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SLOVAK UNIVERSITY OF TECHNOLOGY IN BRATISLAVA
FACULTY OF MATERIALS SCIENCE AND TECHNOLOGY IN TRNAVA

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Dissertation Thesis Abstract

THE PROPOSAL OF THE EVALUATION MODEL FOR THE INDUSTRIAL BUSINESS ANALYTICS MATURITY LEVEL

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SÚHRN

HUSOVIČ, Rudolf: Návrh hodnotiaceho modelu úrovne zrelosti priemyselnej podnikovej analytiky. [Dizertačná práca]. Slovenská technická univerzita v Bratislave, Materiálovotechnologická fakulta so sídlom v Trnave, Ústav priemyselného inžinierstva a manažmentu – Školiteľ: doc. Ing. Jana Šujanová, CSc. – Trnava: MTF STU, 2021. 168s.

Táto práca sa zameriava na hodnotenie podnikovej analytiky v kontexte modelov zrelosti v prostredí priemyselnej výroby. Hlavným cieľom tejto práce je návrh hodnotiaceho modelu pre stanovenie úrovne podnikovej analytiky v priemyselných podnikoch. Prvá kapitola tejto práce objasňuje teoretické pozadie pomocou literárnej analýzy prostredníctvom kvantitatívneho a kvalitatívneho prístupu. V kapitole sú definované a porovnávané modely zrelosti v kontexte podnikovej analytiky. Prostredníctvom dekompozície vybraných modelov sú prezentované hlavné domény vybraných modelov zrelosti. V druhej kapitole sú objasnené metódy, použité v tejto práci. Tretia kapitola sa zameriava na popis hypotéz, základného súboru a analýzu vybraných priemyselných podnikov prostredníctvom dotazníkového prieskumu z hľadiska podnikovej analytiky a identifikácie podnikových problémov. Stanovené hypotézy sú testované prostredníctvom metódy ANOVA. Štvrtá kapitola predstavuje navrhované riešenia vo forme modelov IBAM a JMP. Piata kapitola tejto dizertačnej práce sa venuje zhodnoteniu návrhov. Šiesta kapitola sa venuje prínosom návrhov pre teóriu a prax.

Kľúčové slová: hodnotiaci model, IBAM, JMP, modely zrelosti, podniková analytika

ABSTRACT

HUSOVIČ, Rudolf: The Proposal of the Evaluation Model for the Industrial Business Analytics Maturity Level. [Dissertation Thesis]. The Slovak University of Technology in Bratislava, Faculty of Materials Science and Technology in Trnava, Institute of Industrial Engineering and Management – Supervisor: assoc. prof. Ing. Jana Šujanová, CSc. – Trnava: MTF STU, 2021. 168p.

This thesis examines the evaluation of business analytics in the context of maturity models in the industrial production environment. The primary objective of this thesis is to propose a evaluation model for the industrial business analytics maturity level. The first chapter of this thesis establishes a theoretical foundation through a systematic literary analysis that employs both quantitative and qualitative methods. In this chapter, models of maturity are defined and compared in the context of business analytics. The decomposition of selected models reveals the primary domains of selected maturity models. The second chapter discusses the methodology and the methods. The third chapter describes the hypotheses, the dataset, and the analysis of selected industrial enterprises using a survey in terms of business analytics and problem identification. ANOVA is used to test the established hypotheses. The fourth chapter summarizes the proposals and describes the IBAM and the JMP models. The fifth chapter of this dissertation is devoted to evaluating the proposals. The sixth chapter is focused on the theoretical and practical implications of the proposals.

Keywords: Business Analytics, Evaluation Model, IBAM, JMP, Maturity Models

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INTRODUCTION

Let us ask a simple question: *"How would we deal with the information about our future?"* From our perspective, the predicted future is not predetermined and can be changed in the moment of understanding those things that will happen. We can predict the future using various predictive methods, estimate future causalities by understanding past events, or using e.g. extrapolated data. But the question is not what the future is, but how to move towards it (if it is according to our plans) or correct future events (if we led out of the path). Therefore, we have to ask the following question: *"What steps should we take towards the 'right' future?"* After asking the appropriate question, our future is not just predicted, but with the help of the right tools, could be prescripted.

We are living now in the time of the Fourth Industrial Revolution. The concept of Industrie 4.0 is driven by nine technologies: additive manufacturing, augmented reality, autonomous robots, Big data and analytics, the cloud, cybersecurity, horizontal and vertical system integration, IIoT and simulation (BCG Global 2021). Every day are published 500 million tweets, sent 294 billion emails, made 5 billion searches and four terabytes of data are created from each connected car (World Economic Forum 2021). There are 40 times more bytes stored than there are stars in the observable universe. From this unfathomable large amount of data, only 0.5 percent is analysed in any way. It is estimated that from all the stored data, only 25 percent has potential value (Davenport et al. 2014). The future competitive advantage is how companies will be able to grasp the power of data.

1 LITERATURE ANALYSIS OF THE CURRENT STATE OF THE BUSINESS ANALYTICS MATURITY

The literature review was conducted from 2015 to 2021 using scholarly articles, books, reviews, and web pages. The language of the articles mainly was English. The following diagram represents the systematic literature design. To specify relevant and research-oriented literature, we used mixed quantitative search methods to build the most relevant literature basis. We designed two datasets. The first one focused on maturity models and the second one on business analytics. Dataset was obtained using designed queries focused on field tags, booleans, parentheses location, focusing on SQL structure and its logical operators. In some cases, modified query sets were applied to create the correct search query string for communicating with scientific database systems to determine the most relevant information.

1.1 Quantitative Literature Analysis

Using the quantitative approach for extracting the dataset, we determined the data collection's date limit as an end in the first quartile of 2021. We have resulted with outputs presented in the following chapters.

For this literature review, we named the group of articles, books, notes and similar, publications in terms of terminology declaration. To bring the desired outcome, we had to describe our data to get to understand them well. Datasets were extracted from scientific databases via conducted queries. All publications as a set of records (P), contain sub-sets Maturity Models (MM), Capability Models (CM), and Maturity Frameworks (MF) deal with a methodological approach or research. However, this dataset may contain publications that might be not relevant or focused on our scope.

