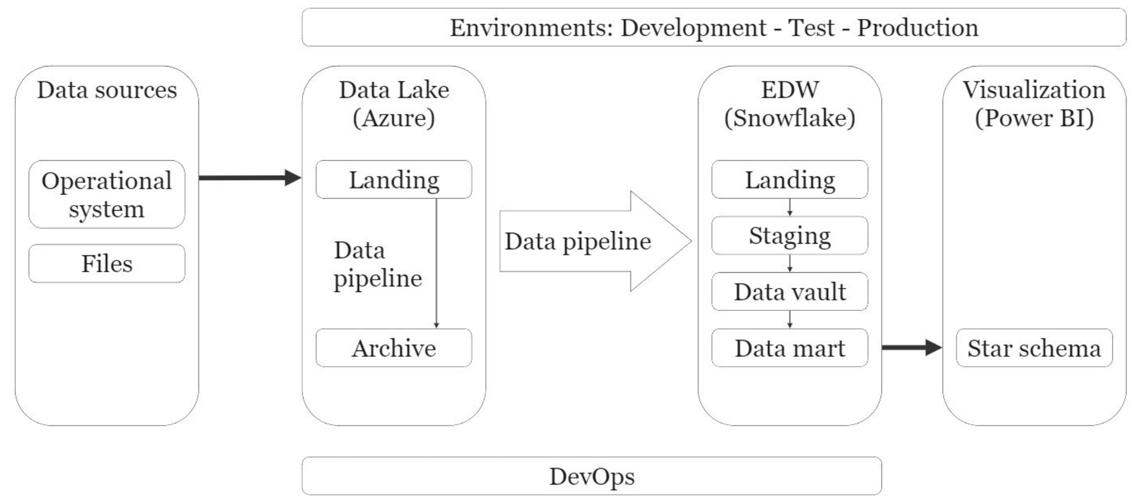

FIGURE 11 The architecture of the implemented BI system. The figure created by the author based on the project documentation.

The existing software and platforms in Company were considered when choosing Azure cloud storage as the platform for the data ingestion. Additionally, the arguments supporting the choice include advanced analytics, machine learning, and artificial intelligence features along with built-in cyber security measures. The actual data warehouse is a cloud platform Snowflake, that was selected as it provides suitable computing and scaling possibilities and more effortless deployment than comparable platforms. Snowflake enables data sharing from the reader account regardless of the receiver not using Snowflake.

Operational data from CF ranges to 67 tables including reference tables which contain numeral codes and text definitions to complement the operational data tables. The largest dataset concerns the measurement of logs in the sawmill reception, as the daily volume is massive and there are numerous fields of data including different measurements and quality information. Additionally, internal files are loaded to Data Lake or created as Snowflake objects such as tables and views.

To build a BI tool, the standard BI software must be installed and configured according to the specifications of the company (Wieder & Ossimitz, 2015).

Azure storage accounts were created for three environments as well as in Snowflake: development environment with test data from CF for initial development, testing environment for production tests, and production environment. An open-source infrastructure configuration tool Terraform was used in the deployment. Users and roles were configured for each environment as access management is an important part of cyber security along with ensuring appropriate firewall settings.

The data pipeline automation in Azure Data Factory transfers the received CF files from the landing container to the staging area of DW and copies them to an archive that stores all the old files. Since the files are loaded to DW as raw files before transformation, this pipeline follows the extract-load-transform (ELT) process instead of the traditional ETL. The last step in the pipeline is transforming the staged files into DW objects. The objects are created with the command line tool Data Build Tool and self-hosted integration runtime (SHIR) compute infrastructure located in the local server. The data pipeline is under Git version control which is managed in Azure DevOps. The pipeline is triggered automatically according to the set time.

The premise of data modeling is the understanding of the concepts and relationships in the source data and the business environment. The data architect from the consultant company had previously worked in the forestry sector, which was beneficial. In addition, the structure and characteristics of the source data were analyzed. Modern tools like Snowflake automatically recognize the data types (e.g. text string, integer, timestamp). In data vault modeling, the business keys are identified based on the critical path of the business process (Inmon & Linstedt, 2014). The data of the timber supply chain was modeled in Snowflake in the form of a data vault where business keys are in hub tables, the descriptive information in satellite tables, and the keys required to form relationships in link tables.

