Influential Factors on Technology Sourcing for the Use of Deep Learning

Jonathan Masior[1], Gözde Kara[2] and Sven Schimpf[3]

[1] University of Stuttgart, Institute for Human Factors and Technology Management, Jonathan.Masior@iat.uni-stuttgart.de
[2] Stuttgart, karagzde@yahoo.com
[3] Fraunhofer Institute for Industrial Engineering IAO, Sven.Schimpf@iao.fraunhofer.de

Various companies found an effective way to outsource their development efforts in open source communities. The availability and easy accessibility of resources such as high computational capability and distributed processing, open source software, and sophisticated libraries, enable competitions within open source communities to develop the best predictions with deep learning algorithms. To train and to develop learning models this ecosystem requires high quality, consistent, structured data.

The research on technology sourcing decisions is a well-documented realm, which automated software still did not penetrate. Influential factors on the sourcing decision of product technologies derived from an in-depth literature analysis. The essential requirements for models of sourcing decisions and intelligent decision support algorithms are juxtaposed. The purpose was to respond to current trends and develop a logical structure for datasets significant as an input to deep learning software. The resulting models are applicable on various complex decisions and analyses in strategic technology management by communities, researchers, and companies, which develop and train learning models based on their own, individual preferences.

1. Introduction

The motivation for this work is to enable a new approach on technology sourcing decisions and therefor create an exemplary case for further investigations in the area of strategic technology management. The goal is the development of a structured basis for the application of modern deep learning methods on the technology sourcing decision. This ground work is an in-depth literature research, a collection and structuring of the influential factors on these decisions. The collected objects thereby meet certain requirements given by the decision process and working principles of layered neuronal networks.

The question about technology sourcing decisions has been around for many years. New forms of technology or innovation sourcing such as open source communities make these decisions more complex. Focus areas are strategic technology management and technology sourcing. In an in-depth literature analysis, previous research publications have been gathered and evaluated. The focus was set on primary research sources that defined the indicators from case studies, empirical analyses or theoretical derivations. Most of the considered sources agree that the make-or-buy decision is a matter of input factors, namely the determinants on decision-making, and output factors, which are possible ways of technology acquisition. They describe the manner in which technological knowledge is acquired. Usually this decision is made on basis of a determined roadmap or strategy regarding the type of technology. For this study, we assume that the choice for a specific technology is already made. The influencing input factors have been extracted from relevant literature and have been discussed. Quality aspects of these influences

Cite as: Masior, J., Kara, G., & Schimpf, S. (2017). Influential Factors on Technology Sourcing for the Use of Deep Learning. Proceedings of the R&D Management Conference 2017, Leuven, BE, July 1st to 5th.

have been stated and the relevant influences have been selected. Beyond the area of technology sourcing and acquisition, also the thematic fields of R&D sourcing and strategic make or buy decision in R&D have been considered within the study.
In literature a special forms of make-or-buy decision is described. Authors refer to it as the outsourcing of manufacturing activities, manufacturing technologies, contract manufacturing, or manufacturing strategies. This decision is related to the degree of vertical integration and refers to the in-house development of technologies. These process technologies differ in a few aspects from product technologies.

Various researcher studied the different modes of outsourcing and in-house R&D, summarizing the possibilities (e.g. (Daim and Kocaoglu, 2008), (Chiesa et al., 2000)). Traditional sourcing options can be in-house research and development (R&D), purchasing knowledge or different forms of research collaborations. These options are complemented by new mechanisms of technology sourcing such as crowdsourcing, start-ups or social technology development platforms (Harrison et al., 2016), (Blind et al., 2012). However, this work deals with the collection and structuring of the decision input, which influences the sourcing decision.

In an iterative approach, findings were collected, analysed and discussed after each search cycle. The findings then are classified according to dimensions derived from literature dealing with strategic technology management.

2. Deep Learning

The current excitement about deep learning came from started in the year 2012. At that the time, there was a competition called ImageNet Challenge which encourages encouraged all concerned people to compete regarding in recognising and labelling images automatically. In 2010, the winning system could correctly label an image 72% of the time. Then in 2012 a new system showed even better performance and got 85% accuracy with by using a novel technique known as "deep learning algorithms" (for humans the average performance rate is 95%). Following this success, in 2015, another system achieved to surpass human performance for the first time with 96% accuracy (The Economist, 2016).

Deep learning is very capable concept for pattern recognition and machine learning. It uses a system, based on principles of neural networks, that adapts impacts and casual links between controllable input and outcomes (Abdallah et al., 2017). A neuronal network is a net of little processing units that perform computing non-sequentially. An important concept of its application is supervised learning in the so-called training phase, where the learning model is given a set of predicted input-output pairs. The learning model does not consider the connections directly but an abstract composition or representation of it - the convolutional layers (Schulz and Behnke, 2012). Not all of these layers are visible. Nonetheless, they can serve to define the abstract components of the decision problem and give opportunity for supervised learning, i.e. training the learning model to connect the input parameters in a certain way. The requirements therefor are to structure the decision problem into schemas: input-out and convolutional layers.

Three major tendencies differentiate deep learning. The most widely used (Ng, 2017) type of deep learning is "supervised learning" which provides training a system with the aid of a labelled set of examples. The most important feature of this approach is that the system can learn directly from the labelled data without any guide by an expert or rule set. Another approach is unsupervised learning which needs training a network by subjecting it to a huge number of examples. It is not told what to look for, instead, the network learns to recognise features and cluster similar examples. In this way, it can reveal hidden groups, links, or patterns within the data. It can be helpful when people do not know what these look like. The last approach is called reinforced learning and takes place between supervised and unsupervised learning techniques. It involves training a neural network to interact with an environment. From this interaction it gets feedback.