1.1.1 Overview of Publication Types

Dataset of the literature records contains: Proceeding papers (49.29%), Articles (41.98%), Reviews (2.83%), Book chapters (2.49%), and the least appearing publications are Early accesses (1.16%), Editorial materials (0.75%), Meeting abstracts (0.58%), Corrections (0.25%), Books (0.17%), Book reviews (0.17%), Letters (0.17%), Data papers (0.08%), and News items (0.08%). Proceeding papers and articles are two main groups that dominate the whole dataset. In analysed datasets, a significant part present review

1.1.2 Selection of the Publications Over the Time Period

The following chart represents the distribution of all publications over the years since the year 1981, finishing with the first quartile of 2021. We can clearly spot the increasing trend over the years; however, a slight drop in 2019-2020

1.1.3 Most Active Authors

Our finding shows that more than 2658 authors/researchers worldwide deal with maturity models in their way - as a method for improvements or as methodology itself. And over 630 in the field of business analytics. All of the authors in the dataset are single authors in a single publication or publication written in co-authorship. However, few of them shows a tendency in their specialisation in maturity models or business analytics. If we exclude authors who have published less than three publications on this problem, we get the total number of 106 authors for maturity models and 630 for business analytics, which creates eight larger groups.

1.1.4 Most Active Research Organisations

In the following graphical representation (Figure 13), we can see the most active research organisations across the world. The first three positions in the field of maturity models are occupied by the University of Coimbra (17) in Portugal, the University of St. Gallen (13) in Switzerland, followed by the University of Utrecht (10) in Nederland. We spotlight, that the Slovak Republic did publish one relevant research publication in University of Economics in Bratislava by Carvalho, Pereira, Rocha (2019) titled Development Methodology of a Higher Education Institutions Maturity Model, which is located in scientific databases and therefore in our dataset. Business analytics is characteristic for over 392 organisations.

1.1.5 Most Active Countries

Research has shown that the most active countries in dealing with maturity models are the USA (157), PRC (103), Germany (92), England (82), Brazil (68), Netherlands (48), Spain (48), Australia (46), Portugal (43), Canada (35), France (35), Switzerland (30), and Poland (29).

1.1.6 Historically Most Cited Publications

According to the database system managed by Clarivate, the records are articles published in the selected years. However, in some cases (the newest records), the tables include Early Access articles that are fully peer-reviewed, citable, and published but have not been assigned a volume, issue or page number, which does not lead to a discrepancy with our aim of work. The table is presented in Appendix A, is representing the most cited publications focused on maturity models and business analytics, from perspective of historically most cited maturity models publications.

1.1.7 Most Cited Recent Publications

According to the fact that we already have found a quantum of literature before this research, however not based on scientific databases. The business analytics field is the narrow field of focus that has resulted in 287 scientific publications; therefore, we conducted to forge the "business analytics" subset in our maturity models dataset to support to elaborate already done research in this field. The presented logical formula explains how the dataset was modified for conducting the most probably proper subset of records.

1.1.8 Keywords Visual Analysis

In the following chapter, we are dealing with a visual analysis of keywords. These keywords were collected across all accessible scientific databases from all accessible research papers and publications which are dealing with Business analytics and Maturity models. Each section was analysed separately. Keywords were collected using the combination of Mendeley software and VoSViewer applying Microsoft Researcher API access.

1.1.9 Conclusion

If we start with a trivial observation and we may conclude with the idea that the number of the tools and methods used for literature review decreases with the researcher's maturity of expertise. Analogically, the more experienced the researcher is, the smaller number of the tools he/she needs to make relevant conclusion/findings. The less experienced scientist needs to use more methods and tools to achieve the same or similar result – which is correct. And that leads us to knowledge management.

1.1.10 Discussion on Dataset Processing

The limitation of the selected quantitative approach is that the quantification based on publication citations in the literature table is not telling us 100% correct answer. Some publications still can be purposeless for our research area. The reason is that the record count of most active authors, regions or organisations, doesn't deal with the paper's quality but shows us the possibility that the publication may be written by mature author/s or researcher/s in the field. Therefore, if we deal with the term quantity, to demonstrate the significance of publication, we should combine them with the citations number. After that, we might get the most relevant subset to spotlight the right publications for further qualitative research using MaxQDA analytic software.

1.2 Qualitative Literature Analysis

We considered more than 2000 scholarly articles, books, and surveys (scientific and professional literature together) and literature review published in (Husovič 2017). In the first phase, we made a screening of the publications according to the relevance. We excluded those that were very specific in the subject, method, or geographic location. In the second phase of text coding, we apply automatic coding using MaxQDA software. For the coding, we have used keywords: business analytics, analytics, framework, readiness, capability, maturity, business intelligence, artificial intelligence, predictive, prescriptive, and autonomous. During the third phase, we have gone through thorough text analysis refining the existing coding in groups: definition, strategy, organization, management, technology, data, quality, skills, change, culture, process, customer, finance, production, marketing, and human resources. In the last phase, we applied MaxQDA visual tools as Code Relations Browser and Code Maps to identify a relationship between the codes and text content.

1.2.1 Business Analytics Historical Overview

"The field of business analytics was born in the mid-1950s, with the advent of tools that could produce and capture a larger quantity of information and discern patterns in it far more quickly than the unassisted human mind ever could (Davenport et al. 2014)." The history of humans is a history of decisions. Reports are not the result of computerised data processing.

The first relevant mention of the maturity model was in 1988 by Humphrey, W.S. in an article called *"Characterizing the Software*

Process - A Maturity Framework". This publication is considered the first solid publication, which builds the foundation for all of the following maturity models.

In (Davenport et al. 2014) and (Davenport 2018) are presented four eras of business analytics:

- Analytics 1.0 – data centric approach with a foundation in data management and warehousing. "Design of data marts and tools for extraction, transformation, and load (ETL) is essential for converting and integrating enterprise-specific data. Database query, online analytical processing (OLAP), and reporting tools (Chen et al. 2012)."
- Analytics 2.0 – big data with external sources from the internet and public data.
- Analytics 3.0 – new data sources as sensor-based Internet-enabled devices equipped with RFID, barcodes, and radio tags generating mobile and sensor-based content (Chen et al. 2012).
- Analytics 4.0 – AI application (Davenport 2018).

1.2.2 Business Analytics

Business intelligence hereafter also referred to as (BI), business analytics (BA) and Big data are interrelated terms. In keeping with the issue, some authors (Burk and Miner 2020; Kudyba 2014) see the term business analytics as an umbrella covering the different analytics (see above mentioned (Marr 2016)). According to (Chen et al. 2012; Varshney and Mojsilović 2011; Rai 2018; Computerworld 2009), business analytics is the more recent term, and it focuses on the analytical components of business intelligence; therefore (Chiang et al. 2012) use the term business intelligence and analytics to emphasis the purpose of the analysis. Mostly are as equivalent terms used business analytics and data analytics or simply analytics (Albright and Winston 2020) (Baesens 2014). In (Sircar 2009), the difference between business intelligence and business analytics is in who is using the term. The IT community uses the BI, and the business community uses BA.