Facts with transactional data and dimensions with context data are created as views on top of data vault tables in Snowflake, so they are simultaneously refreshed depending on the pipeline trigger that creates the data vault tables. Power BI connects to Snowflake to fetch the data from the data mart that is then organized in a data model following star schema (example figure in chapter 4.3). In addition to data mart schema and information schema, there are separate schemas in Snowflake for source tables, staging tables, data vault objects, and objects shared via read account.

Visual reports in Power BI are based on datasets including data from Snowflake and in certain cases complemented with additional data. The consulting company created a visual theme according to Company brand styles and model report pages showcasing different visualizations of data. Custom applications can be built on Microsoft Power Platform utilizing the datasets and visualizations, and input data from end users can be stored back to DW. The data flow running backward sets a challenge for structured data modeling as it is not handled through the pipeline functions.

6.2.2 Intervention and evaluation

During BIE cycles, the researchers and practitioners of the ADR team build several versions of the IT artifact that intervene with the organization and are then developed based on continuous evaluation (Sein et al., 2011). The implementation and building of EDW followed the path introduced in the fourth chapter. After requirement specification the data sources were examined, and technologies and integrations installed and configured. Every cycle included modeling, loading, and testing a new dataset both to DW and then to visual report.

In the first cycle, the tasks were overlapping as there were resources reserved for different responsibilities. For example, the visualization was designed simultaneously with data modeling. The first model reports were designed to plan timber delivery amounts from each area.

From the perspective of reciprocal shaping and mutual learning, visualization was the most challenging part of ADR. In Company, the strongest capabilities for BI competence lie in the knowledge and experience of the required timber supply chain indicators and preferred ways of presentation. It is more rational to create visualizations without an intermediary role when the skills and resources exist already in Company. Consequently, the visualization was the first part of EDW process decided to be created in-house after the first cycle.

The deployment phase lasted one year and consisted of three cycles. In this project, the process of modeling, loading, and testing the datasets remained quite similar through the cycles except for the visualization. The need for additional cycles was assessed based on the perception of the capability to manage the system in-house. In addition, the evaluation was related to visualizations for the end users and emergent factors, both discussed in the next chapter.

Regarding the intervention in the organization, it is important to note that the timber supply chain had adopted a new operational system only four months before the beginning of the deployment phase of the BI system. The time frame of the cycles was affected by the resource allocation and the delays in source data discussed in the next chapter. Ultimately, the BI system was welcomed as the tool for independent reporting customizable for timber supply chain needs.

6.3 Reflection and learning

It is valuable that in ADR the reflection and learning stage is parallel to problem formulation and BIE stage, as there are emerging factors not directly related to the versions of the artifact. The principle of this stage, guided emergence, grasps the balance between structured research method and the openness to the unexpected. According to Sein et al. (2011, p. 44), "authenticity is a more important ingredient for ADR than controlled settings."

One factor was the allocation of responsibilities between Company and the consultant company, and the right timing to move from outsourcing to in-house responsibilities. As there are two people in Company for maintaining and developing the timber supply chain EDW process, accessible and low-code technology selections were preferred. The building of EDW and data modeling expertise by the consultant company accelerated the process significantly and created a solid foundation for managing and developing the environment and the processes.

The cycles were performed in project-based collaboration until an adequate level of familiarization with the system was reached and the participants moved to need-based collaboration. It is important to notice that BI management is responsible for both the data stage and the information stage of BI (Wieder & Ossimitz, 2015), that is DW and visualization. The time and effort for system integrations and access management configurations for several environments have increased with every tool added next to the basic ELT process.

Secondly, changes in source data from the operational system had a significant impact on the cycles because the data modeling, especially automation, is highly dependent on the structure of the source data. The alterations caused extra work and waiting time for certain expected tables and fields led to delays in two cycles. As the data share is executed via exports instead of a shared instance, this dependency remains a risk factor for data availability. As a solution developed during the cycles, the ADR team advanced more frequent meetings and established communication practices in trilateral collaboration with the operational system vendor.

Sein et al. (2011) define three kinds of contributions resulting from the cycles of the BIE stage: design principles for research, the specific artifact for the demand of the practitioners, and utility for the end users. These are discussed as proposed in the tasks of this stage; the design, then the principles, and finally the intervention to the organization (figure 12).

