

## Article

# Decision Making in Service Shops Supported by Mining Enterprise Resource Planning Data <sup>†</sup>

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**Abstract:** This research examines the application of Enterprise Resource Planning (ERP) systems in service shops, focusing on the specific challenges unique to these environments compared to those in the manufacturing sector. Service shops, distinguished by their smaller scale and variable demands, often need different functionalities in ERP systems compared to manufacturing facilities. Our analysis is based on detailed billing records and monthly cash flow data to deliver critical insights into businesses' performance for service shop managers. This study analyses ERP data from 27 service shops over 35 months. It is based on detailed billing records and monthly cash flow data to deliver critical insights into businesses' performance for service shop managers that support managerial decision making. Our findings emphasise the importance of incorporating additional contextual information to augment the effectiveness of ERP systems in service contexts. Our analysis shows that simple, standardised data mining methods can significantly enhance operational management decision making when supported with visuals to support understanding and interpretation of the data. Moreover, this study suggests potential directions for future research aimed at improving business analytics and intelligence practices to optimise the use of ERP systems in service industries. This research contributes to the academic discourse by providing empirical evidence on utilising ERP data in service shops and offers practical recommendations for ongoing operational improvements.

**Keywords:** data mining; enterprise resource planning; business performance; service centre



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## 1. Introduction

This study examines service workshop operation management using existing Enterprise Resource Planning (ERP) data and asks what insights could support decision-making processes. It builds upon an exploratory study [1], which discussed the common challenges service shop management personnel experience with ERP data.

Traditionally, ERP systems have been implemented to integrate business processes and support managerial decision making [2]. However, service organisations are outside the initial target zone of many ERP vendors, which instead develop products for manufacturing companies [3,4]. According to Waurzyniak [4], service shops challenge ERP system developers due to their small size, changing demands, process maturity, and the high costs of implementing ERP systems. In addition, ERP systems are more often designed

for financial reports and control [2]. As such, managers are left to work using ad hoc screenshots (Figure 1) to help with operational management decision making outside the financial domain. Nevertheless, the transactional data contained within the ERP dataset of a firm provides a resource for supporting business understanding and operational decision support [5–8].

ZA50 Projektreporting mit PSP-Elementen		Datum: 26.03.2024		
Projekt (PRO) / Element (ESP): Bezeichnung:		Benutzer: TAKALBER		
gehört zu Leistungsauftrag: zugeteilt zu Profit-Center:		Seite: 1 / 2		
IDS-Projekt? (X = JA):		Kontenstruktur:		
Termine zum Projekt:		Planversion: 11 Budget		
Termine zum Element:		Berichtszeitraum: 1 2023 - 12 2024		
Erlös- und Kostenarten (ohne Umlagen!)	Plan	Ist	+/- CHF	+/- %
30110 Projekterträge		-72,150	-72,150	
30600 Ertrag aus Publikationen		-28	-28	
30690 Übriger Ertrag		-4,097	-4,097	
30795 Rundungsdifferenzen		-0	-0	
*** Erträge Dritter		-76,275	-76,275	
35035 Ertrag HSLU Forschungsfinanzierung allg.		-9,550	-9,550	
*** Beiträge Konkordat		-9,550	-9,550	
38100 Abgr. angefangene Arbeiten		4,387	4,387	
** Abgrenzung angefangene Arbeiten		4,387	4,387	
*** Total Aktivierung / Abgrenzung		4,387	4,387	
**** Total Erlös		-81,438	-81,438	
530200 Leistungen Dozierende		12,800	12,800	
530300 Leistungen Assistierende / Wissensch. MA		47,446	47,446	
* Personalkosten aus Leistungszeit		60,246	60,246	
** Total Personalkosten intern		60,246	60,246	
58041 Reisespesen		1,366	1,366	
58042 Verpflegungs- und Übernachtungsaufwand		3,664	3,664	
58070 Personalanlässe		418	418	
58090 Übriger Personalaufwand		2,053	2,053	
*** Personalnebenkosten		7,500	7,500	
**** Total Personalkosten		67,747	67,747	
60000 Fremdmieten kurzfristig		231	231	
* Raumkosten Dritte		231	231	
** Total Raumkosten		231	231	
62110 GwG Informatik Software/Lizenzen		358	358	
* Informatikkosten Dritte		358	358	
** Informatikkosten		358	358	
64200 Projektleistungen Dritter		3,400	3,400	
** Unterrichts- und Projektkosten		3,400	3,400	
66400 Repräsentationsspesen mit Dritten		12	12	
** Repräsentationskosten		12	12	
*** Total Sach- / Infrastrukturkosten		4,001	4,001	
**** Total direkte Kosten		71,748	71,748	
***** Ergebnis VOR Umlagen		-9,690	-9,690	

Figure 1. An example of a typical screenshot from an ERP system (own illustration in German).

The development of ERP systems was initiated by industrial manufacturing companies [9], so the functionalities are primarily focused on physical operations. Since service operations have become increasingly crucial for the economy and manufacturing companies, service elements have an increasing fundamental impact [10,11] on the economy [12]. The management accounting function must emphasise service functions in its practice to consider their rising importance. Also, cost accounting is rooted in manufacturing, and transferring the financial accounting instruments to the service operations is complex. Service is immaterial and not stackable in a way that is possible with products.

Consequently, fixed costs and capacity management are more important in service operation management. This must be considered in relevant performance indicators focussed on the service industry [13]. Management accountants aim to provide management with helpful information to make better decisions. Service managers are the essential customers of this information. Management accountants need to develop tools that give service management better information despite the weaknesses of ERP systems. In their role to ensure management rationality [14], they are supposed to provide information efficiently to support decision making by operational and strategic managers.

In this paper, the authors (who represent a mix of disciplines, including business improvement, data science, finance and control, and operation management) were provided with a set of data from the ERP system of a service provider which repairs a range of industrial equipment. The company has provided repair services on equipment manufactured by others for over 60 years. Most of their repair services are based on a model of “clean, strip,

inspect, repair". As the repairs were undertaken independently, the firm had to create its own repair process and bill for the materials. The ERP system captured these core processes and the costs associated with the transactions; yet, the service shop managers only received the ERP data as a monthly cash flow statement. The system was set up to provide monthly financial statements based on the transactions logged in the ERP system, and the workshop managers and the operation leads confirmed that they were using it to help with planning and control. This was outside the ERP system's initial requirements and outside the finance department's direct control, apparently being a grassroots initiative.

Prior studies [2,5,6,8] confirmed that ERP data provide a log of business transactions as a basis for financial reporting, and firms such as SAP have invested in tools like HANA to extract insights from these data. Other studies have considered data for decision support within businesses as customer service support [15] and data mining for business analytics [16], as well as knowledge assimilation and more advanced decision support [17,18]. Others have considered manufacturing firms or pure service businesses, but not industrial repair and overhaul businesses providing workshop and field-based services. For these reasons, the research question for this paper is *"how can service shops drive better decision making with insights from ERP system data?"*

## 2. Literature Review

The research question examines benchmarking and decision making to support management planning, control, and performance in service shop operation management [19]. Using ERP data for operation management has been identified [20] as a strategic and tactical approach in manufacturing firms and made-to-order businesses [21,22]. However, many implementations focus more on the financial than the operational aspects of a business, which is consistent with the financial reporting focus (from finance to control) for most ERP systems [2] (p. 403).