The ImageNet Challenge (The Economist, 2016) revealed the capability of deep learning. With this not only artificial intelligence (AI) the community started to focus on the issue and as well did the technology industries. Google, Facebook, Microsoft, IBM, Amazon, Baidu and other firms have made some of their deep-learning software available free on an open-source basis (The Economist, 2016). In relation to this, there are also other platforms, which serve pure or structured data (e.g. Kaggle (Kaggle Inc., 2017)) where people can get, explore and publish their own data with using their own and trained intelligence codes.

3. Sourcing decisions

It has been a frequently increasing problem for many years that technology focused companies find themselves confronted with a rising technological complexity of products, services and business models, an ubiquitous integration of subsystems and a rising number of available technologies and technology providers on a global level. Once this highly dynamic environment is analysed using methods for identifying and evaluating relevant technologies, decisions have to be taken. Technologies can be seen as investments, which need the right timing of introduction and the best way of adaption into the company's portfolio.

A first look in literature for technology acquisition theory shows that the sets of determinants on sourcing decisions are very complex. Early theories try comprehensive approaches by decision frameworks that give examples for determinants but no comprehensive lists, e.g. (Fine and Whitney, 1996), (Venkatesan, 1992).

For decisions in this context different aspects need to be considered to ensure the economic efficiency, growth and competitiveness of the company. The challenge is to recognize the technology-sourcing route, which is the most profitable, in compliance with the company's strategy, which aligns with the company's capabilities, or even promises the highest performance by the selected options. Decisions on technology sourcing are directly linked with companies' resources and technological capabilities and are able to shape the future of a company (Cetindamar et al., 2013)

Today's decision-making is mostly based on subjective, individual perceptions. It is hardly transparent and rarely considers the environment or performance indicators. Furthermore, the decisions are done single-handedly without external support and mostly without any automated approach (Cano and Perez-Bustamante, 2006), (Brannemo, 2006). Decisions are therefore not replicable and knowledge gets lost.

3.1 Synonyms

Literature gives different terms for the decision-making of technology acquisition. The following terms were found in literature and can be used synonymously: technology acquisition mode, sourcing of technological knowledge not-invented-here phenomenon (NIH), technology make-or-buy decision or technology rout. They describe the manner in which technological knowledge is acquired. Some user of the acquisition mode buy, develop the technologies in-house or cooperate with partner companies in order to share development resources but also the development outcome (Huang et al., 2008).

3.2 Decision subject: product technologies

Another important consideration is the definition of the decision subject. Some literature sources lack in differentiation of the technology acquired. Authors refer to the outsourcing of manufacturing activities (Baines et al., 2005), (Baines, 2004) manufacturing technologies (Chen and Small, 1996), contract manufacturing (Kim, 2003), or manufacturing strategies (Welch et al., 1992). The decision addresses the degree of vertical integration and refers to the in-house development of technologies. These process technologies differ in a few aspects from product technologies as stated in (Schuh and Klappert, 2011). Process technologies support or enable manufacturing processes, product technologies are applied in products delivered to a customer. Outsourcing decisions of process technologies have a significantly different value in a company's strategy. "Access and control of markets", "capital commitment", "use of employees" or "production competences" are some examples for strategic values of process technologies (Gretzinger, 2008). It is difficult to differentiate the literature on this subject. However, this work tries to focus make-or-buy decisions, which refers to product technologies.

3.3 Model types

In order to structure the influential factors and find abstract layers a closer look reveals the form of the factors in the models. The following chapter differentiates and explains the model types by

- Decision procedure
- Theoretical approach for developing the model
- Level of abstraction (indicators)
- Measurement type of the influential factors
- Strategy factors (drivers)

The models found in research literature follow different approaches. To narrow the field down, search focused on models with the definition of influencing factors. In contrast, some sources developed stage processes or formal methods to guide through the decision path by answering either open or closed questions (Humphreys et al., 2000), (Humphreys et al., 2002), (Venkatesan, 1992), (Slowinski et al., 2000).

A measurement for data quality and therefor for the applicability of the influential factors is the theoretical approach of the research as defined by (Price and Shanks, 2008). Some findings derive influential factors theoretically (Schneider and Zieringer, 1991), other generate them empirically or from interviews and feedback (Liou and Chuang, 2009), (Howells et al., 2003). The latter approach may be more significant but lacks in systematic theory and possibly inconsistency.

The major part of the frameworks refer to the transaction cost economics or developed extensions of it (e.g. (Krzeminska, 2008)). Another part of the findings derived the model from the resource-based view on the company or focused on institutional factors such as companies' competences to gain competitive advantages (Chiesa and Manzini, 1998) , (Hemmert, 2002). Some of the findings combine the economic view and the competition strategy (e.g. Arnold, 2000). The focus on the relationship and evaluation of the partners or providers is also an important approach (e.g. (Arranz et al., 2007), (Howells et al., 2003)). Newer sources include more of the technology attributes or sourcing object itself such as "complexity" or "maturity" of the technology (Daim, 2010), (Ranft and Lord, 2002), (Chiesaet al., 2000). These aforementioned sources try to determine concrete factors, independent of their measurability. As (Schneider and Zieringer, 1991) shows the economic or transaction-based views have the advantage to include indirectly failure influences caused by human or environment. Other sources address the environmental factors directly under the realm of inhibition or promotion (e.g. (Sen and Rubenstein, 1990), (Schneider and Zieringer, 1991)).

As explained the influential factors are defined as objects on different abstract levels. We define a basic factor, which is a not divisible, commonly defined object, represented by a numeric value as an "indicator". An influential factor usually means an aggregation of one or more indicators. An indicator can be the result of a methodological analysis or an attribute of something, such as “costs”, “exports to sales ratio”, “appropriability of a technology” or “relation to partners”, which can be evaluated directly and relatively quick.. Factors, which have no common definition, would depend on a subjective evaluation without a value reference. They remain with the name “influential factor”.