1. Reflect on the design and redesign during the project.
2. Evaluate adherence to principles.
3. Analyze intervention results according to stated goals.

FIGURE 12 Tasks in the reflection and learning stage of ADR (Sein et al., 2011, p. 44).

At the beginning of ADR, the design artifact with several layers of modeling, a complex data ingestion ecosystem, and a robust, highly scalable warehouse compared to the extracted data amount seemed exaggerated. However, the data extent after one year had already proved the need for this kind of system. Several modeling layers are practical when creating several versions and alterations to the data since the original versions remain intact. In the future, data marts can be separated based on different departments. The data lake has yet to ingest only structured and semi-structured data. The real test for the storage is when the data is extracted from several systems. The BI system is still at the beginning of the road that leads to leveraging the whole scale it offers.

When compared to the demands presented in the problem formulation stage, it can be argued that the reference architecture and the design choices were correct for the organizational context. Of the sixteen demands, fourteen have been replied and the design solutions are presented in table 7. Modern reports, data-sharing capabilities, automated processes, and scalability are highlights of the design artifact. The two demands in cursive are technically enabled but not fully deployed yet. More frequent refresh cycles are considered based on the need and discussed with the vendor of the operational system. Some tools for optimization have been utilized but their role in the future will increase.

TABLE 7 The design solutions of the BI system for the problems and demands defined in the problem formulation stage (see table 5 in chapter 6.1).

Problems	**Demands**	**Design solution**
Dependence of the ERP vendor	Access to own operational data	Data exports to the data lake
Low refresh cycle frequency	*More frequent refresh cycles*	*Data pipeline*
Several sources of data	Single source of data	EDW
Data inconsistency	Data consistency	Data Vault
Data redundancy	Data normalization	Data Vault
Lacking data historization	Time travel capabilities	Data Vault & EDW
Legacy system with uncertain future support	A modern system with support	Data lake, EDW & visualization software
Unconnected tools	Comprehensive ecosystem	Data lake, EDW & visualization tools
Lacking one scalable solution	Scalable system for expansion	Data lake, EDW & visualization tools
Greater vulnerabilities by multiple systems and sources	Continuous cyber security improvement	Embedded security of BI system tools supporting Company's cyber security policies
Scattered reporting	Standardized reporting tool	Visualization software
Manual processes	Automated processes	Automatized data pipeline (data lake – EDW – visualizations)
Manual optimization	*Advanced tools for optimization*	*Computing capacity and tools in data pipeline and EDW*
Outdated visual reports	Modern visual reports	Visualization software
Reports and collaboration in separate environments	Collaboration embedded in reports	Collaboration platforms (Teams, Power BI)
Lacking infrastructure for data sharing	Data sharing capabilities	EDW

As Wieder and Ossimitz (2015) claim, data quality is affecting information quality and decision-making. The system can be technically perfect but useless without the necessary data. The company and vendors surrounding a BI system create an ecosystem. The collaboration between all three is valuable. The timing for cooperating with the consultant company was excellent since the resources were limited because of the new operational system and a new employee starting in the BI system project. The standard deployment of the system without trial and error, and high-quality modeling for efficient querying was rational and probably a cost-saving strategy at that time.

The BIE cycles were most apparent regarding the development of the visualization. Compared to the organization-dominant BIE form, in IT-dominant BIE the version is tested by the end-users later during the development cycles (Sein et al., 2011). This project was not completely IT-dominant in BIE stage as the intervention to the organization was anticipated and the visualizations were soon utilized in operations. The visualizations and custom applications support collaboration which was required in the problem formulation stage. Reports can be embedded in Teams channel to improve availability. End users can save certain filters and selections in a report, save it as a bookmark, and share the bookmark with comments to other report users.

During the first cycle, the model report required input from the end users. After the cycles and with the development of EDW, there is now only one application required for optimization in this use case without intermediate steps and additional tools. Since the selections can be saved from the application to EDW, the clear definition of Company's EDW as an analytical database compared to operational is slightly challenged but still accurate due to the small volume of transactions. The training for end users, the operation experts, was organized in Teams. Based on the feedback, the application was simple, and only minimal changes to the layout were expressed.