1.2.2.1 **Business Analytics Definitions**

“The popularity of analytics is on the rise along with the data resource gathered by any business. In today’s world, data is collected and stored, not merely in terabytes but in petabytes or in even higher orders. All real-time transactions over the net, customer preferences, customer demography and other detailed information are stored in vast data storages; resources are even pooled across all sorts of social and other network sites. (Basu and Basu 2016, p. 1)”

Gartner Group defines Business Analytics (hereafter also referred to as BA) as *“solutions used to build analysis models and simulations to create scenarios, understand realities and predict future states. Business analytics includes data mining, predictive analytics, applied analytics and statistics, and is delivered as an application suitable for a business user. These analytics solutions often come with prebuilt industry content that is targeted at an industry business process (for example, claims, underwriting or a specific regulatory requirement) (Gartner 2021).”* The other opinion on Business Analytics is, that “*it* *is a scientific process of transforming data into insight for making better decisions (Camm 2013).”*

Therefore:

BA = business problem + data + analytical tool + analysis + result interpretation + decision

1.2.2.2 **Business Analytics Framework**

The application of business analytics in business practice also raised the problem of organizations’ BA readiness. T. H. Davenport, in his publications (Davenport et al. 2014) and (Cochran 2019), present as key factors:

- Data
- Skills
- Organization and management
- Technologies.

In (IDC 2019) research, the company resistance to change is recognised as one factor hindering efficient business analytics. Another factor identified as critical for the BA implementation is the organizations′ culture related to the data, information and knowledge use (McKinsey 2016).

Raising importance is put on data quality and data security (World Economic Forum 2021).

In the scholarly articles, there is a consensus in areas of business analytics implementation in business functions:

- Finance
- Marketing
- Customer relationship management
- Supply chain
- Human resources
- Production.

The only limitation for effective implementation is available datasets.

1.2.2.3 **Business Analytics Maturity**

In our case, the business analytics maturity is a model for evaluating organizations ability to conduct data exploration and make decisions effectively - by measuring their stage in terms of various levels of data comprehension. In our field of focus, we analyse following areas of interest to decompose all accessed models:

A. Organization Capability
B. Technology Capability
C. Data Management Capability
D. Production Capability
E. Business Analytics Capability

A. Organization Capability

Organizational capability is represented by the company's ability to manage resources effectively to gain a competitive advantage. There are different methods and models, whereas CMMI (Capability Maturity Model Integration) (CMMI 2021) is widely used in organizations or enterprises. The CMMI provides a roadmap that guides improvement from ad hoc activities to disciplined and consistent processes for achieving business objectives related to (CMMI 2021).

B. Technology Capability

According to (Rodríguez Salvador et al. 2018), there are currently two highly accepted approaches for technology maturity assessment:

i. Future-oriented Technology Analysis (FTA) - with mainly qualitative maturity assessment tools.
ii. Technology Readiness Level (TRL) - a nine-level scale that quantitatively describes "increasing levels of technical maturity based on demonstrations of capabilities".

C. Data Management Capability

Developed by EDM Council members, DCAM - the Data Management Capability Assessment Model – is the industry standard framework for Data Management (EDM 2014).

D. Production Capability

With the digitisation of the industry and Industry 4.0 concept, implementation of BA in production closely relates to the smart manufacturing capability of the organization.

To assess a manufacturing company's readiness level for starting the digital transitioning process, that is an aspect of smart manufacturing concepts and to identify a manufacturing company's strengths, weaknesses, opportunities, and to create a roadmap for investments in digitalization and transitioning to smart manufacturing (Carolis et al. 2017a) designed **DREAMY** (Digital Readiness Assessment Maturity model) focused on five main areas: (1) Design and Engineering; (2) Production Management; (3) Quality Management; (4) Maintenance Management; (5) Logistics Management.

SMSRL (Smart Manufacturing System Readiness Level) is a method for assessing a factory's readiness to incorporate emerging ICT technologies to become a smart factory developed by (Jung et al. 2017). The model concentrates on four dimensions: (1) Organizational, (2) IT, (3) Performance management and (4) Information connectivity maturity.

MOM/CMM (Manufacturing Operations Management / Capability Maturity Model), designed by MESA (MESA 2021), is a questionnaire-based assessment tool designed to help evaluate the maturity and readiness of manufacturing enterprises from the factory operation management perspective based on ISA 95 standard (ISA 95 2016) oriented on four operational areas: (1) production operations management, (2) quality operations management, (3) inventory operations management, and (4) maintenance operations management. Comparison of the models in **Error! Reference source not found.**.

E. Business Analytics Capability

Developed business analytics capability models have different approaches. One approach, described in (Wells 2016), is oriented on the analytics maturity level.

The next chapter is devoted to summarising the previously used methods in quantitative and qualitative literature analysis and introduces other methods for the following analysis.

2 AIM, METHODOLOGY, AND METHODS OF THE DISSERTATION THESIS

At this chapter, we can begin to directly concentrate on scientific aims, approaches, methodology, and methods, which are the foundation of our research. While the next chapter is established for further analysis, the latter chapter is devoted to our proposals. In this chapter, we will focus on:

- Aims and sub-goals,
- Methodology and methods,
- Research question and hypotheses.

2.1 Aim of the Dissertation Thesis

The dissertation thesis is focused to design the maturity model for evaluating maturity of the business analytics in industrial production enterprises, focused on processes which creates the business value as the supporting components for the production. Therefore, we have formulated the research aim in following statement.

The dissertation thesis aim: *Based on the literature review, quantitative and qualitative analysis, propose the model for evaluation of the level of industrial business analytics maturity.*

To achieve this aim, we have formulated following subgoals:

1) Analyse literature of the current state of the business analytics maturity
2) Quantitatively analyse the datasets
3) Qualitatively analyse the datasets

4) Statistically analyse the datasets
5) Propose the model for evaluation of the level of industrial business analytics maturity
6) Contribute to the theory, research and practice via proposed model

2.2 Methodology and Methods of the Dissertation Thesis

In our research, we already have used some of the following methods; however, some of presented method such as hypothesis testing are a core method for our analysis. Overall methodology and methods were applied in presented areas, which are summarized in following order:

i. **Qualitative Research**:
    a. Systematic literature analysis
    b. Case studies
    c. Expert interviews
ii. **Quantitative Research**:
    a. Hypothesis testing via questionnaire and statistical methods
    b. Literature review
iii. **Analysis and Synthesis**:
    a. Literature Review
    b. Questionnaire
iv. **Composition and Decomposition**:
    a. Maturity models literature review
    b. Maturity model proposal
v. **Statistical Methods**:
    a. Questionnaire
    b. Hypothesis testing

vi. **Graphical methods**:

a. Literature review
b. Questionnaire

2.3 Research Question and Hypotheses

To achieve presented aim of the hypothesis via the sub-goals, we have conducted following research question and hypotheses. Each of the presented hypotheses is model hypothesis for formulating several sub hypotheses, which are tested individually afterwards (computed automatically by SPSS software), depending on the questions.

