

A SURVEY OF THE APPLICATION OF MACHINE LEARNING IN DECISION SUPPORT SYSTEMS

Complete Research

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Abstract

Machine learning is a useful technology for decision support systems and assumes greater importance in research and practice. Whilst much of the work focuses technical implementations and the adaption of machine learning algorithms to application domains, the factors of machine learning design affecting the usefulness of decision support are still understudied. To enhance the understanding of machine learning and its use in decision support systems, we report the results of our content analysis of design-oriented research published between 1994 and 2013 in major Information Systems outlets. The findings suggest that the usefulness of machine learning for supporting decision-makers is dependent on the task, the phase of decision-making, and the applied technologies. We also report about the advantages and limitations of prior research, the applied evaluation methods and implications for future decision support research. Our findings suggest that future decision support research should shed more light on organizational and people-related evaluation criteria.

Keywords: Decision support, DSS, machine learning, artificial intelligence.

1 Introduction

The support of decision-makers in organizations by computers is a major field of research of the Information Systems discipline. As progresses were made in artificial intelligence (AI), scientists suggested to increase the impact of management support by incorporating AI tools that can be applied to weakly structured, knowledge-rich, non-quantitative decision domains (Simon, 1987). This idea led to the emergence of intelligent decision support systems (iDSS) as a sub-discipline of decision support systems (DSS) research. A particular technology used within iDSS research is *machine learning* (ML), which allows DSS to obtain new knowledge or to adapt to the user or changing environment.

Whilst there are several meta-studies analyzing the DSS field of research in general and some sub-fields like Group DSS and Negotiation Support Systems, only little work has been done to study the application of ML in DSS. Prior studies incorporate several ML techniques in a DSS and assess them by using metrics for prediction quality or prediction costs. A deeper qualitative investigation about the design factors is missing so far. For bridging this gap, we examine publications in selected outlets of the DSS community over the last 20 years to gain knowledge about ML applied to DSS, their contributions to DSS and the design factors of the applications. The design factors address in particular the supported phases of decision making (Simon, 1960) by ML and the contribution of ML to decision support. We also examine the literature for the evaluation methods used. Was it done observational, analytical, experimental, descriptive or by testing? This study is exploratory and interpretative in nature and our main research questions are as follows:

RQ1: What ML technology is applied to aid decision support?

RQ2: What ML technology is applied in the different phases of decision-making?

RQ3: What ML technology is applied in the different application domains?

RQ4: What are the contributions and limitations of ML to decision support?

RQ5: What are the evaluation methods used?

The remainder of the paper is as follows. In section 2, we provide an overview of the theoretical background of ML incorporating DSS and discuss prior studies. In section 3, we introduce our research method and design, including the identification of the research sample. In section 4, we present the results of our study, followed by a discussion in section 5. Then, we conclude the paper.

2 Theoretical Background

In this section we discuss the evolution of DSS, the foundations of ML, and prior surveys relevant to our research questions.

2.1 Decision Support Systems

The emergence of the DSS research stream is based upon the idea of using computers for supporting decision-makers (Bonini, 1963). The work of Gorry and Scott Morton (1971) is one of the foundations of the DSS academic area. In their work, they introduced a framework for managerial decision-making support by combining Simon's model of decision-making (Simon, 1960) and Anthony's categories of management activity (Anthony, 1965). The definition they provided for the term DSS as *systems supporting decision-makers in semi-structured or unstructured decisions* is widely used today, as well as the application of Simon's model of decision-making (Arnott and Pervan, 2007). In the following decades, DSS research diverged to a multidisciplinary field comprising mainly Information Systems, Operations Research, Decision Theory, and Organizational Studies.

Since Simon suggested to incorporate AI tools in DSS in the 1980s, AI researchers joined the DSS research community clarifying its multidisciplinary character. This heterogeneity led to the emergence of numerous DSS approaches, all focusing on different aspects of managerial decision-making. In literature, a multitude of DSS sub-classes are distinguished, including Group DSS, Negotiation Support Systems, Knowledge Management based DSS, and iDSS. In addition, related concepts like Expert Systems, Business Intelligence or Data Warehousing are often subsumed under the DSS field of research as well (Arnott and Pervan, 2005).

Much of recent development and research is done in the Model Based Management Support. This sub-field of DSS research incorporates AI, knowledge and models for judgment and decision. It is supposed that these developments lead to flexible, adaptive DSS and reduce the effort needed in developing the knowledge base – a time and cost intensive process in DSS development.