The BI system provides information for all the timber supply chain activities introduced in the second chapter. There are now nine visualizations shared with end users. They are typically dashboards with several pages, some of them created for the executives. An emergent, but somehow expected factor was the scope expansion outside the wood procurement as there is an evident need for custom-made reports.

6.4 Formalization of learning

ADR is not completed when the design artifact has been created and the lessons of the process are learned. In the tasks of the fourth stage, a class of field problems defined in the first stage is addressed, and generalized outcomes are presented (figure 13) (Sein et al., 2011). The problem was defined as the optimization of a supply chain. This is still a valid classification since the theory and the case study have brought insights into the initial problem.

1. Abstract the learning into concepts for a class of field problems.
2. Share outcomes and assessment with practitioners.
3. Articulate outcomes as design principles.
4. Articulate learning in light of theories selected.
5. Formalize results for dissemination.

FIGURE 13 Tasks in the formalization of learning stage of ADR (Sein et al., 2011, p. 45).

As outlined in the second chapter, optimization in this research means a tool for decision-making by finding the optimal solution or solutions for the example cases of the timber supply chain. Optimization can support prescriptive analytics and answer the question: What should I do and why? (Delen & Ram, 2018).

In the supply chain, this question should be transformed into "What should we do and why?". In supply chain management, cooperative efforts are seen as a strategic choice as the objective of the whole supply chain is to provide value to the end customer (Mentzer et al., 2001). The challenge of the supply chain with different overlapping time frames and several partners is that the conducted suboptimizations may not result in optimal decisions from the long-term strategic perspective (Rönnqvist, 2003). If the complex supplier-partner-buyer chains resemble a supply chain inside of the main supply chain, like the wood procurement inside the sawmill operations, the risk for suboptimization increases.,

The BI system is a tool designed to store data from all the supply chain processes and provide the necessary computing capacity for complex optimization tasks. The system is designed according to the requirements of the supply chain. Collaboration emerged as a key factor in BI implementation from two perspectives. To create a complex tool to match the optimization challenges, collaboration with external experts can be a solution. Secondly, collaboration with the vendor of source data is the key element to ensure data quality. Data quality affects the information quality, which defines the quality of decision-making (Wieder & Ossimitz, 2015).

The design and evaluation of the BI system must involve all relevant business units (Wieder & Ossimitz, 2015). A BI solution does not only consist of BI tools and IT infrastructure but also the processes supporting BI objectives (Wieder & Ossimitz, 2015). The demand for custom reporting suggests that in-house maintenance and development of the system should be considered concerning the skills and resources available in the organization.

The BI system has proved to be a tool for decision-making at the strategic and operational levels. Supply chain BI competence means that decision-making is supported at several levels (Sangari & Razmi, 2015). A centralized EDW with scalable data modeling supports the organization-wide objective toward the end customer.

The results of ADR for optimization of a supply chain can be summarized in two conclusions:

- Instead of suboptimization efforts, supply chain optimization requires collaboration through the whole supply chain towards a shared objective to provide value for the end customer.
- A solution including a scalable BI system with a centralized EDW and adequate processes to support decision-making at both strategic and operational levels supports the optimization of a supply chain.

7 SUMMARY AND CONCLUSIONS

The purpose of the research was to study BI implementation in the context of timber supply chain optimization. First, the motivation for the study and the gaps in previous research were presented in the introduction. In the second chapter, the concepts of supply chain followed by the characteristics of timber supply chain were examined. The research was limited to the timber supply chain as forest management and silviculture activities, mill processes, and sales to resellers or end customers were excluded from the research scope. The timber supply chain, i.e. wood procurement, was defined as the supplier for the sawmill supply chain. After the timber supply chain activities, purchasing, timber harvesting, transport, and sorting, and the data related to the activities the optimization was defined in the context of this study, and optimization possibilities for the timber supply chain were introduced.

In the third chapter, the concepts of business intelligence, BI evolution, and BI competence were studied as a background for the theory of data warehouse implementation and the case study. The fourth chapter examined the implementation of a data warehouse via the elements of DW in the order they are implemented and operating in the ETL process. First, the planning and selection of DW reference architectures, then source data, data vault, data marts, and visualization and analytics were studied. The detailed study of software, hardware, and integration selections was excluded from the research since the selections are dependent on the business environment.