Research Question: *Does business analytics, in terms of data management and data quality management, positively influence the business problems of the company?*

Seeking the answer on this research question, we have selected the strategical point of view on the issue and therefore, we are decomposing this research question into two main hypotheses models (as the strategical areas) which are presented:

Model for Null Hypothesis (H0a):

Statistical relationship exists between business performance [Q2.1 – Q2.8] and data management strategy [Q1.1].

Model for Alternative Hypothesis (H1a):

Statistical relationship does not exist between business performance [Q2.1 – Q2.8] and data management strategy [Q1.1].

Model for Null Hypothesis (H0b):

Statistical relationship exists between business performance [Q2.1 – Q2.12] and data quality management strategy [Q1.2].

Model for Alternative Hypothesis (H1b):

Statistical relationship does not exist between business performance [Q2.1 – Q2.12] and data quality management strategy [Q1.2].

3 ANALYSIS OF THE CURRENT STATE OF SELECTED BUSINESS PROBLEMS IN THE CONTEXT OF BUSINESS ANALYTICS

As soon as composing a comprehensive literature review was developed to fully understand the background of the issue by the most recent findings in the field of maturity models and business analytics, we may continue the research. The research was designed to develop a credible reflection on the problem. In the study, we focus on verifying a solid output, which will lead us to design an industrial business analytics maturity model.

3.1 Descriptive Analysis of the Target Group

According to our field of study - industrial engineering and management, the research sample contained only the set of industrial subjects, whose main activity is industrial production (e.g. vehicles manufacturer) or the subject is a producer of parts in the production chain (e.g. manufacturer of automotive components). We composed the dataset via data extraction from a proprietary database of business contacts.

3.2 Questionnaire Distribution and Collection

The proprietary dataset contained 3917 possible respondents; therefore, the questionnaire was distributed to 3917 business representatives electronically by email addresses. To maximise the return rate, we developed the following strategy for managing responses, consisting of the three waves for questionnaire distribution.

3.2.1 Questionnaire design

To conduct the questionnaire, we have used a general maturity model questionnaire published under the title Data Management Maturity (DMM) Model by CMM Institute and CMMI 2.x model enriched by questions that follow analytics advance of the company and its potential. CMMI 2.x and DMM was used as a modified template for questionnaire design. CMM 2.x is designed to identify business problems to set corrective measures via the proposed model. The industrial subject's data potential is measured using a type of production machines that are accommodated in production, its digital capability, and company operating information systems. The questionnaire is attached as Attachment D. Question areas designed for the questionnaire are:

- data strategy,
- data handling,
- data processing,
- knowledge management,
- business problem identification.

3.2.2 Conclusion

After describing our respondents as the target group, we continued with estimating the minimum responses to deliver relevant outputs. Preparation has shown that four major groups exist in the field of industrial production in the Slovak republic. These groups are classified under the letter C in the SK NACE classification database. Those groups are specified and quantified in Attachment 1. According to the given proprietary dataset, which contained 3917 subjects classified in our focus field, the estimate of the necessary number of respondents was 100 – which equals to desired 3,91% response rate.

3.3 Results of the Research

After questionnaire distribution, we have collected 112 questionnaires. The response rate meets the minimum requirements and slightly overcame the expectations. Therefore, we declare brief summarisation of the segments:

A. Target group:

SK NACE Section C - Industrial Production

SMEs and large enterprises, excluded micro-businesses

B. Questionnaire results:

Number of questionnaires distributed	**3917**
Number of questionnaires returned	**112**
Number of evaluated questionnaires	**112**

C. Contact person

1) Declared representatives (business owner or declared responsible leader),

2) first contact person (in some cases).

D. Time period

The time period of distributing and collection of the questionnaire was within 10.2.2021 and 17.3.2021.

After processing the results via IBM SPSS – the statistical software for quantitative analysis, we have found the following findings presented in next sub-chapter.

3.3.1 Descriptive analysis

The following conclusions came from the questionnaire analyisis. Most respondents do not have integrated data management with a business strategy. Most respondents do not have a data management department. Most respondents do not have a data quality management strategy. Analysis also shows that most respondents do not have a data management strategy and most respondents do not even have a requirement for data management. As the analysis showed, most respondents do not have data lifecycle management. Most respondents do not have services and products that do not meet customer needs. Most respondents do not have customer complaints about services or products provided; it is a positive finding in terms of services. Most respondents are not concerned about the inconsistent provision of services or products. Respondents witness the failure of the delivery time of a product or service on important occasions. Most respondents said that a lack of customer understanding was not identified as a business problem. Product or delivery delays are a major problem for select companies, which plays an important role in service satisfaction. Most respondents do not encounter poor product / service quality. And the latest observation showed that most respondents are neutral about building a sustainable infrastructure.

3.3.2 Reliability Analysis

To assess the reliability in this study we used, Cronbach's Alpha, an index of reliability. For the instrument to be reliable. To compute Cronbach's Alpha for our dataset we used we used SPSS software and gained dataset of the answers. According to authors (Nunnaly & Bernstein, 1994), the coefficient in early stage of research should be minimum 0.7, therefore Cronbach's Alpha should not be less than 0.7. In our analysis, we achieved value of 0.847, for 21 answered question and sub-questions

3.3.3 Inferential Analysis

Inferential analysis uses data from a survey to draw conclusions regarding the broader group from which was taken the sample. We need assure that our sample correctly represents the group because the purpose of inferential analysis is to draw conclusions from a sample and generalize them to a group/category. Our workflow is impacted by this requirement. We studied the effect of the variables on the respondent feedback (analysing each selected question individually) in the ANOVA table.

3.3.4 Hypothesis Testing - Data Management Strategy

The H1a set of hypotheses are concerning Data Management Strategy on the performance of the businesses.