2.2 Machine Learning

AI researchers have developed numerous ML techniques that can be classified in several ways. One taxonomy differentiates learning principles that infer from the particular to the general (inductive learning) from those applying a general rule to particular instances (deductive learning), and inferring from particular cases to other particular cases (transductive learning). Most ML techniques are based on inductive learning and infer general concepts from example data.

ML techniques can also be classified by the amount of inference required in the reasoning process to obtain new knowledge. The range spans from simple memorizing of facts that doesn't require any inference at all (rote learning) over learning performed by instruction, by analogy, and by examples to learning by observation with increasing need of inference (Carbonell et al., 1983).

Another commonly used taxonomy is based on learning paradigms. Learning can thereby be achieved by using training data that has been prior labeled by domain experts (supervised learning), by using unlabeled data (unsupervised learning), a mixture of both (semi-supervised learning), and by some kind of rewarding system, which strengthens solution strategies leading to good decisions and weakens those leading to inferior decisions (reinforcement learning). For example, classification methods like support vector machines (SVM) are based on supervised learning while clustering techniques (e.g. the k-means algorithm) are based on unsupervised learning. Reinforcement learning is often applied in robotics and software agents.

All these different types of ML techniques with their strengths and weaknesses are applied in different fields of application. Until recently, literature has informed only little about strengths and weaknesses of different ML techniques and their impact on DSS.

2.3 Prior Surveys

There are several reviews of DSS research publications. A comprehensive review addressing the DSS field in general is Eom's series using a bibliometric approach for investigating the intellectual structure of DSS research and DSS applications. The series covers more than 980 articles published between 1971 and 2001. As one of the results, Eom identified the reference disciplines of DSS research and the contributions of cognitive science and AI to DSS (Eom, 2008). Another review series uses content analysis in overall reviews of the DSS field of research. The authors analyzed 1,146 articles published from 1990 to 2005 in terms of DSS research, regarding the underlying methodical and theoretical foundations and the application of Design Science Research (DSR) in DSS development. The results reveal that almost half of the investigated articles do not refer to judgment and decision-making literature at all (Arnott and Pervan, 2007).

Many other recent surveys don't consider the overall DSS research area, but focus on distinct research streams. Reviews investigating the iDSS and knowledge based DSS (KBDSS) research streams are related most closely to our work. A study analyzing the application of KBDSS in financial management confirms the usefulness of applying domain knowledge to DSS and concludes with the suggestion to combine KBDSS with techniques of the field of AI to increase the effectiveness of decision support (Zopounidis et al., 1997). A review of iDSS application published in 2005 concludes that the employment of ML in DSS seems to be growing in importance, but there are still too few applications (Mora et al., 2005).

Further information concerning the application of ML in DSS can be found in surveys assessing ML techniques applied to DSS. In assessments of classification methods without the usage of domain knowledge, SVM performed better than artificial neural networks (ANN), naïve Bayes and decision tree learning methods. With usage of domain knowledge, the SVM was outperformed by the other techniques (Sinha and Zhao, 2008), (Delen, 2010). Also, assessments revealed that ensemble methods dominate the individual ML techniques they are conducted of (Polikar, 2006), (Delen, 2010). Assessments concerning different types of ANN models for application in decision-making support confirm the suggestion that ANN can always be used to improve decision-making (Hill and Remus, 1994). Although, the performance (e.g. error-rate) of the different models depends on the task and the amount and type of the used data (Etheridge et al., 2000).

A selection of prior literature reviews and surveys relevant to this paper is presented in Table 1. The research work is classified by the research stream the reviewed literature is located to (e.g. iDSS), the object of research of the review (discipline or applications) and the research method applied in the review (e.g. content analysis). Reviews that focus on the DSS discipline examine the literature for the research methods used, reviews that focus on applications examine the proposed artefacts.