Implementing ERP systems depends strongly on the business and its processes [23]. Furthermore, many ERP systems are built around product manufacturing and logistics. Ideally, the requirements should include, among other aspects, the business performance, the customer benefits, and the strategic benefits. Managers increasingly expect ERP systems to provide decision support based on business metrics, requiring machine learning algorithms. Behera and Dhal [24] confirmed that ERP systems provide limited visuals and decision support in many implementations and deliver complex financial information that is less useful.

According to Černý [25], considering the data science perspective of the business intelligence analysis of ERP systems is often limited as it restricts the additional contextual information available in the broader ecosystem. Often, these additional data are in an unstructured form and so are seldom used [26]. In contrast, the focus of ERP systems is generally on structured financial data (and metrics) and, in some cases, other operational data and metrics [27]. To gain the full value from ERP systems, there is a need to standardise the reports and metrics across often dissimilar operations to help compare them to different business units within the firm.

### 2.1. Data mining to Gain Operational Insights

The literature [28,29] considers ERP systems to provide a suitable resource for data mining (i.e., cloud computing, big data analytics, and AI) to support business analytics; yet we must also be aware of its limits [30,31]. Accordingly, data mining [32] can reveal insights within a firm and has been used in many different business areas, including the sales function, customer support, and manufacturing [5,7,8,15]. It is increasingly used for forward-looking business analytics [16] coupled with machine learning and other techniques. Other studies [2,6,33] describe using ERP systems to support Lean or continuous improvements within firms in different manufacturing contexts, including in SMEs similar in size to the typical service workshops. The maturity model [34] provides a

five-level model with examples showing how and where ERP systems can support “pull production” in firms.

Outcome predictions, categorical predictions and classifications, and anomaly detections are usually used to inform business decisions through operational insights [2,6,33]. While this can be achieved with a small amount of data, the accuracy increases considerably with more data to feed the algorithms [35]. Linear regressions, for instance, can be trained swiftly. However, they may need more accurate methods, such as neural network regression, that require much longer training times. Similarly, categorical prediction can be achieved through multiclass logistic regression or multiclass neural networks, which require longer training times but are more accurate. However, increased accuracy comes at a cost [36], despite capturing big data, finding patterns with clear causality, and creating models based on the insights [31]. Therefore, according to Tan et al. [37], the future of business data quantities and usage patterns will have to adapt to allow businesses to operate effectively.

## 2.2. Benchmarking

Benchmarking can improve an organisation’s performance by comparison with others, as described in the literature [38]. Often based on external benchmarks, it can be used internally to consider cross-business performance and support knowledge management and continuous improvement [39]. With the use of business analytics systems based on ERP data [27,40,41], further insights can be gleaned [17]. Some research [38,39] describes how ERP data can be valuable in building models and benchmarks; it also confirms that ERP data could be used more effectively, as there are barriers to their application. Černý [25] states that this is why we often build off-system systems, assuming that the cost of coding and ongoing maintenance create barriers. Nevertheless, off-system systems can cause data quality and comparability issues, which are only discovered later. When models cannot quickly be built, benchmarking combined with visuals can support decision making in a business, and this approach has been used in several environments [42–45].

## 2.3. Decision Making

There have been broad discussions on information and knowledge as we shift from an industrial-based society towards an information-, and more recently, a knowledge-based society. Decision making is predicated on information and knowledge [46]. The relationship between data and decision making can be defined through the Data–Information–Knowledge–Wisdom (DIKW) model described by Ackhoff [47]. The DIKW model defines information as a unit based on data; it can only be regarded as information if placed in a framework that people can use, recognise, decode, and evaluate. From the knowledge management perspective, information is only valuable when it is relevant to the person using it.

Decision making is enhanced when data are presented in a form such as a clear visual representation [38,46,48] that allows a team to assimilate it into knowledge and deliver actionable decisions and forecasts [49,50]. ERP data can and should support decision making [18]. Colson [51] places decision making within the context of AI and simultaneously places people at the centre of the decision-making processes. However, AI is brought into the decision-making workflow. This is managed by allowing the machine to identify the possible actions, integrating “other information” into the process, and applying human judgment to create a business decision. Digital twins can support decision making within several use cases. In their paper, ERP data were one of the data sources used in the model [52].

Metaxiotis, Psarras, and Ergazakis [53] considered production scheduling support by combining ERP data with AI. An example of advanced decision support is based on digital twins using ERP data [54]. The two papers support each other as they describe how, today, with Industry 4.0 technology, production data can support production planning. In the intervening period, computing power increased, generating different production options

more rapidly. The literature [51,52,54] confirms that only some of the necessary data to support decision making are contained within one system and that managers must integrate external information and knowledge when making decisions [55,56]. In parallel with the use of AI with ERP data analysis in supporting decision making, Colson [51] described how mathematical models have been used to support planning and assessment in economic analysis. Similarly, using empirical evidence and advanced econometric models in export markets, similar methodologies have been compared to analyse ERP data for service shop management [53].

#### 2.4. Decision Making and Sustainability

There is a growing awareness of sustainability, and companies have to consider the consequences of their business on the planet (environment) and people (their workforce and other stakeholders) in addition to their traditional emphasis on profit (i.e., the triple bottom line [57]). Through government initiatives, companies have to change their business models and consider the influence of their business on the environment and the effects of environmental change on their business. By reporting to the public, the pressure on companies to change their behaviour has increased [58,59].

Besides regulatory pressure, there is also a direct effect on companies' profits. For example, illness leads to an increase in costs and the loss of resources for a service business. This results in unsatisfied customers and, consequently, reduced company profits. Firms with a people-oriented culture generally have less absenteeism [60]. Such firms typically have a better work/life balance for the employees and one where excessive overtime or periods of the underutilisation of staff are limited. A firm's more efficient use of fixed assets (e.g., equipment) preserves natural resources and reduces costs [61].

In many cases, there is a complementary relationship between the sustainability targets and company profitability. Although there are other issues where companies have a trade-off between sustainability and the firm's overall profitability [62,63], companies can prioritise their efforts on those measures that increase profits. The ERP data can provide an input to improve decision making and the triple bottom line.

### 3. Research Approach and Methodology

Given the practical nature of the research problem and the how-type research question, the case study research method was used to guide the process of exploratory data analysis [64–66]. The data were collected from the ERP system for multiple service centres of a service provider that repairs various industrial equipment. They were analysed to develop an understanding of their main characteristics using statistical graphics and other visualisation methods. This approach allows for the building of models and algorithms that support decision making. Andrienko and Andrienko [67] describe how to apply a systematic approach to the exploratory data analysis of temporal data that are similarly structured to the ERP data. The inputs of such a process are a dataset that has been processed and cleaned; the ERP data used in this study were, in essence, a processed dataset that had been partially cleaned. The unit of analysis for this study was the ERP data provided by the firm and how they could be used to support decision making.