Therefore, for the set H0a:

H0a1: Statistical relationship exists between services or products provided did not meet customer needs and the data management strategy

H0a2: Statistical relationship exists between inconsistent service or product delivery and the data management strategy

H0a3: Statistical relationship exists between insufficient understanding of customer needs and the data management strategy

H0a4: Statistical relationship exists between product/service delivery delay and the data management strategy

H0a5: Statistical relationship exists between insufficient quality of the product/service and the data management strategy

H0a6: Statistical relationship exists between worldwide events, e.g. COVID-19, which caused fundamental changes in business processes and the data management strategy

H0a7: Statistical relationship exists between inflexible response to external incidents and the data management strategy

H0a8: Statistical relationship exists between problems in the supply chain and the data management strategy

And for the set H1a:

H1a1: Statistical relationship does not exist between services or products provided did not meet customer needs and the data management strategy

H1a2: Statistical relationship does not exist between inconsistent service or product delivery and the data management strategy

H1a3: Statistical relationship does not exist between insufficient understanding of customer needs and the data management strategy

H1a4: Statistical relationship does not exist between product/service delivery delay and the data management strategy

H1a5: Statistical relationship does not exist between insufficient quality of the product/service and the data management strategy

H1a6: Statistical relationship does not exist between worldwide events, e.g. COVID-19, which caused fundamental changes in business processes and the data management strategy

H1a7: Statistical relationship does not exist between inflexible response to external incidents and the data management strategy

H1a8: Statistical relationship does not exist between problems in the supply chain and the data management strategy

After designing the hypotheses, we have set the following decision rule: *Reject Null hypothesis if p-value < 0.05, otherwise do not reject*. On that basis, the following decisions were made, and conclusions reached (Table 10):

Table 1 ANOVA table for the first set of hypotheses (own processing)

Question: Have any of the above problems occurred in your company in the last period (half a year)?		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Status**
H0a1 [Services or products provided did not meet customer needs]	Between Groups	0.844	2	0.422	2.470	0.090	Not rejected
	Within Groups	17.773	104	0.171			
	Total	18.617	106				
H0a2 [Inconsistent service or product delivery]	Between Groups	0.448	2	0.224	0.825	0.441	Not rejected
	Within Groups	28.225	104	0.271			
	Total	28.673	106				
H0a3 [Insufficient understanding of customer needs]	Between Groups	2.883	2	1.441	5.490	0.005	Rejected
	Within Groups	27.304	104	0.263			
	Total	30.187	106				
H0a4 [Product/service delivery delay]	Between Groups	0.461	2	0.230	0.879	0.418	Not rejected
	Within Groups	27.259	104	0.262			
	Total	27.720	106				
H0a5 [Insufficient quality of the product/service]	Between Groups	1.119	2	0.559	1.893	0.156	Not rejected
	Within Groups	30.438	103	0.296			
	Total	31.557	105				
H0a6 [Worldwide events, e.g. COVID-19, caused fundamental changes in business processes]	Between Groups	0.409	2	0.205	0.684	0.507	Not rejected
	Within Groups	31.105	104	0.299			
	Total	31.514	106				
H0a7 [Inflexible response to external incidents]	Between Groups	0.684	2	0.342	0.706	0.496	Not rejected
	Within Groups	50.363	104	0.484			
	Total	51.047	106				
H0a8 [Problems in the supply chain]	Between Groups	0.103	2	0.052	0.223	0.801	Not rejected
	Within Groups	24.084	104	0.232			
	Total	24.187	106				

3.3.5 Hypothesis Testing - Data Quality Management Strategy

The H0b set of hypotheses, are concerning Data Quality Management Strategy and businesses performance.

Therefore, for H0b:

H0b1: Statistical relationship exists between services or products provided did not meet customer needs and the data quality management strategy

H0b2: Statistical relationship exists between customers complained about delivered services or products and the data quality management strategy

H0b3: Statistical relationship exists between failure to meet the delivery date of the product/service and the data quality management strategy

H0b4: Statistical relationship exists between insufficient quality of the product / service and the data quality management strategy

H0b5: Statistical relationship exists between problems in the supply chain and the data quality management strategy

And for H1b:

H1b1: Statistical relationship does not exist between Services or products provided did not meet customer needs and the data quality management strategy

H1b2: Statistical relationship does not exist between Customers complained about delivered services or products and the data quality management strategy

H1b3: Statistical relationship does not exist between Failure to meet the delivery date of the product/service and the data quality management strategy
H1b4: Statistical relationship does not exist between Insufficient quality of the product / service and the data quality management strategy
H1b5: Statistical relationship does not exist between Problems in the supply chain and the data quality management strategy

Therefore, we have set the following decision rule: *Reject Null hypothesis if p-value < 0.05, otherwise do not reject it*. For quality data strategy, the businesses performance does not differ with different statuses of quality data management strategy (Table 13).

Table 2 ANOVA table for the second hypothesis (own processing)

Question: Have any of the above problems occurred in your company in the last period (half a year)?		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**	**Status**
H0b1 [Services or products provided did not meet customer needs]	Between Groups	0.669	2	0.334	1.950	0.147	Not rejected
	Within Groups	17.998	105	0.171			
	Total	18.667	107				
H0b2 [Customers complained about delivered services or products]	Between Groups	0.271	2	0.135	0.564	0.570	Not rejected
	Within Groups	25.165	105	0.240			
	Total	25.435	107				
H0b3 [Failure to meet the delivery date of the product/service]	Between Groups	1.200	2	0.600	2.457	0.091	Not rejected
	Within Groups	25.652	105	0.244			
	Total	26.852	107				
H0b4 [Insufficient quality of the product/service]	Between Groups	2.071	2	1.035	3.617	0.030	Rejected
	Within Groups	29.486	103	0.286			
	Total	31.557	105				
H0b5 [Problems in the supply chain]	Between Groups	0.161	2	0.081	0.348	0.707	Not rejected
	Within Groups	24.026	104	0.231			
	Total	24.187	106				

3.4 Conclusion of the Research

Because with all the first set of hypotheses, for $p > 0.05$, the null hypothesis was not rejected in the majority of the instances. The hypothesis H0b4 was rejected due to the lack of significance between values ($p < 0.05$). However, we prove that there is no significant output gap in selected business situation. According to the second set of hypotheses, the fact that $p > 0.05$, the null hypothesis was not rejected in the majority of the instances in either. To the extent that there is no significant output gap in either business situation.

4 PROPOSALS OF THE EVALUATION MODEL FOR THE INDUSTRIAL BUSINESS ANALYTICS MATURITY LEVEL

The following chapter focus on model design. According to analysis, expert interviews and gained insights, we have noticed that the maturity continuum appears in all maturity models that nearly every organisation moves through in managing business data. With the seen findings, the following section is devoted to our proposals. Additionally, according to our findings, any organization goes through a series of rising and declining stages of sophistication regarding handling data.