Investigated Research Stream	Research Focus	Research Method	Research
DSS General	Discipline	Bibliometric	(Eom et al., 1993), (Eom, 1996), (Eom, 1999)
DSS General	Discipline	Content Analysis	(Arnott and Pervan, 2005), (Arnott and Pervan, 2007), (Arnott et al., 2007), (Arnott and Pervan, 2012)
DSS General	Application	Bibliometric	(Eom and Lee, 1990), (Eom, 2004)
DSS General	Application	Content Analysis	(Eom and Kim, 2005)
iDSS	Discipline	Conceptual Research	(Mora et al., 2005)
KBDSS	Application	Survey	(Zopounidis et al., 1997)
ML	Application	Survey	(Delen, 2010), (Etheridge et al., 2000), (Hill and Remus, 1994), (Sinha and Zhao, 2008)

Table 1: Prior studies on the DSS field of research

The review of related work revealed that the literature provides evidence for the usefulness of ML techniques in DSS, but insufficiently informs about the factors that impact the usefulness of ML incorporated DSS.

3 Research Method

We applied a literature review that follows the content analysis method of Weber (1990). Therefore, our research approach consists of three major phases: development of a review protocol, literature selection, and the review by applying the review protocol. Literature selection was performed in three steps, namely selection of the appropriate outlets, searching for potentially relevant articles with a defined search string, and manual selection of the articles relevant to our work. The overall process is illustrated in figure 1.



Figure 1: Our research process

Our review differs from prior work as we focus on a very specific sub-field of DSS research, namely the application of ML to DSS. Expert Systems, Business Intelligence, and other approaches similar to DSS are not taken into account. This allows us a more specific research than studies concerning DSS research in general.

3.1 Review Protocol

The review protocol covers four aspects that address our research questions. In the following, the four aspects are presented and described briefly.

3.1.1 What ML Technology is applied?

The research field of AI knows several ML techniques. The primary task was to examine what ML techniques have been applied to decision support. Furthermore, in combination with the results gained from the next two aspects, we investigate the means-end-relation of the application of ML techniques to aid decision support.

3.1.2 What Decision-Making Phases are supported by ML?

Simon's model of decision-making knows three phases in the decision-making process: *intelligence*, *design* and *choice* (Simon, 1960). Intelligence consists of recognizing and formulating the problem or situation that calls for a decision. Based on the problem, the alternatives are developed in the design phase and then evaluated in the choice phase for choosing the best suiting alternative. In a later work, he extended the model by the fourth stage *implementation* (Simon, 1997). ML may support a DSS in one or more of these stages. Because DSS are not supposed to implement decisions but to support a decision-maker, the original three phase model is used in this work. This aspect gives a suggestion about what phase is suitable to be supported with ML and the ML technique that is appropriate for a particular decision-making phase.

3.1.3 What are the Application Domains of ML aided DSS?

Much of the work has been done in 3rd party funded research projects and is therefore often limited to specific domains. We wanted to gain knowledge about the domains that seem to be appropriate for incorporating ML in decision support and if there is a relation between particular ML techniques and domains.

3.1.4 What are the Contributions of ML to Decision Support?

Learning in general is mainly performed in two ways: knowledge acquisition and skill refinement. Thus, ML contributes to DSS in two major realms: through supporting the acquisition and refinement of problem-solving knowledge and solution strategies, and through enabling DSS to adapt and evolve to be more efficient and effective in decision-making support (Shaw, 1993). With this aspect we gained knowledge for investigating which ML techniques are used for knowledge acquisition and for the ability to adapt. Furthermore, it revealed the focus and advancements of the research over the last 20 years in aiding decision support with ML but also revealed limitations of prior research. We also examined the articles for the reported advantages and limitations of the proposed approaches. This knowledge allowed us to draw implications for future research in DSS.

3.1.5 What are the evaluation methods used?

IT artifacts have to be evaluated for their utility, quality and efficacy (Hevner et al., 2004). Evaluation methods have to be selected with respect to the artifact and relevant evaluation metrics. Hevner et al. (2004) suggest to evaluate the artifact observational (in a case study or field study), analytical (by static analysis, architecture analysis, optimization, or dynamic analysis), experimental (in a controlled experiment or simulation), by testing (functional or structural), or descriptive (informed argument or scenarios). We examined the evaluation section of the articles for information about the applied evaluation methods, in some cases the information is also provided in the results and discussion sections.

3.2 Literature Selection

The literature selection phase consisted of four steps: identifying the appropriate outlets, deriving the term used for searching in the journals and proceedings, performing the search to find potentially relevant articles, and manually examining these articles for relevance.