#### *Methodology*

An ERP dataset of monthly cash flow and invoicing data from 27 service centres in one region was analysed. The data were provided as flat CSV files to be imported into MS Excel, SPSS, Microsoft Power BI, or R version 4.1.2. Additional contextual management data to support the analysis were collected separately, and additional tables were created. The steps applied to the ERP data were as follows:

1. Data cleaning;
2. The collection and integration of contextual information;
3. Data structuring into business units and workshop locations;
4. The exploration of the invoicing data;

5. The exploration of the monthly cash flows;
6. Benchmarking metrics.

The six steps appear here as a linear approach to exploring the data. However, the process of exploration is more iterative than what is depicted. The chief operations officer was consulted to confirm the findings.

#### 4. Results

Over 35 months, around 3 MB of data from the firm's single ERP system was collected in a CSV file (later moved into Excel), representing the 27 service workshop locations. The billings captured 40,000 lines of data, whereas the monthly cash flows provided 39 data lines per month. The billing data included four key data fields: the "Customer Code" is a unique identifier for each customer; the delivery "Zip Code"; the "Net Sales Value" is the amount on the invoice for goods or services provided; and the "Net Cost" refers to direct expenses associated with producing or delivering the sold goods or services. Interestingly, the net sales value was, in fact, the value on the invoice and may be different to the business's monthly sales as there is a time delay between the sales recognition and the billings. Financial point-of-sale recognition differed from raising the bills in the system; there was often a delay (according to the management) from two to four weeks between shipping and invoicing.

The monthly cash flow data fields outline various financial and operational metrics used in business to measure the performance, costs, and profitability. These metrics are divided into three main categories: the sales and related figures, the costs and overheads, and the profitability measures. First, considering the sales, the metrics range from "Jobs sold", "Hours sold", and "External sales" to "Internal sales", culminating in the "Total sales". These figures help understand the volume and value of sales achieved internally and externally. The "Cost of goods sold", "Labor costs", "Under absorption cost", "Employee social costs", and "Material costs" are among the metrics listed under costs and overheads, providing an insight into the direct and indirect costs associated with the production or provision of goods and services. Additionally, the "Overhead costs", "Overhead recovery", "Admin costs", "Sales costs", "Distribution costs", "Management overheads", and "Rent (nominal)" further detail the expenses incurred beyond the direct production costs, encompassing the administrative, selling, and distribution expenses. The profitability measures include the "Contribution margin", "Gross profit", along with ratios such as "CM/sales" and "Gross profit/sales", offering a glance at the efficiency and effectiveness of sales in generating a profit. "EBIT" (Earnings Before Interest and Taxes), "EBITDA" (Earnings Before Interest, Taxes, Depreciation, and Amortization), "Interest charges", "Profit before tax (PBT)", and variations like "Pre-exceptional PBT" and "Pre-interest PBT" delineate a company's earning capacity before deducting the interest and tax expenses. "Amortization", "Depreciation", "WIP (Work In Progress) provisions", "Bad debt provisions", "Debt provisions", the "Exceptional costs", and the "PBT contribution" further dissect the financial health, accounting for asset depreciation, provisions for various risks, and the exceptional items affecting the bottom line. The metrics provide a comprehensive snapshot of a company's sales performance, cost management, and overall profitability, each playing a critical role in financial analysis and business strategy formulation.

##### 4.1. Initial Analysis in Excel for Data Cleaning

The data were assessed in Excel for correction and validation and were generally consistent. However, there were issues with the invoicing data, where the calculated margins could be huge (i.e., negative and positive outliers). With no apparent reason for this, the outliers were removed from analysis in this study. Discussions with the local individual workshop managers confirmed that there were quality issues with the data as, often, invoices were issued without being linked directly to a repair project. This came about primarily due to additional repairs being needed or due to invoicing separately for the out-of-scope items. At times, invoicing was also used as a price adjustment mechanism,

breaking the clear link between the cost of the goods sold and the invoice value and creating a quality issue with the data. When analysing this type of data, it is necessary to understand its contextual meaning; for example, the data tag “net sales value” was, in fact, the invoice value, but could be confused with the sales volume in the monthly cash flows (Figure 2). The data tags themselves, as well as the data, require cleaning.

Location code	CUSTOMER - CODE	NET SALES VALUE	NET COST	POST CODE	DATE BOOKED IN
L01, B	3372		3.24	1.09 AB21	07-Sep-1
L01, B	4098		3.25	2.6 AB41	28-Oct-1
L01, B	4972		4.16	3.2 AB52	17-Nov-1
L01, B	2941		4.32	3.2 AB21	02-Jul-1
L01, B	4686		4.43	1.57 KT3	19-Feb-1
L01, B	2941		4.56	2.28 AB21	29-Dec-0
L01, B	5614		5	2.5 AB21	18-Mar-1
L01, B	4686		5	4.56 KT3	06-Apr-1
L01, B	4244		5.33	4.49 AB11	19-Jan-1
L01, B	4684		5.65	4.18 KT3	25-Oct-1
L01, B	4020		5.9	4.52 AB21	24-Mar-1
L01, B	4700		6	3.78 AB11	12-Jan-1

Figure 2. Extract from the invoicing data, providing an example of the data provided (note the data are truncated; however, the entire dataset is available).

The monthly cash flow data were used in the management control processes, and every branch manager was sent a month-end cash flow (Figure 3). The sheet evolved, allowing the branch managers to talk knowledgeably with the head of operations, the business unit and other branch managers, and the finance department. All branch managers were used to using the figures and could take meaningful actions based on the sheets. The data contained within the sheets did not require cleaning. Given that the raw data were used for the firm’s monthly reporting, the data themselves were cleaned using finance and control operations. The spreadsheet lacked any visuals or other decision support tools; a comparison with the business unit as an aggregate was also missing, as the data were only provided for the business as a whole and at the individual workshop location.