The analysis of the decision problem by transaction cost economics or strategic technology management uses models that can hardly be captured by one-dimensional, quantitative values. This opens another category of theoretic models regarding the form an influential factor can have. It points out the influences not as determined, quantifiable factors but as a qualitative evaluation such as “technology roadmapping”, “technology portfolio method”, strategic evaluation regarding the “company specificity” or the “legal framework regarding the technology environment” (Schneider and Zieringer, 1991), (Daim, 2010). These factors can be an outcome of qualitative or quantitative methods for analysis, expert estimations or other software applications.

It is clear that a company’s individual strategy influences the sourcing decision. (Chiesa, 2001) displays this as the positioning approach. However, it has to be differentiated what purpose the factors have within the decision. Those decision criteria, which describe a strategic advantage through the decision such as “to increase flexibility”, “to reduce the dependency on suppliers” or “to increase market share”, are far more complex. The strategic considerations and the advantages of individual companies through a specific alternative differ widely. Whereas the environmental indicators are similar for companies which are active in the same domain. Influential factors themselves cannot be defined as strategic outcomes, however, a specific constellation of their manifestation can. Strategic outcomes are called “drivers” (Ghodeswar and Vaidyanathan, 2008).

3.4 List of influential factors on the technology sourcing decision

By applying the filter criteria on the findings in literature the following list of influential factors on the technology sourcing decisions could be derived as seen in Table 1. The categorization is a support for perception and does not claim to represent a logical layer.

Table 1. Part 1 – List of influential factors on the technology sourcing decision, sources: (Brannemo, 2006), (Huanga, Chungb and Linc, 2009), (Hung Lau and Zhang, 2006), (Karlsson, Taylor and Taylor, 2010), (Nakamura and Odagiri, 2005), (Ortiz-Gallardo, 2013), (Swan and Allred, 2003), (Van de Vrande, Vanhaverbeke and Duysters, 2009), (Vanhaverbeke, Duysters and Noorderhaven, 2002), (Venkatesan, 1992), (Veugelers and Cassiman, 1999), (Allred and Swan, 2004), (Beneito, 2003), (Brannemo, 2006), (Buchowicz, 1991), (Canez, Plattz and Probert, 2000), (Chiesa, 2001), (Chiesa, Mazini and Tecilla, 2000), (Del Canto and Gonzalez, 1999), (Ford and Farmer, 1986), (Goehlich, 2009), (Hemmert, 2004), (Hung and Tang, 2008), (Hung Lau and Zhang, 2006), (Karlsson, Taylor and Taylor, 2010), (Kurokawa, 1997), (McIvor, Humphreys and McAleer, 1997), (Nakamura and Odagiri, 2005), (Ortiz-Gallardo, 2013), (Sen and Rubenstein, 1990), (Stock and Tatikonda, 2008), (Sumrit, Anuntavoranich and Vadhanasindhu, 2012), (Swan and Allred, 2003), (Van de Vrande, Lemmens and Vanhaverbeke, 2006), (Vanhaverbeke, Duysters and Noorderhaven, 2002), (Veugelers and Cassiman, 1999), (Walker and Weber, 1984), (Watjatrakul, 2005).

Finance	
Influential Factor	Value
Total Cost of Acquisition	High ; Low
Production Cost	High or Low
User's Expected Costs	Appropriate ; Not
Vendor Costs	High ; Acceptable
Total Cost	More Capable Than External Sources ; No Competent External Sources
Financial Autonomy	= (Equity / Total Assets) * 100
Degree of Financial Autonomy	= Total Own Funds / Total Debts
Amortisation	= Depreciation Costs / Net Turnover
Average Wage	= Labour Costs / Total Employees
Amount of Sales	Logarithm of The Average Value of Sales
Budget Authority	Adequate ; Insufficient
Financial Resources	Increase ; Decrease
Capital Participation	High ; Low
Annual Savings	Logarithm of estimates
Cost and Risk Obstacle	Risks Too High ; No Suitable Financing Available ; High Costs of Innovation ; Long Pay-Back Period ; Innovation Cost Hard to Control ; Uncertain Introduction ; Time
Market	
Influential Factor	Value
The Degree of Competition	High ; Low
Competitive Intensity	High ; Low
Size of Market	Big ; Small
Propensity to Export	= Exports / Sales 1 = ratio is 0% 2 = 0% < ratio < 10% 3 = 10% < ratio < 25% 4 = ratio > 25%
Exports (Commercial Resources)	1 = Export 0 = Not Export
Environment Turbulence (Market and Industry Uncertainty)	High ; Low
Relevance for Competitive Advantage	High ; Low

Intensity of Competition	High = many competitors, perfect competition ; Medium = several competitors, oligopoly ; Low = no competitors, monopoly
Market Demand Uncertainty	High = unforeseeable circumstances ; Medium = challenging forecasting with some surprises ; Low = easy forecasting with no surprises
Capability	
Influential Factor	Value
R&D Capability	High ; Low
Asset Specificity	High = irreversible investment (knowledge acquisition) ; Low = reversible investment (capital expenditures)
Assets	= Volume of The Firm's Total Assets / Average Volume of The Assets of The Whole Sample
Skilled Workers	= Average Percentage of Engineers and Technicians / The Total Number of Workers
Core Activities	Related ; Not
Core Competence	To improve business focus ; To increase competitiveness ; To leverage the firm's skills and resources ; To enhance customer satisfaction
Lack of Opportunities for Innovation	Technological ; External Technical Services ; Cooperation
Technical Skills and Assets to Perform the Process	High ; Low
Machine and Physical Assets Capability	Yes ; No
Technical Experience	High = extensive experience with similar products ; Medium = same experience with related products ; Low = new team with no relevant product experience
Technology Specific	
Influential Factor	Value
Technological Relevance	High ; Low
Level of Risk	High ; Low
Technological Competency	High ; Low
Familiarity	More ; Less
Product Familiarity	Yes ; No
Technology Maturity	High ; Low
Strategic Relevance with Strategy	Strategic ; Commodity
Justified Investment	Yes ; No
Technology Life Cycle	Mature ; Embryonic
Technology Complexity	High= connection and interaction of advanced systems ; Medium= connection of simple systems ; Low= simple unit