The literature sample comprises articles published from 1994 to 2013 in major outlets of the DSS research community. The selection of the outlets relevant to our work was conducted by using journal rankings in the first place. Researchers suggest to use journal rankings to base literature analysis on

high quality research (Levy and Ellis, 2006). We merged the journal rankings of AIS¹, SCImago² and VHB³ and took only journals under consideration that publish research related to DSS. This method is applied in order to ensure the identification of high quality outlets and to take into account that journal rankings should not be considered to be exhaustive. Furthermore, merging the results of several rankings decreases the impact of subjectivity a single ranking may suffer of. To ensure that the major DSS journals are taken into account, the occurrence of the term ‘decision’ in a journal’s title led to the inclusion of the journal even when it is not listed in a ranking. We also considered the proceedings of the ICIS and the ECIS as two major IS conferences.

In a second step, we conducted a search in title, abstract, and keywords to identify relevant articles. Therefore, the search query considers the decision support component as well as the systems’ ability to learn and takes into account term combinations as well as known synonyms and abbreviations. The resulting search term is as follows:

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(intelligent OR intelligence OR smart OR AI OR 'machine learning' OR
knowledge) AND (DMSS OR DSS OR decision AND (support OR aid)) OR iDSS OR
iDMSS OR KDSS OR KDMSS
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The search for this query in the top fifteen journals of our ranking led to 311 results, published in 13 outlets. We analyzed title and abstract of all articles manually to limit the base of potentially relevant literature. We only considered articles that applied ML to DSS. In a last step, we applied our review framework on the remaining articles to conduct our review. At the end, 52 articles remained that concern the application of ML for decision support and thus are relevant for our work. These articles are published in the outlets Information Systems Research (1), Decision Support Systems (33), Decision Sciences (5), Journal of Management Information Systems (3), Management Science (4), ICIS Proceedings (3), and ECIS Proceedings (3). This distribution illustrates what outlets are important for the DSS sub-field of research concerning the application of ML techniques.

4 Results

In this section, we present the results of our literature review. The structure of this section results from the review protocol as presented in section 3.1 and thus directly addresses our four research questions.

4.1 Applied ML Techniques (RQ1)

Seven major learning techniques have been identified: ANN, SVM, Evolutionary Algorithms (EA), Decision Tree Learning (DTL), Bayes Learning (BL), Case Based Reasoning (CBR), and Pattern Recognition (PR). Table 2 summarizes the occurrence of the single ML techniques in absolute and relative frequencies. Because the authors of some articles have applied several ML techniques in one approach, the sum is greater than the sample size.

	ANN	SVM	EA	DTL	BL	CBR	PR	Others	Σ
Abs. freq.	22	6	12	7	3	5	3	14	72
Rel. freq.	30.6%	8.3%	16.7%	9.7%	4.2%	6.9%	4.2%	19.4%	100.0%

Table 2: ML techniques applied to DSS

¹ <http://ais.site-ym.com/?JournalRankings>

² <http://www.scimagojr.com/journalrank.php>

³ <http://vhbonline.org/service/jourqual/jq2/>

The majority (33 articles) applies supervised learning strategies. 12 articles use an unsupervised learning strategies and four articles apply reinforcement learning. Three articles use semi-supervised learning, an approach that combines supervised and unsupervised learning.

In 13 articles (25.0%), multiple ML techniques were applied in combination. Reasons for combining several methods are for instance to improve the learning process (reducing misclassifications, or overfitting) or to provide learning abilities in multiple areas of decision-making. The most frequently used combination of ML techniques is ANN combined with EA, applied in 46.2% of all combining approaches, respectively in 11.5% of all articles. In three articles, ANN have been combined with DTL.

4.2 The Phases of Decision-Making Supported by ML (RQ2)

According to Simon's decision-making model, a DSS can support decision-makers in one or more of the three phases of the decision-making process. Thus, ML techniques can aid DSS in these phases to improve the provided decision support. Table 3 depicts the number of articles supporting one or more of the three phases of decision-making.

Phase	Number of articles (N=52)				Σ
Intelligence	13 (25.0%)	12 (23.1%)	-	5 (9.6%)	30 (57.7%)
Design	10 (19.2%)		11 (21.2%)		38 (73.1%)
Choice	1 (1.9%)	-			17 (32.7%)

Table 3: Combinations of the phases supported by ML

The relation between the applied ML technique and the supported phase is presented in Table 4. The results show, that ANN and EA are favored to support DSS, independently of the phase. Besides these two techniques, the intelligence phase is often supported by DTL and SVM. Other popular ML techniques are CBR, DTL, and SVM for the design phase, and CBR and SVM for the choice phase. The only technique never used in one phase is DTL.