	Jul-1x Actual	Aug-1x Actual	Sep-1x Actual	Oct-1x Actual	Nov-1x Actual	Dec-1x Actual	Jan-1y Actual	Feb-1y Actual	Mar-1y Actual	Apr-1y Actual	May-1y Actual	Jun-1y Actual
JOBS SOLD	145	133	115	100	130	106	102	103	132	134	119	123
HOURS SOLD	8,842	6,808	9,146	7,592	5,855	5,341	6,534	9,238	8,450	6,800	6,126	7,361
EXTERNAL SALES	376	356	413	435	339	259	283	414	485	318	280	282
INTERNAL SALES	18	18	5	9	3	10	24	4	22	39	35	30
TOTAL SALES	394	373	418	444	341	269	307	418	507	357	315	312
COST OF SALES:												
LABOUR COSTS	137	107	144	123	95	94	106	153	134	111	101	127
NON-PROD LABOUR	(2)	(12)	2	4	4	4	(14)	(5)	(6)	1	3	(6)
WORKS NI & SUP'N	12	14	12	12	12	12	16	10	13	12	13	15
MATERIAL COSTS	85	86	102	129	81	42	48	95	152	102	71	40
JOB EXPENSES	1	4	2	3	1	4	5	4	3	2	2	6
ADD BACK WIP PROV. MOVE.	0	0	0	0	0	0	0	0	0	0	0	0
MAN. GP	161	174	157	175	149	113	147	162	211	129	124	131
% TO SALES	40.8%	46.7%	37.5%	39.4%	43.5%	42.0%	47.7%	38.7%	41.6%	36.1%	39.4%	41.8%
WORKS OVERHEADS	27	31	30	34	30	29	26	37	29	25	28	28
OVERHEAD RECOV.	7	(6)	13	3	(2)	(8)	(16)	10	4	7	(8)	(1)
ADD BACK BAD DEBT PROV. MOVE.	0	0	0	0	0	0	0	0	0	0	0	0
STAT. GP	127	149	114	138	121	92	127	114	178	96	105	104
% TO SALES	32.1%	40.0%	27.3%	31.1%	35.5%	34.3%	44.6%	27.3%	35.2%	27.0%	33.2%	33.3%
ADMINISTRATION	9	10	12	11	10	11	10	10	11	11	11	8
SELLING	11	12	11	13	13	13	11	11	13	13	13	11
DISTRIBUTION	8	6	6	6	6	8	8	7	8	7	7	6
ALLOCATED OVERHEADS	4	4	4	3	4	4	4	4	4	4	4	4
NOTIONAL RENT	12	12	12	12	12	12	12	12	12	12	12	12
EBITDA	83	105	69	93	77	46	93	71	131	50	59	63
DEPRECIATION	10	10	10	10	10	9	10	9	10	10	10	10
AMORTISATION	0	0	0	0	0	0	0	0	0	0	0	0
EBIT	73	95	58	83	67	37	83	62	121	40	49	53
NET INTEREST	0	0	0	0	0	0	0	0	0	0	0	0
UNDERLYING PBT	73	95	58	83	67	37	83	62	121	40	49	53
% TO SALES	18.4%	25.4%	14.0%	18.7%	19.6%	13.7%	27.1%	14.8%	23.9%	11.3%	15.6%	17.0%
WIP PROVISION MVNT.	5	(0)	(5)	(1)	(0)	(0)	1	(3)	9	53	(2)	7
DEBT PROVISION MVNT.	10	14	1	2	(17)	(6)	(5)	6	1	3	3	(16)
PRE INT. RECH. PBT	58	81	62	81	85	42	87	59	111	(15)	48	62
INTERNAL RECHARGES	10	10	10	10	10	10	10	10	10	10	10	10
PRE EXCEPTIONAL PBT	48	71	52	71	75	32	77	49	101	(25)	38	52
EXCEPTIONAL COSTS	0	0	0	0	0	0	0	0	0	0	0	0
PBT CONTRIBUTION	48	71	52	71	75	32	77	49	101	(25)	38	52
No of Employees	44.5	43.5	43.5	43.5	43.5	44.5	44.5	44.5	44.5	44.5	44.5	44.5

Figure 3. Example of the annual cash flow actual sheet provided to workshop managers (note the data are truncated; however, the full dataset is available).

#### 4.2. Collection and Integration of Contextual Information

Initial analysis confirmed that the contextual information needed to be included: the floor space for each workshop and the hierarchical relationship with the business (e.g., its sub-business unit based on the business model, not the location). Contextual information supports the broader interpretation of the data and helps to frame the data within the larger picture. The information was stored in a separate system within the finance department, while the contextual data were stored outside the ERP system and had to be collected manually. The firm considered it too difficult for the value created to link the contextual data and information with the data in the ERP system as they were stored in separate systems. Černý (2020) [25] proposed considering the firm’s broader ecosystem to harvest the contextual information.

#### 4.3. Structuring of the Flat Data

The business structure was used to create a synthetic consolidation of the invoice data and the cash flows. This created business-level and business unit perspectives of the datasets and individual branches (Table 1). The data collected did not provide consolidation at the business unit or business level on the same basis as the data from the individual branches. For this reason, synthetic consolidation was needed, although this may consider intra-business trading fully. This confirms that data cleansing to remove the artefacts is an important activity that should be given more focus. Creating a synthetic consolidation may have introduced errors in the data due to internal sales and the impact of transfer pricing rules. Intra-firm trading occurred every month and represented consistently less than 5% of sales, which was considered unimportant for this study.

**Table 1.** Business unit and workshop location designation.

BU	Location	BU	Location	BU	Location	BU	Location
A	L03	B	L01	C	L02	D	L04
A	L11	B	L07	C	L05	D	L06
A	L15	B	L08	C	L09	D	L12
A	L26	B	L14	C	L10	D	L22
		B	L16	C	L13	D	L24
		B	L17	C	L18	D	L27
		B	L19	C	L20		
		B	L25	C	L21		
				C	L23		

#### 4.4. Exploration of the Invoicing Data

The invoice data (total invoice value) were initially plotted by month and location to allow for the assessment of the data and their form, as shown in Figure 4. The plot is close to the raw data, yet provides an overview of the business regarding the raw size. The apparent volatility in the billing volume per month may, therefore, be a poor comparison of performance on a monthly basis; yet, on an annual basis, the total billings should be close to the total sales for this industrial workshop location.

The invoicing data were then explored using a set of scatter plots before moving on to box plots, which offered more insights than the final scatter plots. The visualisations’ purpose (or, during the early stages, the expired purpose) is stated in the Results, along with a short description of the relevant findings.