Strategic Importance of Subsystem	High ; Low
Chances of Gaining Technology Lead	Yes ; No
Technology Uncertainty	High ; Low
Technological Newness	High ; Low
Product Technology Dynamism	Increase ; Decrease
Technology Type	1 = Operational Technology ; 0 = Non-Operational Technology
Technology Modularity	Yes ; No
Technological Innovation Distance	Small ; Big
Technological Complementarity	Yes ; No
Technological Codification	High ; Low
Tacitness of Technology	High ; Low
Technological Improvements	High ; Low
Difference in Manufacturing Process	Yes ; No
Technology and Equipment	Available ; Not
Time	Long ; Short
Differentiation	1= The Firm Asserts to Offer a Non-Standardised Product ; 0= Otherwise
Resources	
Influential Factor	Value
Internal R&D Personnel	Available ; Not
Internal Information Sources	Information within the company ; Information within the group
Networking of R&D Personnel With Other Firms/Institutions	Yes ; No
Non-Strategic Resources	High ; Low
Available Resources	Yes ; No
Availability and Quality of External Sources	Yes ; No
Scientific Information Sources	Universities ; Public Research Institutes ; Technical Institutes
Importance of Lack of Information	Qualified Personnel ; Personnel to Innovate ; Information on Technology ; Market Information
Organisational	
Influential Factor	Value
Business Ties	Strong ; Weak
Managerial Capability	High ; Low
Organisational Skills	High ; Low
Quality of Business Climate	High = superior conditions, favorable environment for investors, advanced economy ; Low = unacceptable, very high risk
Experiences in R&D Cooperation	Yes ; No
Experiences in Joint Venture	Yes ; No

Experiences in Make-or-Buy Decisions	Yes ; No
Experiences in Managing Technology Integration	Yes ; No
Experiences in Design Choices	Yes ; No
Organisational Complexity	High ; Low
Quality Measures	Available ; Not
Learning Orientation	Extend and Improve Its Technical Knowledge ; Not
Protection Mechanisms	Available ; Not
Lack of Experience in Cooperation	High= integrated enterprises, regular subsequent inter-organizational transactions ; Low= firms do not have access to all the relevant information to make an investment decision
External Technology Integration (ETI) Project Experience	Yes ; No
Learning	High ; Low
Company size	below 50 ; below 200 ; above 200 and below 500 ; above 500 ; over ten-thousand
Export Intensity	= Sales From Exports / Total Sales
Resistance	Yes ; No
Cultural Distance to R&D Operations	Significant ; Not
Spatial Distance to R&D operations	Greater ; Not
Ease of Imitation	Yes ; No
Freedom of Internal Exchange of Information	Yes ; No
Strength of Internal Communication Network	High ; Low
International Interaction	Effective Communication With Source ; High Degree of Coordination With Source ; Cooperative Relationship With Source
Assets Specialisation	Highly Specialised Assets ; Not
Assets Divisibility	Possibility to Isolate That Needed Part (or Functionality) ; Not
Distance Between Marketing and R&D	High ; Low
Product Dynamism	Increase ; Decrease
Mobility of Personnel	High ; Low
User Participation	Specification ; Implementation ; Selection
Leverage	= Long and Short Term Liabilities / Equity
Criticality of Integration Project	Yes ; No
Degree of Similarity	High ; Low
Degree of Fit	High ; Low
Changes in Specifications	High ; Low
Ownership of The Process	Yes ; No
Ability to Cope With Volume Changes	Yes ; No

Supplier Selection	Available ; Not
Inventory Control	Available ; Not
IT Development	Available ; Not
Engineering Changes System	Available ; Not
Training Schemes	Available ; Not
Continuous Improvement Programme	Available ; Not
Technical Support	Available ; Not
Environmental Uncertainty	High ; Low
Design Feasibility	High ; Low
Vertical Integration	= Value Added / Sales
Content Identification	Ill ; Not
Strategy	
Influential Factor	Value
Appropriability	Tight ; Weak
Necessity of Innovation	No Need for Innovation Because of Earlier Innovations ; Little Interest for Innovations by Customers
Diversification of Company's Line of Business	High ; Low
Competence	Enhancing ; Destroying
Fit With Business Strategy	Yes ; No
Facilitating Market Penetration	Yes ; No
Strategic Vulnerability	High= sensitive influence on core competences ; Low= no relation to core competence
Strategic Awareness	High ; Low
Collaboration / Cooperation	
Influential Factor	Value
Relationship Analysis	Compatible Suppliers and/or with Little Threat of Competition ; No
Vertical and Horizontal Relationship	Vertical ; Horizontal
Broadness and Narrowness	Broad ; Limited ; Learning Oriented
Phase of Innovation Process	More ; Less
Sector of Activity	Similar ; Different
Original Country	Similar ; Different
Different Knowledge Bases Among Potential Partners	High ; Low
Prior Direct Ties	Exist ; Not
Network Distance	Number of Common Partners
Intra Industry and Inter Industry Ties	Long ; Short
Domestic and International Ties	Available ; Not