4.1 Generalised Business Analytics Maturity

In this chapter, we are reporting and describing a generalised business analytics maturity design. Therefore, we will start the first level of a representative organization that is low in data and technology and consequently low in maturity. This level is referred to as the formalisation level. At this level, companies use on-demand analytics to respond to each request for details. There is no reuse, and the data collection phase is often overseen by a manager or employee who changes data or records, necessitating a manual effort to maintain and distribute. According to research, companies in this stage will often use several methods across individuals with low analytical capacity (low on technology or skills). The usage of these tools will also bridge the organization's development into level two – the level of repeatability.

Organizations started to understand they had a lot of operating records and a lot of desktop analytics with nested hypotheses at level two, the level of repeatability. If certain conclusions are to be updated, each particular report must be opened and edited. Business users deserve to be in control of their research, which is no longer feasible due to data safety as a preventative step until data exploitation. They may want more direct links to common logic so they can collaborate with their teams.

The company continues to see that the various sets of evidence must be brought together to have a coherent narrative at the third level – the level of formalisation. This is more noticeable incorporate sessions where there are various interpretations of the reality and participants are unable to make judgments. For organisations that have advanced beyond a certain level.

Following the formalization level, companies move to the fourth level, which is the measurements / managed level. Organizations started to understand that their data was not clean and needed to be pre-processed once they reached this point and had a data warehouse and BI network in place. When an organization's data usage becomes increasingly standardized, data consistency tools can be utilized to enable improvements to a larger scale, and data management compliance solutions will be used to organize essential characteristics into solid databases and hierarchies that the business will agree on and monitor. The business would most likely form data governance teams to handle the data, which brings us to the final level – optimization.

Organizations are becoming more and more mature in terms of constructing data centres and governing their data as they go to the optimisation level. They soon found that the scale of the data footprint was slowing the information's usability. This forces businesses to choose between two tactics. The first strategy is to archive and back up your data. Inactive documentation is offloaded and stored in a dedicated database, freeing up processing processes from antiquated archives that are barely viewed and allowing them to run more quickly. The second approach is to use a data warehousing appliance to improve the efficiency of the data warehouse.

4.2 IBAM Model Description

Industrial Business Analytics Maturity (shortly IBAM) model describes general business analytics technical and managerial applications across the industrial company. Presented meta model is consisting of the data & technology potential, in terms of maturity, which contains also the infrastructure aspect of the processes. The second part is consisting of the business and management aspect of the company (see the Figure 1).

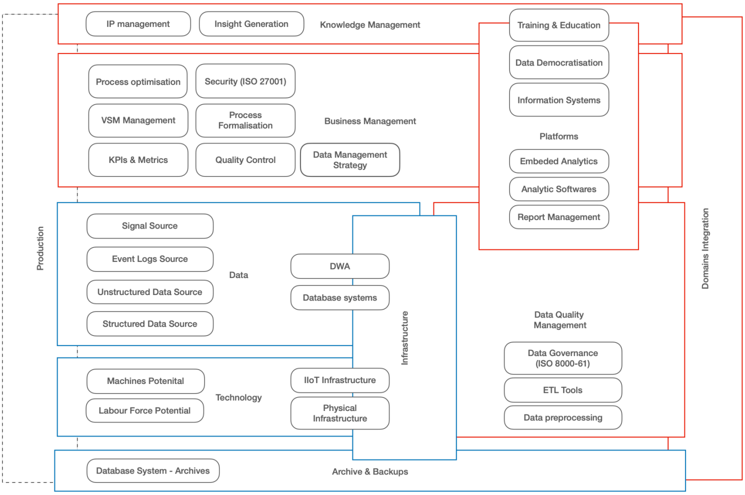

Figure 1 IBAM Meta-Model: Overview of sub/domains in IBAM model (own processing)

Industrial business analytics maturity model, such as it's meta-model, is based on purposely selected domains and sub-domains, which are described in this chapter. During the review of the knowledge focused on business maturity models and data management maturity models, we have decomposed, enriched and composed the maturity models to design and propose this presented IBAM model. Processed models were illuminated in the qualitative literature analysis.

The IBAM model (v1.0.0 – versioning is explained later in this chapter) is consisting of 36 subdomain and questions (Table 3) that are oriented to estimating the maturity via an assessment-oriented questionnaire. The versioning of the model and the reason why we are using this form of model numbering, is illuminated later in this chapter. The questionnaire is conducted out of the sub-domains which are describing the domain aspect of the model.

Table 3 Domain proposition (own processing)

Domain	Sub-domain
Data	Structured Data
	Unstructured Data
	Event Logs
	Signals
Infrastructure	Database System Management
	Archive Management
	DW Appliance
	Physical Infrastructure
	IIot Infrastructure
Technology	Labour Force
	Machinery
	Embedded Analytics
Data Quality Management	Data Preprocessing
	ELT Tools
	Data Governance
Platforms	Report Management
	Analytics Software
	Information Systems
	Data Democratisation
Management	KPI & Metric
	VSM
	Process Optimisation
	Quality Control
	Production process
	Data Security
	Data Management Strategy
Knowledge Management	IP Management
	Insight Generation
	Training & Education
Domain Integration	Data Integration
	Infrastructure Integration
	Technology Integration
	Data Quality Management Integration
	Knowledge Management Integration
	Platforms Integration
	Management Integration

4.2.1 Test of the Domain Eligibility

In terms of applicability of the IBAM model, the company has to be eligible for the IBAM model assessment evaluation; therefore, we have designed a test of eligibility for the IBAM model selected domain evaluation. The test is designed as a checklist for subdomains. Each question is a carrier of score 1 or 0. If the question is answered as “I don’t know”, the question should be consulted with the department, which has the most common competencies with the selected domain. Therefore, the question should be answered only as yes or no.

Depending on the domain eligibility score the company is eligible for IBAM model evaluation according to the following criteria:

A. maximum allowed subdomains missing is 8,
B. only one sub-domain per one domain can be missing.

After passing presented criteria, following rule has to be applied (Table 4):

Table 4 Eligibility score

Score	**Bellow 78%**	**78-86%**	**89-92%**	**95-97%**	**100%**
Missing domains	More than 8	8-5	4-3	2-1	0
Eligibility	Not eligible	Rarely eligible	Fairly eligible	Mostly eligible	Fully eligible

4.3 JMP Model Description

Journey of the Maturity Potential – shortly JMP model is a generalised and simplified model for maturity growth of the business analytics in the adjusted in companies. It describes their path to its full maturity. This model was developed also to provide a clear and simplified description of business analytic maturity models for truthful verification of the business analytics, which is also suitable for educational purpose as an essential tool (Figure 2).