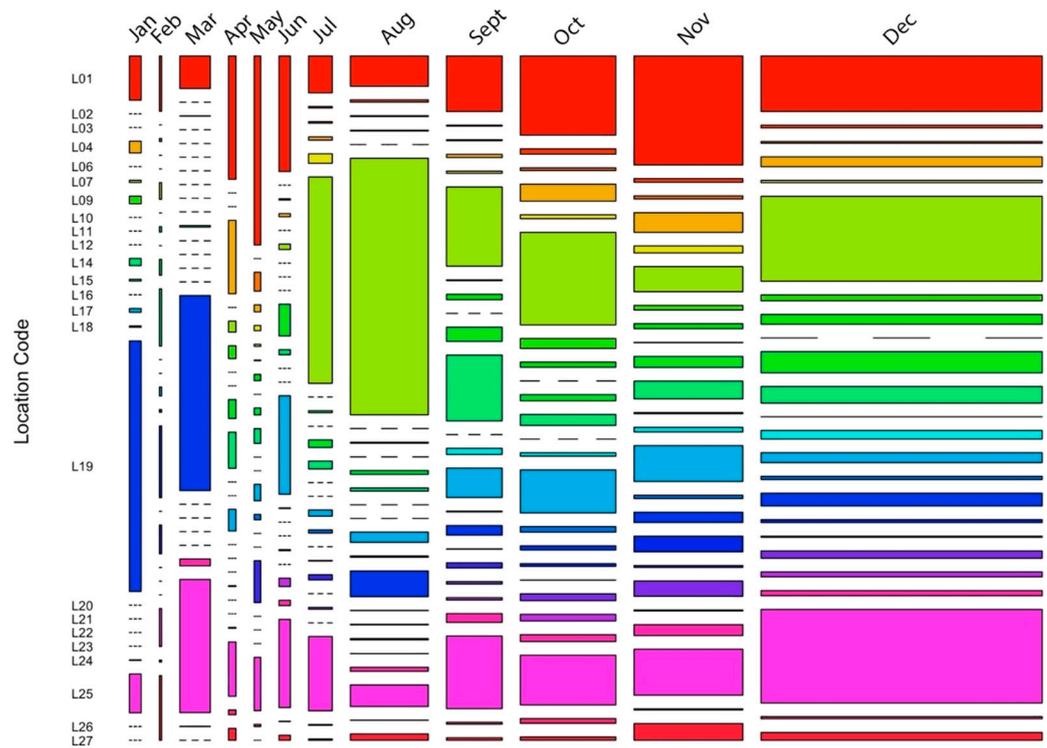


Figure 4. Initial plot of the invoice data against month and location.

Here, internal benchmarking shows high levels of variance in the size of individual jobs and the margins per job. Figure 5 shows the breakdown from the business to the BU and finally to location 01 (L01), allowing consolidation to be created as part of the flat data structure. Location 17 (L17) has a Gross Profit (GP) margin that is slightly lower than the average for business unit (BU) B; it has long tails, whereas L19, with lower-level variance, provided a more reliable projected GP. Improvement in individual service shops' performance (e.g., no invoices with less than zero GP) could improve the firm's margin overall. The box plots for the individual locations from one BU allow for comparison for each location and provide the comparisons with the other BUs and the business in aggregate. Noise in the data from the scatter plots required additional contextual information to be collected to understand the challenges with the data quality. The discussions confirmed that many invoices were created for billings without directly matching the costs. Interestingly, the anomaly data appear to be associated with the smaller invoice values, and a filter applied at  $\pm 80\%$  GP margin may offer a pragmatic approach to data cleansing.



**Purpose**

- By learning from poor performing jobs overall business performance can be improved
- Consider whole business, business unit and individual shop

**LO 01**

- Has an average GM within the average range
- Is operating within a lower end of the range
- Has a longer tail and may require additional support

Figure 5. Invoicing data provided statistical insights into the operations based on the business, business unit and individual location.

The analysis of the customer base confirmed that the top ten customers on the consolidated business or at the business unit level contributed less than 10% to the total sales volume (Figure 6). However, when drilling down to the individual service centres, the top ten customers often contributed 30% or more of the total sales, so losing two key accounts could create challenges for a service shop. This information was available from the invoice and was not actively used by the business for account management. For instance, it was not used to confirm local over-reliance on a small customer base or identify the common accounts shared with different workshop locations, nor was it linked to market segment dynamics. In many cases, the discovery of the top ten customers contained unexpected names due to small repeat orders that “just arrived”, rather than large projects that were more well known by the management.

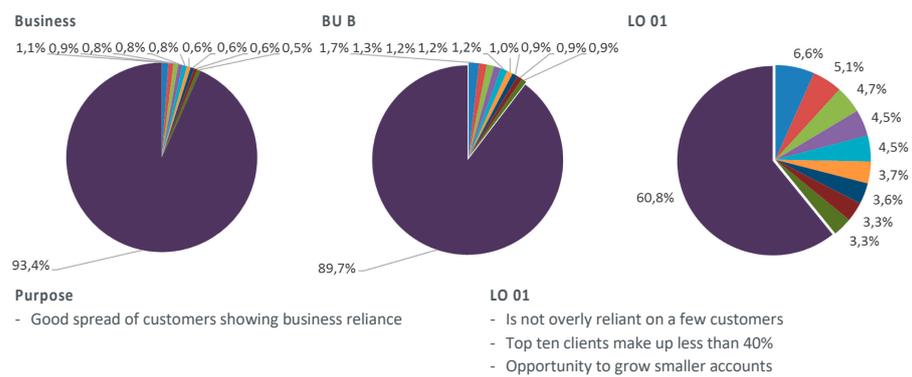


Figure 6. Top ten customers for the business, business unit, and location 01.

The reliance on large orders is an insight into the underlying business model (Figure 7) and the risk of missing targets due to failing to win a large order. The firm focused on the overall business reliance on single customers and large orders, rather than undertaking detailed customer analysis at the business unit level, providing new insights for the managers. There is a significant difference in operation management when a firm deals with many small jobs, rather than a few large projects. Also, a business that relies on a few large projects to fulfil the order intake may be at risk, as the frequency of large orders may appear somewhat random. The statistical analysis of the frequency of large projects could be estimated with a Monto Carlo simulation, which would then support the firm’s risk management.

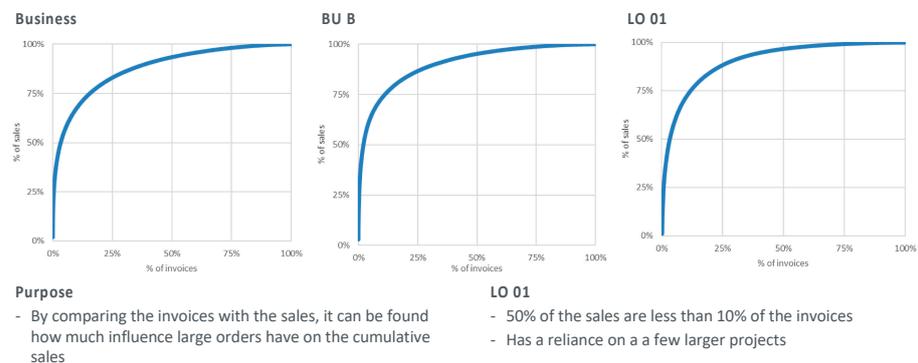


Figure 7. Invoice size analysis for the business, business unit, and location 01.

Using customer postcodes helped visualise the geographic distribution of the customer base (Figure 8). However, we assumed that the invoice address was the ship-to address, but the data showed this was only sometimes the case. The ease of the analysis (completed using Excel) surprised the management and provided new insights into the relationships between the different workshops. One manager asked if it would be possible to overlay the

market information to understand if they were serving the “local” markets. Discussions within the firm confirmed that there could be problems with confusion between the ship-to and bill-to addresses. This suggests a problem with both the data quality and the data structure. Overcoming this challenge is not easy, as it can be completed inside or outside the ERP system, with pros and cons.