ML Technique	Intelligence		Design		Choice	
ANN	11	25.6%	15	30.6%	7	26.9%
SVM	4	9.3%	4	8.2%	3	11.5%
EA	7	16.3%	9	18.4%	6	23.1%
DTL	6	14.0%	4	8.2%	0	0.0%
BL	2	4.7%	2	4.1%	1	3.8%
CBR	3	7.0%	5	10.2%	5	19.2%
PR	1	2.3%	3	6.1%	2	7.7%
others	9	20.9%	7	14.3%	2	7.7%
Σ	43	100.0%	49	100.0%	26	100.0%

Table 4: Phases of decision-making supported by ML

4.3 Application Domains of ML-Aided DSS (RQ3)

Three major application domains can be identified. The financial domain was addressed most frequently, followed by manufacturing and retail. 36.5% of the applications are distributed over other domains and 21.2% of the articles doesn't address any domain. The results as presented in Table 5 show that ANN have been applied most frequently in general work, followed by financial and retail applications. In comparison to the overall distribution, ANN is more often applied in retail, SVM in finance, and EA in manufacturing applications.

ML Technique	No Domain (N=11)		Financial (N=10)		Manufacturing (N=7)		Retail (N=5)		Others (N=19)		Overall (N=52)	
ANN	5	35.7%	4	30.8%	2	22.2%	4	50.0%	7	25.0%	22	30.6%
SVM	1	7.1%	2	15.4%	1	11.1%	0	0.0%	2	7.1%	6	8.4%
EA	3	21.4%	1	7.7%	3	33.3%	0	0.0%	5	17.9%	12	16.7%
DTL	0	0.0%	1	7.7%	1	0.0%	2	25.0%	3	10.7%	7	9.7%
BL	1	7.1%	0	0.0%	0	0.0%	0	0.0%	2	7.1%	3	4.2%
CBR	0	0.0%	1	7.7%	1	11.1%	0	0.0%	3	10.7%	5	6.9%
PR	0	0.0%	1	7.7%	0	0.0%	0	0.0%	2	7.1%	3	4.2%
others	4	28.6%	3	23.1%	1	11.1%	2	25.0%	4	14.3%	14	19.4%
Σ	14	100.0%	13	100.0%	9	100.0%	8	100.0%	28	100.0%	72	100.0%

Table 5: Domains of application for ML-aided DSS

4.4 The Contributions of ML to DSS (RQ4)

ML contributes to DSS in two major areas: knowledge acquisition as well as evolving and adaption. As shown in Table 6, in most of the articles, ML contributes to knowledge acquisition and to knowledge acquisition in combination with adaption and evolvement. Contributions to only adaption and evolvement are scarce.

Contribution	Number of articles (N=52)		Σ
Knowledge acquisition	34 (65.4%)	15 (28.8%)	49 (94.2%)
Adaption	3 (5.8%)		18 (34.6%)

Table 6: Contribution of ML on DSS in the articles

The results presented in Table 7 show the frequency of the application of a ML technique to the two realms of DSS. For both tasks, knowledge acquisition and adaption and evolvement, ANN and EA are the most frequently applied ML techniques. The application of ML to both DSS realms in 15 articles (see Table 6) explains why the sum of the columns are higher than the number of applications of this ML technique as presented in Table 2, and also why the sum of the results of both task areas (bottom line) is higher than the sample size.

ML Technique	Knowledge acquisition		Adaption	
ANN	22	31.9%	7	28.0%
SVM	5	7.2%	2	8.0%
EA	12	17.4%	6	24.0%
DTL	7	10.1%	0	0.0%
BL	3	4.3%	1	4.0%
CBR	5	7.2%	3	12.0%
PR	3	4.3%	2	8.0%
others	12	17.4%	4	16.0%
Σ	69	100.0%	25	100.0%

Table 7: The different ML techniques and the DSS realm they contribute to

We also examined the articles for the advantages and limitations of their proposed ML-approach. Many articles report higher effectiveness in their task, compared to non-ML approaches. Dependent on ML technique or task, higher effectiveness hereby refers for example to more accurate forecasts, more generalizable models or less classification errors. Further advantages have been achieved by the time that is needed for a specific task. This is as well for the run time as for the design and implementation of a DSS. Especially the latter case has a huge impact on DSS application, because the acquisition of domain knowledge is a heavy time consuming task in the design of a DSS. Table 8 summarizes the reported advantages with exemplary contributions.