Capability of Suppliers	To Enable Partnering ; To Improve Service Quality and Customer Service ; To Increase Competitive Advantage
Number of Suppliers	Enough ; Not
Direct Competitors	0 < number ≤ 10 ; 10 < number ≤ 25 ; 25 < number
Supplier Proprietary Technology	Yes ; No
Cost Reduction Activities With Supplier	Yes ; No
Collaboration With Suppliers	Yes ; No
Vendor Competitiveness	High ; Low
Network of Contacts	Adequate ; Not
Trust in Vendor	High ; Low
Cultural Trust	Engineering ; Non-Engineering
Close Competitors as Information Sources	High ; Low
Others	
Influential Factor	Value
Impediments to R&D by Administrative and Legal Barriers	Yes ; No
General R&D Subsidies	Available ; Not
Subsidies for Collaborative R&D Protection of IP Rights	Available ; Not
Governmental Demand for Final Products	Available ; Not
Buyer Tools and Equipment	Similar ; Different
Buyer Manufacturing Technology	Strong Experience ; Not
Vendor Reputation	Poor ; Good
Perceived Urgency	High ; Low

3.5 Implications

A core aspect of the models, as of models in general, is to simplify the complexity of reality and make it pragmatic as strategic decision support. Models always deal with the trade-off between relevance, scope and precision (Price and Shanks, 2008). Either the model specifies on an aspect of the decision such as a resource-based view or it encompasses all possible variables, but provides factors on an abstract level. Therefor a field of influence sums up many influential factors. Deep learning works with such aggregations of objects. It can map these structures on various levels and integrate them in the learning model. Most of the found models deal with a reasonable amount of about a dozen of decision criteria. It would be hardly practicable to create a list of influential factors because of the adaptable nature, level of abstraction and complex calculations such as transaction costs varying from use case to use case. However, the possibilities given by todays hard- and software arises the aspiration not to restrict the amount of factors. Rather the goal is to find the selected list of structured factors that qualify the first step of the computed decision support.

Another challenge is the redundancy of the models. The decision support models vary among each other on abstract levels. Some are even extensions of earlier consistent models in order to include missing factors. Nevertheless, the distinction of the factors in the different models in order to provide consistency is a requirement for the input dataset.

The sharing or re-using of experiences demands a comparable decision subject. In terms of data quality and to be used in automated software tools indicators should be transferable to quantitative representation and be characterized through a finite amount of possibilities so that factors always have a clear characteristic. The completeness of range is also effecting the replicability. Decisions on technology sourcing should be repeatable under the same configuration of influences. Purpose of the decision and strategic background needs to be separated clearly from the influencing factors.

4. Automated support for sourcing decisions

The intention at this point is to give a brief overview of decision support approaches. For a more extensive overview, see (Mardani et al., 2015). In the following, the research is characterized by representative examples.

The beginnings of deep learning can be traced back to 1965(Abdallah et al., 2017). Since the 1980s also the methodological decision support for technology sourcing appear in various literature sources. Approaches, which combine both the sourcing decision and automated analysis, are numerous. The processes of automating the decision support or using methods that are more complex requires a certain standard of input factors (Kahraman and Yanık, 2016).

Most of the research conducted have similar goals. The technology sourcing decision appears as a problem with a discrete amount of solutions. The solution is selected as the best alternative by preference criteria of the decision maker (Price and Shanks, 2008). Assuming that the theoretic model with the factors of influence on the decision is given, the findings show two major outcomes. Firstly, the findings try to define the strength of impact or so-called weights of the influences on the decision. Secondly, the outcomes show especially the interdependencies between these influences. This is a major challenge. In classical AHP process, the evaluation of interdependencies is done a priori by a team of experts or managers. However, the results are strongly biased by the person evaluating the procedure. In addition, it takes much effort by the responsible persons.

The influential weights of the factor differ from use case to use case based on the deciding company, the object to be outsourced and the business environment. A support for decision-making through a template or a learning model, on which the individual preferences are considered, would be of high value.

(Liou and Chuang, 2009) developed a multi-criteria model for selection of outsourcing providers. Their model works with eleven highly relevant factors derived from workshops with the company's management. They refer to attributes of the providers. The methodology uses the analytical network process (ANP) and the decision-making trial and evaluation laboratory method, which already consider weighted interdependences between the factors. The outcomes include the weighted influence of each decision criterion.

In addition, the work of (Li and Wan, 2014) deals with the selection of a provider. They developed a method out of the fuzzy set theory and decision-making models such as linear programming technique for multidimensional analysis of preference and the technique for order preference by similarity to ideal solution that considers the subjective bias.

Many sources consider neural network-based or fuzzy multi-criteria decision-making (e.g. (Özkan and İnal, 2014), (Golmohammadi, 2011), (Chen and Lin, 2002), (Turban et al., 2007)). Some of them such as (Hwang et al., 2007), (Hayashi et al., 2009), (Lee et al., 2008) apply the analytic hierarchy process (AHP) or analytic network process (AHP) with fuzzy variables on make-or-buy decisions.

(Humphreys et al., 2002) developed a formal method for make or buy decision especially considering the costing system and competitive implications of the decision. The specific goal was to encounter the highly complex set of influences by an adaptable knowledge-based system.

5. Deriving the layer model

Existing models on sourcing decision show that redundancies among all models are unavoidable. They partly include the same objects but from different view or abstract levels. (Hall, 2008) says that it is even necessary to have such different views on the decision subject. Given that these views are a possibility to evaluate the decision problem, a layered structure is necessary that shows the basic objects involved in sourcing decisions.

The smallest common factor, the object of minimal abstraction, as defined in chapter 3.3, is an indicator. The basic objects mentioned directly or indirectly in most of the models are the deciding company, the sourcing object, and other technology providing companies, which are all subject to environmental circumstances or conditions. These objects are not part of the input to decision support software. Their attributes, however, are.