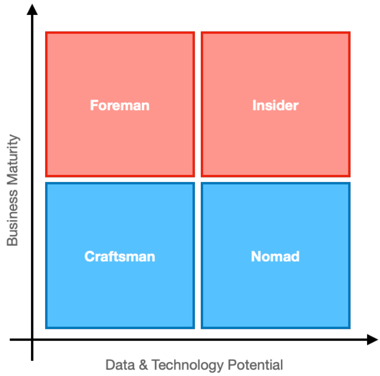

Figure 2 JMP model (own processing)

JMP model contains four personas: Craftsman, Foreman, Nomad, and Insider. Those personas differentiate each other according to their maturity, technology and data potential. At the beginning of this chapter, we have to mention that each persona has its good sides; however, in this model, we aim to demonstrate that possibility to generate as many insights as possible is the right way to take the best advantage in business using analytics.

Craftsman

A craftsman is an eligible person who gained knowledge through education and is a skilled manual worker who makes items or services that are functional. His or her knowledge is precise by empirical practice using the right working tools; therefore, decisions are purely intuitive. Craftsman's profiles as a high-quality knowledgeable worker who generates insights by himself.

Foreman

A foreman is matured craftsman, who's skills were demanded in larger quantities; therefore, he or she had to hire more craftsmen who should copy his or her work routine to fulfil the demand. Foreman is now a highly skilled manager, who manages its craftsmen, controls the quality of the work, distributes the responsibilities, taking care of the accountabilities, formalises the working processes via quality control tools and standardisation, and buying working tools. However, as the manager, he or she has to divide the working time between his or her workers. Therefore, the insight generation and scalability of the business are limited by his or her organisation structure, which has more of a linear trend.

Nomad

A nomad is a worker without fixed tool habitation. Nomad is data observing persona, and a lot of his or her work routine and processes can be digitised. However, in the industrial market, he or she automates all of the work and hire ad-hoc services; therefore, he or she doesn't need to be an empirically skilled worker – technology does the precise job. All the working events are recorded automatically; therefore, future work analysis or diagnostics is not the issue anymore. To generate more business insights, the nomad is limited by the potential of the infrastructure and hardware, which describes a steep linear trend.

Insider

An insider is matured data-driven nomad who has deployed various tools and technology across the organisation to gain and receive data, information, and knowledge as fast as possible. Insider empowers the workers with the technology instead of duplicating the labour force. Insider handles data as a commodity, which has to be processed to gain new valuable insights. Those insights allow his or her business to be data-driven with reasoned and tracked decisions. Technology and working processes generate data that are purposively processed to provide a veracious overview of the business. Insights generation is limited by the potential of technology, data generation, and data analytics, which describes an almost exponential trend.

4.4 IBAM Model Evaluation

In following chapter, we will elaborate each of the proposed domain and sub-domain individually as a component for evaluating the industrial business analytics maturity. Domains and sub-domains are in the form of proposed questionnaire for collecting relevant data which will estimate the current state of the industrial business analytics of the company. The answers will gain score depending on the answered questions. For instance, we introduce first demo question (Q0):

Q0: Select the most suitable for your processes

i. The titled sub-domain is not in common use [1 score point]
ii. The titled sub-domain is in use for on-demand purposes [2 score points]
iii. The titled sub-domain is in use for specified tasks [3 score points]
iv. The titled sub-domain is in use for all tasks [4 score points]

v. The titled sub-domain is managed and optimised for improvement purposes [5 score points]

Each of the offered answer, as it was said earlier, is a carrier of score point/s. In this scenario if we pick answer number iii. The score points we gained for the demo subdomain is 3. If as we continue fulfilling the proposed questionnaire, we gain scores for each of the presented subdomains, which are counted by the method and formulas defined later in this chapter. As we declared earlier proposed questionnaire is containing 36 questions in presented order.

4.5 Domain Score Evaluation

Each answer counts as a carrier of the respondent's score, and each has equal value in the scoring. Since we counted the domain scores, we may evaluate the industrial business analytics maturity using a radar chart. The next step is to approach the domain range (RD) count. This number represents the overall balance or imbalance of the whole business analytics system of domains in the company. The domain range is absolute (positive) number (Figure 3).

If the R_D = 0; the maturity of the industrial analytics is balanced; therefore, we may proceed to maturity evaluation using the level of maturity to set desired outcomes based on its status quo.

If the R_D ≤ 1; the maturity of the industrial analytics is imbalanced; however, still in the range of approval, therefore we recommend evaluating the pitfalls shown on radar graph to set the corrective measures.

If the R_D > 1; the maturity of the industrial analytics is imbalanced; therefore, we may evaluate the pitfalls shown on radar graphical representation and set corrective measures.

The strict rule is that the domain range can be adjusted only by increasing the score of S_{min} and never by decreasing S_{max} values. The R_D can gain decimal numbers; therefore, the acceptance interval is <0, 1).

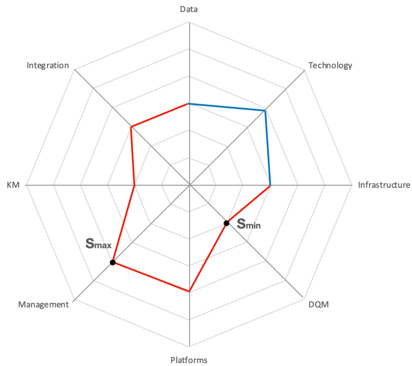

Figure 3 The evaluation of the industrial business analytics maturity (own processing)

According to levels of maturity, the IBAM score can achieve a maximum of 5 overall score points. IBAM score is an absolute number, which can acquire decimal positions, or it can be presented as a relative number. Depending on the overall IBAM Score counted as a sum of all scores divided by the number of domains, is maturity score as follows (Table 5):

Table 5 IBAM Maturity score (own processing)

IBAM Score	(0, 1)	< 1, 2)	< 2, 3)	< 3, 4)	< 4, 5 >
Level of IBAM	Industrial business analytics is informal	Industrial business analytics is repeatable	Industrial business analytics is formalised	Industrial business analytics is managed	Industrial business analytics is optimised

4.6 General Implementation Plan

In this chapter, we will specify the implementation plan, which will break be down into proposed activities and individual steps to achieve the objectives of business analytics implementation to an industrial company. The implementation plan is essential to understand what tasks of the implementation activity will include, e.g.:

- what time will each task consume,
- who will be responsible for the success of each task,
- and what the results of each task will be.