Advantages	Example Contributions
Higher effectiveness than non-ML approach	(Anandarajan, 2002), (Caporaletti et al., 1994), (Das and Gosavi, 1999), (Hagenau et al., 2013), (Spangler et al., 1999)
Higher efficiency than non-ML approach	(Dahal et al., 2013)
Higher degree of automation	(Singh et al., 2006), (Subramania and Khare, 2011)

Table 8: Advantages of ML in DSS

But these advantages are countered by some limitations. For some cases, the ML approaches could not achieve higher effectiveness than these without ML, one article reports about lower effectiveness (Dutta, 1994). It also has to stay in mind, that the advantages reported above may be limited to the problem solved by ML and the case used for evaluation. While technical aspects of the application of ML to decision support like accuracy, classification errors, or computing speed have been reported broadly, the organizational and personnel implications are. Example contributions for this limitations are summarized in Table 9.

Limitations	Example Contribution
Lower effectiveness than non-ML approach	(Dutta, 1994), (Viktor et al., 2000)
Vast amount of domain knowledge or training data needed	(Bohanec and Zupan, 2004), (Chan and Franklin, 2011)
Human assistance was needed to improve ML	(Bohanec and Zupan, 2004), (Viktor et al., 2000)

Table 9: Limitations of ML in DSS

4.5 Evaluation Methods (RQ5)

Our results show that in every article except of one the presented artifact has been evaluated. The most frequently applied evaluation method is simulation, which was reported in 78.8% of the articles. Table 10 depicts the distribution of the evaluation methods in the literature base. The reason that the absolute frequency sums up to 53 is that in one article two evaluation methods are applied, controlled experiment and informed argument.

Evaluation Method		abs. freq. (rel. freq.)	
Observational	Case Study	3 (5.8%)	3 (5.8%)
	Field Study	0 (0.0%)	
Analytical			0 (0.0%)
Experimental	Controlled Experiment	3 (5.8%)	44 (84.6)
	Simulation	41 (78.8%)	
Testing			0 (0.0%)
Descriptive	Informed Argument	3 (5.8%)	5 (9.6)
	Scenario	2 (3.8%)	
None			1 (1.9%)

Table 10: Evaluation Methods

5 Discussion

This study aims at a better understanding of ML application in DSS. The main findings provide evidence that ML is mostly used in the design phase of decision-making to support the acquisition and refinement of knowledge. ANN is the most frequently applied technique either with or without a combination with other techniques. ML is most commonly used in DSS in financial services, manufacturing, and retail as the application domain. Advantages of ML in DSS are higher effectiveness and the reduction of manual work. On the other side, vast amount of domain knowledge and training data may be needed. ML in DSS is mostly evaluated by simulations.

5.1 Contributions

Our research makes two specific contributions to the DSS knowledge base. At first, we report about the trends and state of the use of ML techniques in DSS and IS outlets. We provide insights about the applied techniques, their combinations, the application domains, the supported phases of decision-making, the advantages and limitations of different approaches as well as the applied evaluation methods. While prior studies mainly investigated technical aspects of ML in DSS, this work focuses on non-technical aspects to support researcher and practitioners with knowledge about seminal trajectories of iDSS research.

Beyond this, we identified the current gaps in the literature regarding the evaluation methods used to provide evidences for the efficacy of ML techniques. While past research made important progresses in strengthen technical criteria like precision and recall, we put our focus on evaluation methods to identify a current gap between technological, organizational and people-related issues in evaluation. We found that none of the articles has directly attempted to these issues. This is in particular remarkable since it is well understood that decisions are biased by psychological and social factors (Chen and Koufaris, 2014).

5.2 Implications

These aforementioned unexplored questions provide fertile ground for future research and the potential to make further contributions to research and practice. A major challenge facing researchers in this important area is to include organizational and people-related issues in addition to technical evaluation metrics. Thus, we encourage future research at this levels of analysis. As well as having an impact on researchers, this paper highlights implications our findings might have for practitioners.

What ML Technology is Applied to Aid Decision Support?