This layer model implies that relation-based evaluation criteria are a function of the objects' attributes. For example. An evaluation in strategic context is therefore a function of the case-specific constellation of indicators. The next step would be to define the models of the sourcing decision as the different layers within the learning model. It would exceed the scope of the work to show this.

Following these considerations there are four basic layers: indicators, attributes, objects, and high-level evaluation criteria as shown in Figure 1. These layers include indicators and factors, rather than evaluation criteria. The strategic preferences are an input of the decision problem. The evaluation, e.g. the

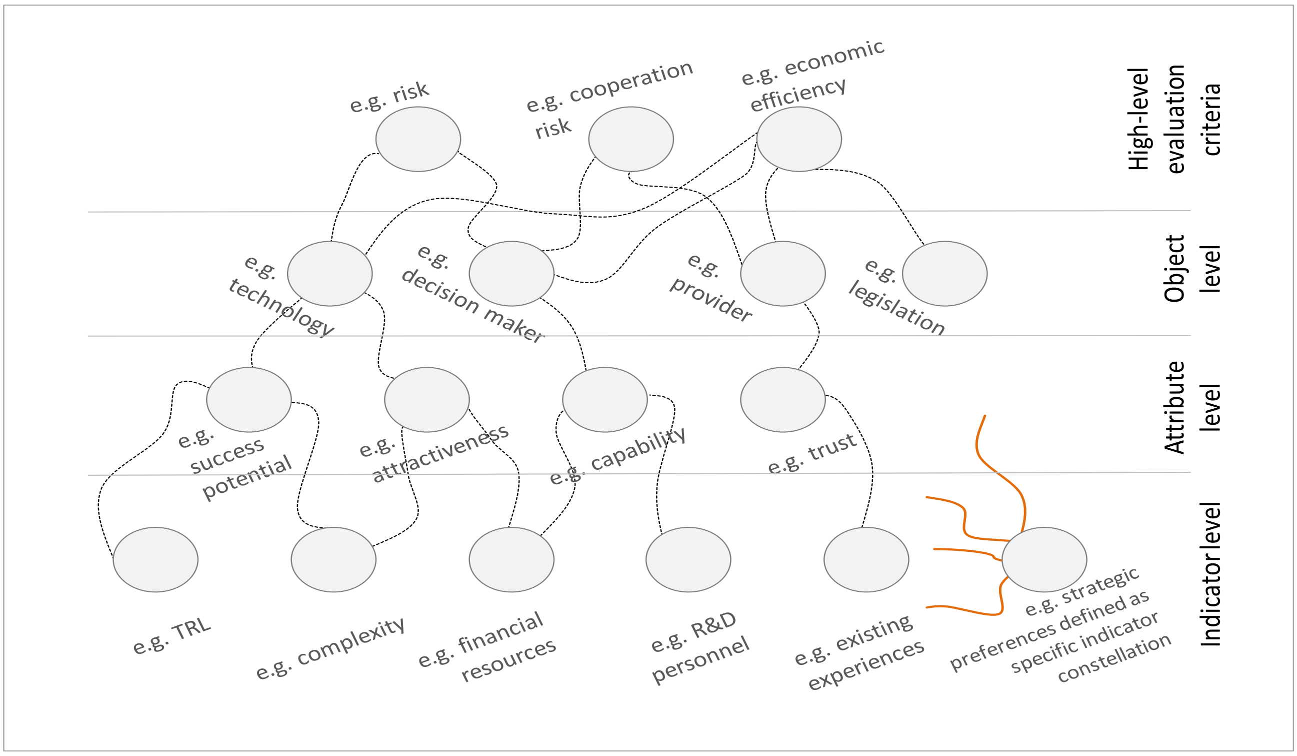

Figure 1. Logical, four-layered differentiation of influences.

trustworthiness, follows from the specific configuration of the lower level objects, e.g. prior experiences and company size. All collected influencing factors can be represented in one layer of this schema.

6. Conclusions

As a respond to significant, current trends in the realm of deep learning a structure for the description of influential factors within models for technology sourcing decisions has been created. Along with it, a comprehensive dataset showing a list of influencing indicators and factors is provided. This especially emerged from readdressing a well-documented decision problem in an in-depth literature analysis. By reviewing and analysing the most relevant sources in research this work defines and differentiates influences more clearly and presents the scientific consensus. The paper also provides the intended support for companies, communities and research in decision-making development. This process has clear requirements. This work meets the requirements to filter out factors that are not usable for intelligent decision support and to provide a structure as a common base for the decision problems.

The high availability of hard- and software to build powerful, learning analysis tools created the demand for high quality data. Still, the question of sourcing decisions is practically not supported with automated software. The approach developed in this work is a significant example for the area of automated decision support in strategic technology management. It covers the first step to generate consistent and complete data on a prediction problem and responds to todays' industrial challenges: a far better understanding and a higher level of transparency on available options in the decision-making process. With this structured approach, the maintaining knowledge and replicating decisions under the same circumstances can be possible. Additionally, a possibility how to approach complex problems in technology management and the requirements on adapting the decision question to deep learning principles is shown.

The usage of these factors in automated software tools can reveal the interconnection of factors and therefore the relations of real conditions in the highly dynamic and competitive economic environment.

9. References

Allred, B.B. and Swan, K.S. (2004) Contextual influences on international subsidiaries' product technology strategy. *Journal of International Management,* **10**, 2, 259–286.

Arranz, N. and de Arroyabe, J.C.F. (2008) The choice of partners in R&D cooperation: An empirical analysis of Spanish firms. Technovation, 28, 1, 88–100.

Beneito, P. (2003) Choosing among alternative technological strategies: an empirical analysis of formal sources of innovation. *Research Policy,* **32**, 4, 693–713.