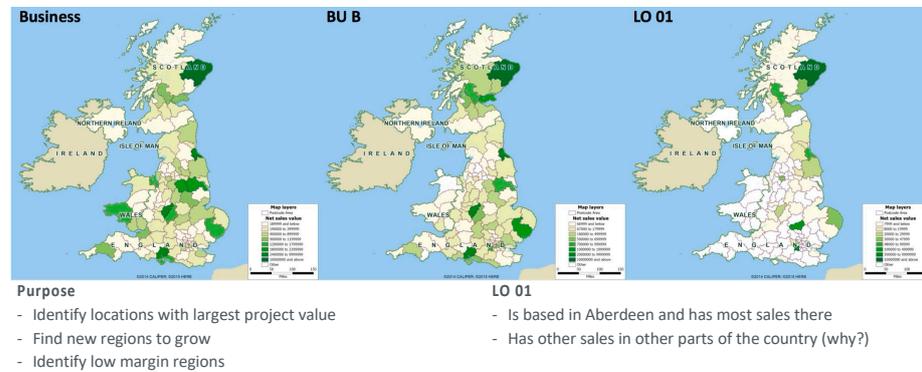


Figure 8. Postcode analysis of business, business unit, and location 01.

#### 4.5. Exploration of the Monthly Cash Flows

The trend data were plotted again at the three different levels of the firm: the whole firm, a single business unit, and a single workshop location. Previously, only the spreadsheets were used, but visuals presented the data in a more actionable form. The upper charts show data on a rolling 18-month basis rather than a financial year basis, and Lean approaches were used to convert the charts into control charts with a regression trend line to provide a form of forecast. The basic regression model was used. There was only a basic understanding of the statistics, and this approach is a new approach with time-series data; it is commonly applied within firms with a Lean/Six Sigma improvement program. The upper and lower control lines represent  $\pm 2$  sigma around the mean. The charts are based on the monthly reconciled data (available data); therefore, more detailed insights may be missing from the charts. The value  $\pm 2$  sigma around the mean was chosen as an arbitrary figure. However, moving to a calculated figure for some charts may be possible in the longer term based on resource limitations.

Figure 9 provides a competitive view of the monthly sales value, which is one of the firm’s key measures. Here, the control charts from Lean are used to visualise the business. A linear trend line was applied to show the likely direction. However, analysis confirmed that there was limited value in statistical fitting due to the volatility seen in the data. It was unclear if this had to do with the time frame of the data or other contextual aspects.

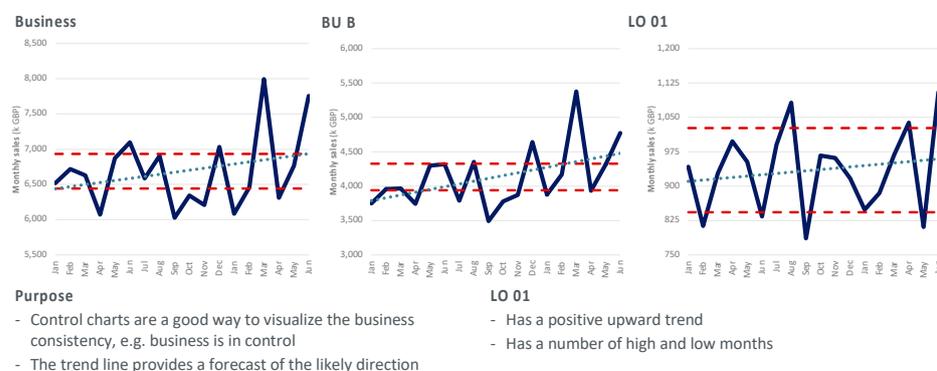


Figure 9. Sales data for the business, business unit, and location 01.

Figure 10 shows the number of booked working hours in the month, with LO 01 showing significant variance month on month. Compared with the monthly under-/over-

absorption, the weakness in management control was evident, as shown in the lower chart. The Sales/Hours increase in value and reflect the knowledge intensity, whereas the Costs/Hours show the change in productivity. The other data combinations (e.g., ROS%, Jobs Sold, and Jobs Dold/Hours Sold) were tested to understand the business dynamics. In several workshops, there was an under-absorption of labour for one month and over-absorption for the next, which was to the detriment of the ROS (in percentage and absolute terms). These data could provide the basis for forecasting and be used to build a business model and understand each business’s dynamics.

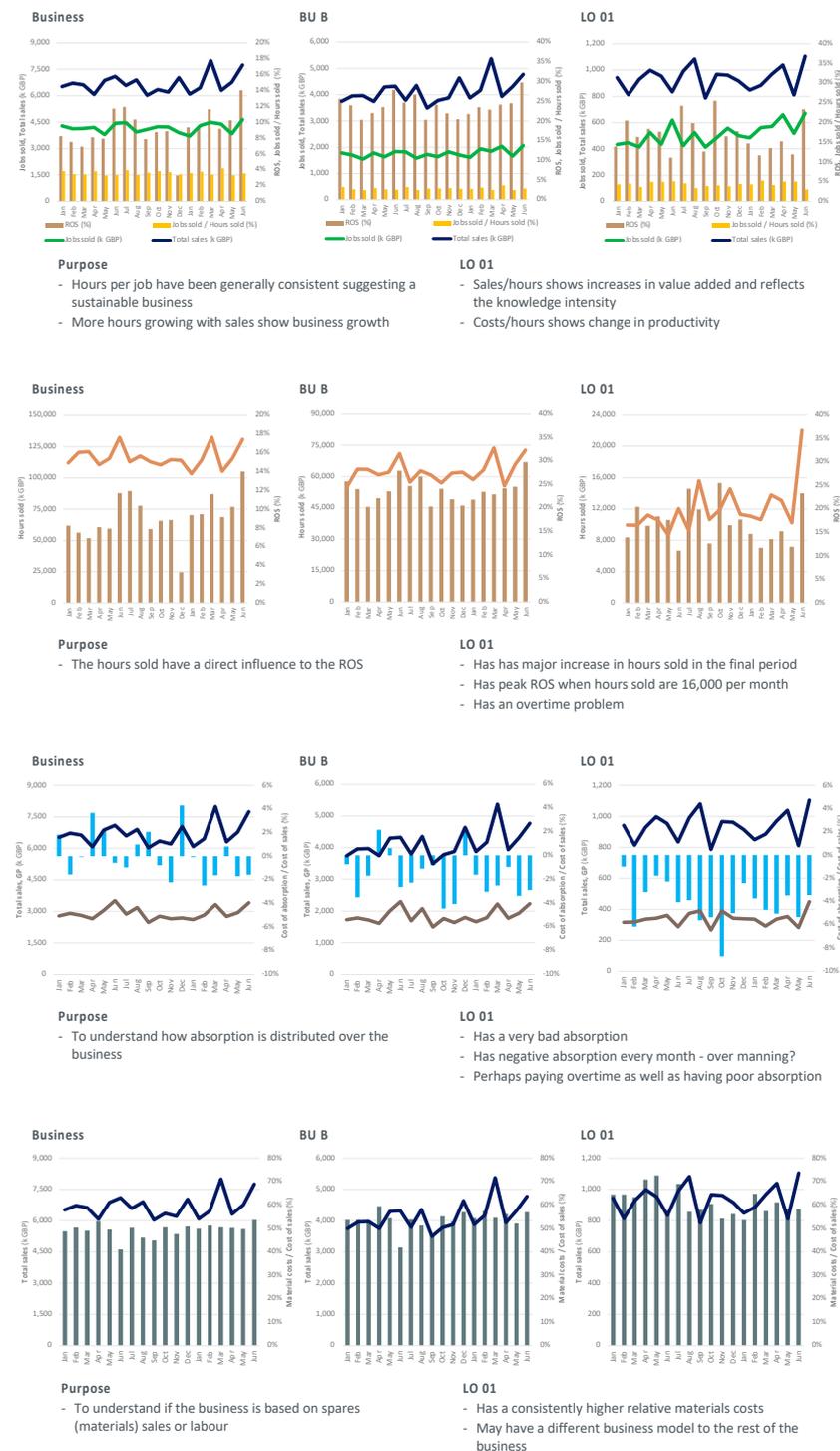


Figure 10. Different perspectives provide different insights into the data for the business, business unit, and location 01.