Based on our survey, ANN is the most frequently applied technique followed by EA. Advantages of ANN are the ability to find also non-linear relationships between independent and depended variables and the availability of multiple training algorithms. Drawbacks are the computational requirements and their behavior as black boxes. It is not easy to reproduce how a particular outcome had been generated. This may be a problem in cases where not only a decision but also the explanation for this decision is needed. ANN rule extraction algorithms may overcome this drawback (Baesens and Setiono, 2003). Our results reveal that every application of EA is in combination with other ML techniques, mostly with ANN. This can be explained by the functioning of EA as search heuristics that are inspired by the evolution and the mechanism of the survival of the fittest. In such cases, EA improve the learning process by generating several models and determining the best fitting one. The application of EA as a single strategy for learning is supposed to be exotic.

These findings can guide future studies in two different ways. At first, it shows the need to study the effects of other – so far understudied – ML techniques on DSS. Secondly, it informs IS research what ML techniques are commonly applied or combined in iDSS. This insight helps to underpin research design and methodology for studying organizational and people-related issues in iDSS.

In practice, a fundamental question for iDSS engineers is, what ML technique are the most mature ones. Our study informs practitioners, which techniques are comprehensively studied in the scientific DSS literature to gain knowledge about what techniques may be suitable for their problem in general. For cases where labelled data for training a supervised ML approached is scarce, unsupervised ML seems to be a promising approach (Wang et al., 2012).

What ML Technology is Applied in the Different Phases of Decision-Making?

Our results show that the design phase of decision-making is most frequently supported by ML, followed by the intelligence phase and then choice (see Table 3). We suppose phases differ in their requirements concerning the supportive techniques. Also, the three phases are based upon each other. ANN and EA are both the mostly applied ML techniques in every phase.

In the intelligence phase the environment is scanned for changes in the situation that may require some kind of intervention. The problem is then formulized as a preliminary work for the next phase. ML techniques may support in both tasks of this phase, although problem formulation is said to be challenging for the supporting technique (Espinasse, 1994). Besides ANN and EA, SVM and DTL seem suitable to be supportive in this phase.

The design phase deals with the formulation and analysis of the decision models. As this models are the basis for decision-making, the design phase plays a big role in decision support. 97% of the support is done in the model formulation and only in 18.2% model analysis is supported. CBR and SVM are two ML alternatives for the ANN and EA combination.

The reason for choice as being the less supported phase in the examined literature may be grounded in two aspects: first, in this phase of decision-making, the choice of the best alternative is just calculated by executing the model developed in the design phase (i.e. the most work is already done) and second, the ‘philosophy’ of decision support systems is to provide the decision-maker with the information needed to carry out the decision and not to take away that work for him. Also, presenting a single alternative to the decision-maker as the best one may be considered as biasing him. Our result that there is only one approach that applies ML to support the choice phase without supporting any of the other phases confirms the first assumption. The second assumption is supported by the result that also in combinations with other phases, choice is supported by ML more or less infrequently. As in the design phase, CBR and SVM are the more often employed ML techniques.

Our literature base does not provide detailed information regarding the underlying set up of the decision problem. Thus, literature is silent about the unit of observation (single person decisions or group decisions) and the concrete class resp. framing of the decision problem (e.g. purchase decisions). In a more general way, we therefore used Simon’s model of decision making in order to cluster different

approaches. This may guide future study designs to investigate the impacts of iDSS in different decision phases. It also informs decision makers in practice in which phases they can expect to be supported by ML techniques and which techniques are well studied for supporting a certain phase.

What ML Technology is Applied in the Different Application Domains?

Our results show that most applications were done in the domains financial, manufacturing, and retail. For ANN there is a peak of application in the retail domain, for SVM in finance, and for EA in manufacturing. Further relations between particular ML techniques and the domains of application could not be identified. This result may indicate that the identified domains as well as the ratio of the different domains is due to our journal selection and very specific scope. But it also suggests that ML is applied in domains with highly structured time series like stock prices, throughput times etc. DSS scientists may benefit from these insights as they reveal understudied domains of applications. Opportunities to extend current research are seen in studying the implications as well as the technical characteristics (e.g. accuracy) of other ML techniques in these application domains or the application of ML in other domains. When studying organizational and people-related issues in iDSS, our findings can be useful to define framings for concrete decision problems like stock picking decisions (financial domain), production planning and scheduling decisions (manufacturing) or the product proposal (retail).