Blind, K., Vries, H. de, and Mangelsdorf, A. (2012) External knowledge sourcing and involvement in standardization-Evidence from the community innovation survey. *Technology Management Conference (ITMC), 2012 IEEE International.* pp. 1–9.

Brannemo, A. (2006) How does the industry work with sourcing decisions? Case study at two Swedish companies. *Journal of Manufacturing Technology Management,* **17**, 5, 547–560.

Brown, L. (2015) *Deep Learning with GPUs*.

Buchowicz, B.S. (1991) A process model of make-vs.-buy decision-making. The case of manufacturing software. *IEEE Transactions on Engineering Management,* **38**, 1, 24–32.

Cánez, L.E., Platts, K.W., and Probert, D.R. (2000) Developing a framework for make-or-buy decisions. *International Journal of Operations & Production Management,* **20**, 11, 1313–1330.

Cano, A.R. and Perez-Bustamante, G. (2006) The Nature of Knowledge and Decisions on Activity Sourcing: An Innovation Model. *Technology Management for the Global Future, 2006. PICMET 2006.* pp. 243–255.

Cetindamar, D., Daim, T., Beyhan, B., and Basoglu, N. (2013) *Strategic planning decisions in the high tech industry*. London: Springer.

Chen, J. and Lin, S. (2003) An interactive neural network-based approach for solving multiple criteria decision-making problems. *Decision Support Systems,* **36**, 2, 137–146.

Chiesa, V. (2001) *R&D strategy and organisation: Managing technical change in dynamic contexts*: World Scientific.

Chiesa, V., Manzini, R., and Tecilla, F. (2000) Selecting sourcing strategies for technological innovation: an empirical case study. *International Journal of Operations & Production Management,* **20**, 9, 1017–1037.

Del Canto, J.G. and Gonzalez, I.S. (1999) A resource-based analysis of the factors determining a firm's R&D activities. *Research Policy,* **28**, 8, 891–905.

Ford, D. and Farmer, D. (1986) Make or buy—a key strategic issue. *Long Range Planning,* **19**, 5, 54–62.

Garling, C. (2015) Andrew Ng: Why 'Deep Learning' Is a Mandate for Humans, Not Just Machines. Retrieved May 30, 2017, from: https://www.wired.com/brandlab/2015/05/andrew-ng-deep-learning-mandate-humans-not-just-machines/

Ghodeswar, B. and Vaidyanathan, J. (2008) Business process outsourcing: an approach to gain access to world-class capabilities. *Business process management journal,* **14**, 1, 23–38. doi: 10.1108/14637150810849382.

Goehlich, R. (2009) *Make-or-Buy Decisions in Aerospace Organizations: Essays on Strategic Efficiency Improvements*: Springer Science & Business Media.

Golmohammadi, D. (2011) Neural network application for fuzzy multi-criteria decision making problems. *International Journal of Production Economics,* **131**, 2, 490–504.

Gretzinger, S. (2008) Strategische Gestaltung des Outsourcing im deutschen Maschinenbau. Eine empirische Studie auf Basis des Resource-Dependence-Ansatzes, 1st edn. Mering: Rainer Hampp Verlag.

Gretzinger, S. (2007) Strategische Gestaltung des Outsourcing im deutschen Maschinenbau: Eine empirische Studie auf Basis des Resource-Dependence-Ansatzes. *German Journal of Human Resource Management,* **21**, 4, 466–471.

Hall, D.J. (2008) Decision makers and their need for support. In: Burstein, F. and W. Holsapple, C. (eds.). Handbook on Decision Support Systems 1. Berlin, Heidelberg: Springer Berlin Heidelberg. pp. 83–102. 10.1007/978-3-540-48713-5.

Harrison, N.B., Gubler, E., and Skinner, D. (2016) Architectural Decision-Making in Open-Source Systems-