The use of these metrics within the business and the visual form of the presentation were new to the management. Visualisation allows the management to understand the operational challenge in a way that the numbers presented in Figure 3 did not. Benchmarking with the other locations and each business unit was also new to the managers.

#### 4.6. Benchmarking Metrics

To understand if the business is based on spares (materials), sales, or labour, the materials cost/COGS was plotted on a monthly basis (Figure 11). Significant differences between the locations and business units were found, reflecting the different business models. For example, one location was an outlier with a high number of sales per square metre. Discussions with the business confirmed that the branch’s sales contained a large volume of field service sales, which was significantly greater than that in most locations.

Core KRIs	12 month							
	Business		BU B		LO 01			
	AVG	SD	AVG	SD	AVG	SD	AVG/SD	
Sales (k GBP)	6,706	1,404	4,198	935	947	97	10.3%	
GP (%)	42.4%	5.4%	45.5%	4.2%	36.4%	2.5%	6.9%	
ROS (%)	9.9%	8.0%	23.7%	5.6%	17.3%	4.7%	27.3%	

Secondary KRIs	Per FTE							Per SQM						
	Business		BU B		LO 01			Business		BU B		LO 01		
	AVG	SD	AVG	SD	AVG	SD	AVG/SD	AVG	SD	AVG	SD	AVG/SD	AVG/SD	
Sales (k GBP)	77.58	1.28	108.03	1.96	111.80	1.05	0.94%	1.54	0.03	2.42	0.04	4.06	0.03	0.86%
Cost of sales (k GBP)	44.61	0.83	57.73	1.15	70.97	0.62	0.87%	0.87	0.02	1.31	0.02	2.58	0.02	0.81%
GP (k GBP)	33.49	0.61	48.17	0.84	40.83	0.52	1.28%	0.68	0.01	1.12	0.02	1.48	0.02	1.18%
EBITDA (k GBP)	12.47	0.59	28.51	0.80	20.51	0.59	2.89%	0.32	0.01	0.68	0.02	0.74	0.02	2.75%
EBIT (k GBP)	11.09	0.59	27.30	0.80	19.75	0.59	3.00%	0.29	0.01	0.65	0.02	0.71	0.02	2.86%

**Purpose**

- By comparing the averages with the standard deviation the consistency of the business can be understood

**LO 01**

- Is doing really well, for almost all KRIs the values are higher than the AVG of the BU and the Business
- Has a large deviation, e.g. ROS or EBIT per FTE and SQM

Figure 11. Example of cross-business benchmarking.

This was an innovative approach to the use of metrics for management. This approach provided a clear benchmark comparison for the business. For example, in Figure 9, LO 01 has a significantly higher volume of Sales per FTE than its peers, which is also reflected in the income per SQM. This suggests that the workshop may have a different business model than the others within BU B. The core and primary metrics can be used to support investment decisions. Discussions with F&C raised the question, “why are you not using our standard metrics in reporting?”

### 5. Discussion

Drawing on the ERP data from 27 service centres, we combined them with the supplementary data and applied data mining to derive useful and usable insights. Using ERP data as a source agrees with the literature [5,20–22]. However, machine learning models and visualisations to support decision making, as seen in this study, were missing from this firm’s approach. The curation of the data and the definitions of useful KPIs enabled us to use machine learning methods and statistical modelling such as general linear regression on yearly time series for data mining purposes.

The data contained within the ERP system provided a solid foundation, but they needed to be added to. A large amount of contextual information required to be included in the system, and it took a lot of work for the management to extract actionable insights from the system’s output and support their decision making. This is a common criticism of ERP systems [24]. A structured visualisation of the data was missing from the firm’s approach, with or without the integration of AI, as visualisations allow the managers to understand the operation, compare with others, and assess the trends more clearly. Control charts are standard in Lean operation management [29,34], but were missing in this instance; they are helpful for operation managers as they can immediately understand what is happening and when there is a deviation. Managers can understand the data intuitively and create their own forecasts, with or without applying statistical tools. However, applying digital

tools, such as SPSS or Matlab, can significantly improve this. Using control charts or simple forecasts allows the managers to discuss simple causality between the inputs and outputs. This can then be translated into a more detailed model of the operation and further support more informed decision making. This finding was supported by Dawson [46] and Agrahari and Srivastava [38]. This is the area where machine learning becomes helpful, as a model of the business can be built from the initial quotation process to the billing process and cash collection. Machine learning can also support capacity planning when, in one month, the company has undergone under-absorption and, in the following months, it undergoes over-absorption. As an approach to exploratory data analysis, this method has been used to explore the data in a structured way and to confirm the usefulness of the dashboard created for management. Correcting this means multiple perspectives on capturing the business operation in a structured way, allowing managers to zoom into individual locations and potentially individual projects in business units and the aggregate business itself. This agrees with Ivanov et al. [19], who decided on the importance of multiple perspectives [25] and introduced the contextual aspects of information and decision making.

Data mining gave new insights into the firm's performance and agrees with the literature [7,8,15]. However, the quality and accuracy of the business insights largely depended on the data quality. While extensive manual data cleansing increased the usefulness of our data, not all the information gaps could be remedied. This shows the importance of defining prospectively which data must be collected and how they must be validated. Bridging the data gaps using interpolation or extrapolation methods only sometimes provides sensible conclusions. With the monthly sales rising through 2009 and declining through 2010, modelling an integrated dataset would not provide sensible results. Fitting generalised linear models to the sales data of each unit for each month in 2009 would largely misrepresent the detected behaviour in 2010, and vice versa. This behaviour depicts how small data and unexpected events, such as economic or environmental crises, prevent reliable predictions. Consequently, data availability, comparability, and reliability are paramount.

What needed to be added was translating the financial data into actionable visual insights that could be used on an operational and tactical basis in the service shops. Also missing was an attempt to draw forecasts from the insights or use them as a benchmarking tool to support an understanding of the business performance [2,5,34,38].