The scope of the tasks will be assessed as part of the implementation plan. Each task's timeline determines how clear the deliverables are and whether the tasks listed will result in the overall activity being completed within the proposed time frame. The implementation plan is a document presented in the table form.

4.7 IBAM Model Processing

As was described, the IBAM model application can be decomposed to the following main parts:

- Test of eligibility
- JMP Model (Assessment)
- IBAM Evaluation

- Recommended implementation plan fulfilment
- Improvement implementation.

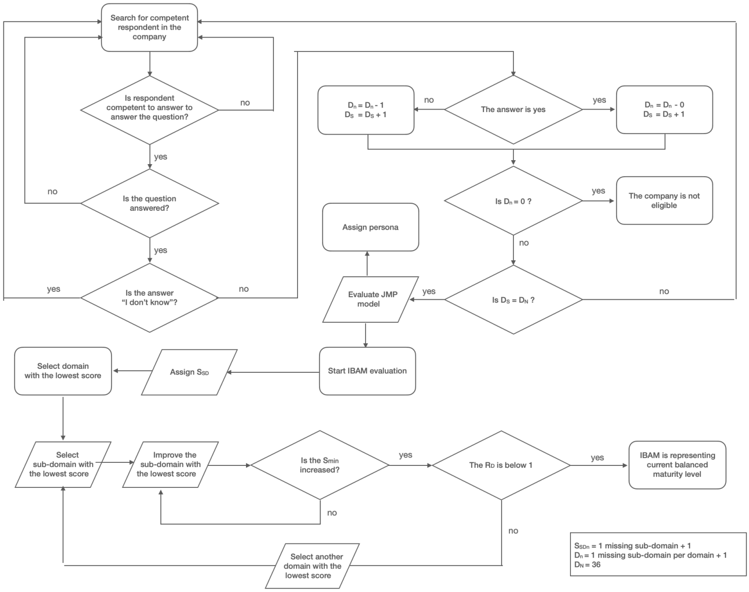

Figure 4 IBAM Model Algorithm

The model starts with the test of eligibility algorithm, which is a simple algorithm that helps to the user decide the correct knowledgeable person as a supporting part for IBAM model components. Output of this test is a brief set of "yes/no" answers which are decomposed in the inputs which are used in JMP Assessment and in the enhanced form to the IBAM questionnaire. After IBAM evaluation we may assign an implementation plan which is, as we said earlier, a recommended document to assess corrective measures in e.g. large companies. After implementation of the corrective measures, we may continue to JMP model second assessment to measure the maturity potential journey – if the company has progressed. Which leads us to the second IBAM evaluation according to the presented algorithm.

4.8 IBAM Model Versioning

To obey the path of improvements for proposed IBAM model, we fully understand that this model may be subject to future changes. Therefore, we have adopted software versioning for IBAM model. Practice has shown that several methods of improvement change are in use widely. According to Preston-Werner (2013), we will emphasize few of them such as the sequence-based identifiers, semantic versioning, or designating development stage. Keeping with the issue, we have chosen the semantic versioning for the future updates or model improvements such as IBAM 1.0.0.

5 EVALUATION OF THE PROPOSAL

After presenting all of the proposals of improved business analytics maturity level in the industrial companies, we conclude this dissertation thesis with an evaluation of the proposals and contributions. The following pages are dedicated to the verification and pilot application of the model in the selected companies. We want to highlight that the IBAM model is a descriptive tool for providing a comprehensive overview of the overall business analytics maturity; therefore, we may proceed to the next chapter focused on verification of the models in the selected industrial company. Proposed IBAM model was applied to the selected industrial companies. The model was applied and evaluated according to the proposed workflow. In all of the cases was developed IBAM Report which is containing the current status quo of the industrial business analytics maturity for the following companies:

- ZF Slovakia, a.s
- Bauer Gear Motor, a.s
- MIKOV Skalica spol. s r.o.
- PRELIKA, a.s.
- LIPTEC s.r.o

Considering the fact that the IBAM report is voluminous in terms of this thesis, we provide only a selected report of the pilot application of the IBAM model for demonstration purposes.

6 CONTRIBUTIONS OF THE DISSERTATION THESIS

Besides providing tools in form of practical proposals and their applications, the dissertation contributes to the following areas:

6.1.1 Contribution for the Theory

In the literature review, we did contribute to the theory by providing an extensive dataset of the scientific and expert publication in the area of business analytics and maturity models. This dataset is included in the appendices so the data can be used for future research. Same as the presented quantitative dataset we have contributed to the theory via comprehensive qualitative theoretical background for the field of focus of business analytics and maturity models.

We have contributed to the theory by providing an extensive but comprehensive questionnaire for industrial business analytics maturity evaluation with the methodological data postprocessing supported on mathematical formulas. The IBAM Model and IBAM Meta-Model as our contributions to the theory bring a comprehensive view on the issue of business analytics maturity models, which we contributed to. On the other hand, the JMP model and Test of Eligibility brings the essential tool for maturity models, in brief, and compact form, but primarily serves to IBAM model as a test of eligibility in form of a checklist. All of the mentioned models are well designed in comprehensive form for educational purposes.

6.1.2 Contribution for the Practice

By designing the IBAM model, we developed the toolkit for evaluation of the industrial business analytics maturity, suitable for large and SME's companies, which are interested in improving its ability in the field of Industry 4.0 or general preparation for smart manufacturing. This industrial business analytics maturity model will benefit each of the company interested in the motioned areas.

6.1.3 Contribution to Education

In terms of providing maturity model, we contributed do education especially to these following areas of interests:

- Business Information Systems
- Information Management
- Knowledge Management

The IBAM model by itself is and flexible study material especially in presented study areas. It is applicable practically and theoretically in process of education. In the area of business information systems, the proposed model provides a tool to evaluate the business information processes in the field of industrial production in terms of maturity evaluation.

CONCLUSION

The goal of business analytics in term of maturity level estimation is to improve decision making by testing current state of the industrial analytics to improve possibilities to analyse large datasets produced by production and managerial process. The idea behind this thesis is to put basis on insight generation which is a different name for finding nonobvious patterns mined from the production process. The main aim of this dissertation thesis was to design the maturity model for evaluating the maturity of business analytics in industrial production enterprises. Keeping in mind that the model has to be focused on processes that creates the business value as the supporting components for the production.

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