Preliminary Observations. *Decision Making in Software ARCHitecture (MARCH), 2016 1st International Workshop*. pp. 16–21.
Hayashi, A., Kino, Y., and Tsuda, K. (2009) Decision Making Process for Selecting Outsourcing Company Based on Knowledge Database. Knowledge-Based and Intelligent Information and Engineering Systems, 300–307.
Hemmert, M. (2004) The influence of institutional factors on the technology acquisition performance of high-tech firms: survey results from Germany and Japan. *Research Policy,* **33**, 6, 1019–1039.
Huang, Y.-A., Chung, H.-J., and Lin, C. (2009) R&D sourcing strategies: determinants and consequences. *Technovation,* **29**, 3, 155–169.
Humphreys, P., McIvor, R., and Huang, G. (2002) An expert system for evaluating the make or buy decision. *Computers & Industrial Engineering,* **42**, 2, 567–585.
Hung, S.-W. and Tang, R.-H. (2008) Factors affecting the choice of technology acquisition mode: An empirical analysis of the electronic firms of Japan, Korea and Taiwan. *Technovation,* **28**, 9, 551–563.
Hung Lau, K. and Zhang, J. (2006) Drivers and obstacles of outsourcing practices in China. *International Journal of Physical Distribution & Logistics Management,* **36**, 10, 776–792.
Hwang, H.S., Ko, W.-H., and Goan, M.-J. (2007) Web-based multi-attribute analysis model for make-or-buy decisions. *Mathematical and Computer Modelling,* **46**, 7, 1081–1090.
Jonash, R. (1996) Strategic Technology Leveraging: Making Outsourcing work for you. *Research-Technology Management,* **2**, 39, 19 ff.
Kaggle Inc. Retrieved May 30, 2017, from: kaggle.com/
Kahraman, C. and Yanık, S. (2015) *Intelligent Decision Making in Quality Management: Theory and Applications*. Cham, Heidelberg, New York, Dordrecht, London: Springer.
Kakas, A.C. (2017) A/B Testing, 317–388.
Karlsson, C., Taylor, M., and Taylor, A. (2010) Integrating new technology in established organizations: A mapping of integration mechanisms. *International Journal of Operations & Production Management,* **30**, 7, 672–699.
Khanna, R. and Awad, M. (2015) *Efficient learning machines: theories, concepts, and applications for engineers and system designers*: Apress.
Kurokawa, S. (1997) Make-or-buy decisions in R&D: small technology based firms in the United States and Japan. *IEEE Transactions on Engineering Management,* **44**, 2, 124–134.
Lee, H., Lee, S., and Park, Y. (2009) Selection of technology acquisition mode using the analytic network process. Mathematical and Computer Modelling, 49, 5-6, 1274–1282. doi: 10.1016/j.mcm.2008.08.010.
Li, D.-F. and Wan, S.-P. (2014) A fuzzy inhomogenous multiattribute group decision making approach to solve outsourcing provider selection problems. *Knowledge-Based Systems,* **67**, 71–89.
Liou, J.J.H. and Chuang, Y.-T. (2010) Developing a hybrid multi-criteria model for selection of outsourcing providers. *Expert Systems with Applications,* **37**, 5, 3755–3761.
Mardani, A., Jusoh, A., and Zavadskas, E.K. (2015) Fuzzy multiple criteria decision-making techniques and applications – Two decades review from 1994 to 2014. Expert Systems with Applications, 42, 8, 4126–4148. doi: 10.1016/j.eswa.2015.01.003.
McIvor, R.T., Humphreys, P.K., and McAleer, W.E. (1997) A strategic model for the formulation of an effective make or buy decision. *Management Decision,* **35**, 2, 169–178.
Nakamura, K. and Odagiri, H. (2005) R&D boundaries of the firm: an estimation of the double-hurdle model on commissioned R&D, joint R&D, and licensing in Japan. *Economics of Innovation and New Technology,* **14**, 7, 583–615.
Ng, A. (n.d.) Lecture 4 - Supervised Learning. Retrieved May 30, 2017, from: https://www.coursera.org/learn/machine-learning/lecture/1VkCb/supervised-learning
Ortiz-Gallardo, V.G. (2013) *Technology acquisition: sourcing technology from industry partners*.
Özkan, G. and \.Inal, M. (2014) Comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems. *Applied Soft Computing,* **24**, 232–238.
Price, R. and Shanks, G. (2008) Data quality and decision making. In: Burstein, F. and W. Holsapple, C. (eds.). Handbook on Decision Support Systems 1. Berlin, Heidelberg: Springer Berlin Heidelberg. pp. 65–82. 10.1007/978-3-540-48713-5.
Schneider, D. and Zieringer, C. (1991) *Make-or-Buy-Strategien für F&E. Transaktionskostenorientierte Überlegungen*. Wiesbaden: Gabler Verlag.
Schuh, G. and Klappert, S. (2011) Technologiemanagement. Berlin, Heidelberg: Springer Berlin Heidelberg.
Schulz, H. and Behnke, S. (2012) Deep learning. *KI-Künstliche Intelligenz,* **26**, 4, 357–363. doi: 10.1007/s13218-012-0198-z.
Sen, F. and Rubenstein, A.H. (1990) An exploration of factors affecting the integration of in-house R&D with external technology acquisition strategies of a firm. *IEEE Transactions on Engineering Management,* **37**, 4, 246–258.
Stock, G.N. and Tatikonda, M.V. (2008) The joint influence of technology uncertainty and interorganizational interaction on external technology integration success. *Journal of operations management,* **26**, 1, 65–80.
Sumrit, D., Anuntavoranich, P., and Vadhanasindhu, P. (2012) Strategic decision for the external technological innovation acquisition mode selection by using an integration of AHP and GRA methods: A case study on a Thai new technology-based firm. IOSR Journal of Business and Management, 6, 1, 29–38.
Swan, K.S. and Allred, B.B. (2003) A product and process model of the technology-sourcing decision. *Journal of Product Innovation Management,* **20**, 6, 485–496.
The Economist (2016) From not working to neural networking. Retrieved May 30, 2017, from: http://www.economist.com/news/special-report/21700756-artificial-intelligence-boom-based-old-idea-modern-twist-not
Turban, E., Aronson, J., and Liang, T.-P. (2005) *Decision Support Systems and Intelligent Systems*, 7th edn.: Pearson Prentice Hall.
Van de Vrande, V., Lemmens, C., and Vanhaverbeke, W. (2006) Choosing governance modes for external technology sourcing. *R&d Management,* **36**, 3, 347–363.
Van de Vrande, V., Vanhaverbeke, W., and Duysters, G. (2009) External technology sourcing: The effect of uncertainty on governance mode choice. *Journal of business venturing,* **24**, 1, 62–80.
Vanhaverbeke, W., Duysters, G., and Noorderhaven, N. (2002) External technology sourcing through alliances or acquisitions: An analysis of the application-specific integrated circuits industry. *Organization Science,* **13**, 6, 714–733.
Venkatesan, R. (1992) Strategic sourcing: to make or not to make. *Harvard Business Review,* **70**, 6, 98–107.
Veugelers, R. and Cassiman, B. (1999) Make and buy in innovation strategies: evidence from Belgian manufacturing firms. *Research Policy,* **28**, 1, 63–80.
Walker, G. and Weber, D. (1984) A transaction cost approach to make-or-buy decisions. *Administrative science quarterly*, 373–391.
Watjatrakul, B. (2005) Determinants of IS sourcing decisions: A comparative study of transaction cost theory versus the resource-based view. *The Journal of Strategic Information Systems,* **14**, 4, 389–415.