Before the case study, the research methodology was introduced in the fifth chapter. The research method and framework, action design research, was studied. The framework principles and tasks were stated to be examined in the next chapter parallel with the case study. The research process and the case company were explained. The research was commissioned by a large Finnish sawmill corporation and the author participated in the ADR team as both a researcher and a practitioner.

The case study was presented in the sixth chapter using the principles and tasks of the action design research framework. The four stages of ADR, 1) problem formulation, 2) building, intervention, and evaluation, 3) reflection and learning, and 4) formalization of learning provided the structure for the case study. In the case study, the class of problems was defined as the supply chain optimization. The formalization of learning was summarized in two conclusions. Instead of suboptimization efforts, supply chain optimization requires collaboration through the whole supply chain towards a shared objective to provide value for the end customer. A solution including a scalable BI system with a centralized EDW and adequate processes to support decision-making at both strategic and operational levels supports the optimization of a supply chain.

The research questions introduced in the first chapter were as follows. These questions are answered based on the case study in the previous chapter.

1) What to consider when designing and implementing a BI system for optimizing the timber supply chain?
2) Did the implemented BI system improve the data management of the timber supply chain?

When designing a BI system for a certain business environment, the specific problems and demands are necessary to identify by asking questions of the employees of the subject domain. Since support from management is crucial for BI competence and the modern BI system contains a centralized EDW for the use of several departments, it is advisable to design a comprehensive solution implemented gradually for the whole organization. In addition, optimization should start from the strategic level. For the timber supply chain, the main objective is to match the timber to the demand of the end customer of the sawmill. The data sources must be considered in the design. Data sources often include operational systems and in the case of external vendors, collaboration is important for the data quality. For optimization, the architecture and technology selections must provide sufficient capacity for storage and computing.

The implementation phase included continuous evaluation of the system and the emergent factors. External experts can perform the implementation efficiently in a standardized manner providing high-quality modeling. After the implementation, the demand for custom visualizations and tools for operational decision-making can benefit from in-house comprehension of domain fields like the timber supply chain. Resources and skills must be considered for both the DW and visualization layer, end-user training, and emerging demand for new custom reports from different departments.

The BI system has already matched fourteen of the sixteen demands defined in the problem formulation stage. More frequent refresh cycles are dependent on the data from the operational system, and advanced tools for optimization are available but not fully utilized yet. In addition, the automatization of processes can be advanced further. The performed model optimizations have proved that the cost savings from the optimized timber supply chain activities are remarkable. As a single source of data with access to own operational data, and a tool for modern, interactive applications the BI system has been approved by users. In the requirement specification phase 28 reporting needs were identified, of which 11 were priority 1. Nine reports have been created, most as a dashboard of several pages, and for different end users also outside of the timber supply chain.

The credibility of a design science research paper can be evaluated against the differences in DSR genres. In ADR, the relationship between the artifact and the organization presents a challenge to the repeatability of the study. However, the design artifact and design principles provide an opportunity for generalization. As the artifact in this study is an established tool, the conclusions emphasize the purpose of a centralized system for an organization and its processes. The study rather validates the conclusions of the literature review instead of inventing new principles.

As presented in the introduction, there is a research gap in the business intelligence adoption, utilization, and success related to procurement. In this research, the role of a centralized data warehouse as support for comprehensive optimization of the supply chain emerged based on the literature review and ADR method. A combined study of forestry, business management, and information systems can provide interesting insights for further research.

This research does not engage with sawmill production or sawmill supply chain other than related to the timber supply chain and the company environment. A comprehensive research of data warehouse technologies or data analytics was also excluded from this thesis.

The influence of a BI system and optimization on timber supply chain performance can be researched later as the visualizations have been used beyond the adoption stages. From the perspective of supply chain BI competence, the collaboration and knowledge sharing with the external partners of the timber supply chain offers a research subject. As Lean practices are adopted in the case company, the points of contact with BI and optimization are obvious as all three concepts aim at streamlining the processes and supporting decision-making. Where forestry, BI, and optimization meet, the questions of sustainability and carbon footprint data emerge as a research interest as well as the possible benefits of machine learning and artificial intelligence use.

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