From a management accounting perspective, the results confirmed the need to adjust the data and add contextual information such as the floor space. This confirms the ERP systems' orientation for financial information and manufacturing settings [13]. Moreover, the resulting data give operational managers a better tool for decision making and help fulfil the objective of management accountants. An essential insight for managers is using cash flow figures compared to revenues. The combination of cash flows and qualitative process information is seldom used [26], but considers the specifics of service operations. Data visualisation is important for improving the quality of decision making [48]. Graphics can support operational managers by improving the decision quality [32]. Since the service workshops are, in principle, equal, benchmarking is important for the operation. That these beneficial improvements for reporting and decision support are possible with small technical efforts (no AI usage necessary) makes the controlling process itself cost-effective. This is in line with other research that shows that AI has great potential for applications in accounting and finance, but only in limited ways [30,32].

Operational decision support was the main focus of the study, yet integrating econometric models into ERP systems [52] could enhance predictive analytics and support strategic decision making in service shops. By applying decision support frameworks [51], these systems could be optimised to better support complex decisions, enabling targeted strategies and policy development.

### *5.1. Understanding What Insights Can Be Learnt from the Data in ERP Systems*

The exploratory data analyses applied here confirmed that data mining is not the key to gaining insights from ERP data. Instead, the cleaning and structuring of the data were

first necessary to integrate the off-ERP information into the datasets before the data mining approaches could be conducted. The authors consider this 'overlooked', as the ERP system was designed to support the firm's financial reporting activities rather than specifically to support operation management. This hints that the operation department's multiple perspectives, backgrounds, and working habits should be considered when exploring and presenting the data. The integration of the Lean control charts provides the operations team with a visualisation that they use on a routine basis; this gives them a fixed point from which they can understand the information provided, and then cognitively build their own operations model. Here, the interactive design can be used to support the business of knowledge within the firm in the long term based on the information presented. This fits the Colson model [51], where information is often held outside the system. Only basic analytical approaches were finally applied to the data. Nevertheless, the authors consider that more can be achieved with machine learning approaches. Prior studies [54] have described how ERP data can support operations planning.

There are significant barriers to implementation: the data quality, the lack of standardisation, and the tacit process knowledge, coupled with the reactive nature of service centres. Nevertheless, overcoming these barriers is more of a mindset change rather than an explicit technology need within the service environment. This study has confirmed that even with the primary ERP data (i.e., billings and monthly cash flows), it is possible to develop improved decision support without moving to more complicated machine learning approaches. Linking the visuals with the business context and more traditional operational excellence approaches increases the value of the insights. Building simple models (e.g., capacity caps based on actual labour capacity) would further support decision making. However, it has been shown that more advanced models can later be developed to support operational planning.

Integrating the actions that impact a firm's sustainability targets should also be incorporated into such systems. For instance, the under- and over-absorption of labour may provide a pointer to excessive hours being worked by some employees, whereas the others are underused. This may impact absenteeism, hence, has a consequence on the people aspect of sustainability. The presentation of the data may also support improved fixed asset utilisation within the firm, highlighting, for instance, where equipment could be shared between two or more service centres. The use of the insights from the ERP system to support the triple bottom line should be further investigated.

### 5.2. Managerial Relevance

This approach moves away from traditional financial reporting and into the domain of business intelligence and analytics. By using ERP data integrated with contextual insights and additional information (i.e., floor areas, employees, etc.), lessons can be learnt and shared within the service network. This should improve the performance and decision support (i.e., operational, tactical, and strategic), becoming the basis of continual improvement. Implementing such a tool needs careful consideration to ensure its usability in management. This study confirmed that the data collection (transactional data), the derived parameters (hypercube dimensions), and the insights should be structured around the individual operational locations, business units, and overall business, so relevant information reaches different managerial levels to support business decisions. By doing so, it became possible to gain new insights into the business.

The management case in this paper was studied to gain more insights from the existing ERP data. Nevertheless, the broader case with other data sources (e.g., MES, CRM, etc.) should also be used to help provide a deeper understanding of the business. The aim is to improve business performance and support management in making better short- and long-term decisions.

### 5.3. Academic Implications

More examples of the performance management of service businesses need to be published. Much of the available data are either at too high a level to allow for detailed analysis or have critical data missing that prevents full analysis. The analysis here confirms that granular ERP data, with some supplementary data, can provide real insights into a firm's performance. The lessons learnt from the analyses demand further investigation and could provide the basis for sharing lessons and experiences within a service business. Statistic-based models could be developed and integrated with business intelligence and analytics solutions to provide forecasting capabilities based on the business structures that the data have described. The models could support decision making at the operational, tactical, and strategic levels.

The integration of traditional operation management with data science within the context of decision making would support the further development of the application of data within a business context. The combination of information visualisation based on relevant data in a structured way is worthy of further research. Colson's [51] model is very helpful, and this study is based on the summarised data model. In contrast, there is an opportunity to move towards a decision-making model that combines AI with human judgment. Nevertheless, this conceptual model needs to be integrated with the realities of operation management.

## 6. Conclusions and Limitations

The analysis of the ERP data gave the firm new insights into the business' performance, and more insights could be gleaned when additional data were added to provide new KPIs. The reports could be generated automatically and shared monthly to support the branch managers, the business units, and the whole firm. The process could be represented as OLAP cubes to provide real-time business intelligence. Transforming these insights into a visual form can offer actionable information, supporting tactical and strategic decisions. For instance, a large difference between the GP% and the ROS% could identify a service centre location where the prices were maintained, albeit with a low total sales volume. Additional market data outside of the ERP would be required to confirm this.

Furthermore, using supervised and unsupervised machine learning algorithms to obtain sensible business insights from the data collected can considerably enhance such a methods' value and prediction accuracy. It is, however, paramount to collect, pre-process, and store the data in adequate data warehouses to allow for accurate AI-driven decision making. Reliable and comparable business data are crucial for sound predictions supporting strategy and risk assessments. Incomplete data hinder the achievement of sound and robust predictions.

Answering the research question, we demonstrate how structured explorative data analysis can support capturing insights from ERP systems, and thereby support decision making. When enhanced with a multidisciplinary team, visualisation, and machine learning, integrating Lean (Six Sigma) approaches can also support this process. However, in terms of limitations, this study exhibits several possibilities for further work. For example, advanced analytics were not applied to the datasets to support long-term forecasting or strategic decision support. The potential remains to create forecasts from the data and business simulations. The usability of the traditional management reports was not investigated in this study (rather, they were the starting point), nor were the useability of new insights regarding their support of the decision-making process. This should be investigated further, as should their integration into the existing processes to ensure the impact within the business. Additionally, the use of datasets in strategic decision support could be investigated further. Such limitations to this study demand further investigations in these areas and present interesting avenues for future research.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/sci6020027/s1>.

**Author Contributions:** Conceptualization, S.W. and F.I.; methodology, S.W. and D.P.; validation and formal analysis, S.W. and F.I.; investigation, S.W. and F.I., data curation, S.W.; writing—original draft preparation, S.W.; writing—review and editing, S.W., D.P., S.B. and F.I.; visualization, S.W. All authors have read and agreed to the published version of the manuscript.

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