Our findings may serve as a guide for practitioners to answer the question, which ML technique holds a high degree of maturity in a certain domain of application. We show, that ML is well studied in finance, manufacturing, and retail. We suppose, that this is due to the well-structured time series in these domains of application.

What are the Contributions and Limitations of ML to Decision Support?

Our results show that most of the ML techniques are applied to acquire and refine knowledge as the basis for decision-making support. This can be explained with the high effort that is needed to build a knowledge model manually by domain experts. In only 34.8% of the investigated articles, ML techniques are (at least) used for enabling the DSS to evolve or to adapt to the environment or to the user. This gap is due to the fact that adaption and evolution of the DSS requires knowledge. The adaption process can be increased, if the knowledge acquisition process is also supported by ML techniques. This is confirmed by the result that 81.3% of the articles that apply ML techniques to support adaption and evolution of the DSS, ML also supports the acquisition of knowledge.

The results in Table 7 show that in both tasks, knowledge acquisition and adaption ANN and EA are the most frequently applied ML techniques. Also in articles that combine ML techniques, ANN and EA are most frequently applied ensemble. One of the three articles that only address adaption but not knowledge acquisition applied SVM, another one maximum likelihood learning, and the last one some kind of preference learning that has not been described in detail.

The examination of the advantages and limitations showed, that ML often increase the accuracy in forecasting and prediction what makes them attractive for decision support. The application of ML also effects the reduction of manual work. On the other side, it is reported that ML also results in the needs for acquiring vast amount of domain knowledge.

We report about advantages and limitations of ML in DSS. A future opportunity to extend our research is to shed more light on the factors influencing the advantages and limitations of different ML approaches. For practitioners, our results provide a guide to the literature to extract engineering knowledge for enhancing ML performance.

What are the Evaluation Methods Used?

Our survey shows that simulation is the evaluation method at hand when it comes to demonstrate the efficacy of the proposed artifact. This may be grounded on the scientific procedure to choose an evaluation method applicable to the evaluation metrics. ML is located in AI research, where efficacy of an artefact is commonly demonstrated by technical metrics (e.g. accuracy). Computer-based simulation provides an appropriate tool for examination artifacts for these metrics. However, when it comes to the development and implementation of a DSS in an organization, the matter of methods from IS research

increases. Whilst there are studies that examine the person-related and organizational factors affecting the usefulness of DSS in organizations, the psychological aspect of ML incorporating DSS is still understudied.

Our findings suggest that after the technical aspects of the application of ML in DSS are well understood, future research should broaden the scope on the effects, iDSS may have in organizational and people-related aspects. Evaluation methods that cover these exigencies, like controlled experiments, case studies (in the meaning of examine the artefact within the organizational context) and field studies provide a fertile ground to contribute to the iDSS knowledge base.

5.3 Limitations

While this article provides insights in trends and current use of ML in iDSS, our work suffers from a number of limitations. Presently, our study is quite descriptive and we provide only little explanations, why different ML techniques are used in different combinations, decision phases and application domains. A key contribution of this research is that the current body of literature lacks in studying organizational and people-related issues in evaluation. Up until recently, our literature basis do not provide evidence for building up a comprehensive cause and effect model for this purpose.

Our focus on DSS within the literature selection is very specific, limiting the scope of relevant work and resulting in a rather small literature base. The scope of our study and thus the literature base could be extended by taking other enterprise information systems into account, e.g. business intelligence, expert systems. For getting more insights in the relation between the domain of application and ML techniques used, outlets of specific domains could be taken into account, for instance information systems in healthcare.

6 Conclusion and Outlook

This paper investigates the use of ML for the design of DSS. Specifically we focused on the factors of ML design that may affect the usefulness of a DSS. We identified 52 articles that have been published in major DSS outlets between 1994 and 2013 as relevant to our work by manual examination. As a result we got a better understanding about the relations between the purpose of the DSS, the contribution of ML to the DSS, and the ML technique that is applied. We suggest that a careful analysis of these aspects within the design and development of ML-incorporated DSS will affect usefulness of the resulting DSS. As a further finding we revealed that the decision-making phases intelligence and design are mostly supported by ML. Most frequent applied ML techniques are ANN, SVM, CBR and DTL. Our study also confirms prior suggestions that the combination of several ML techniques may lead to higher effectiveness, in particular the optimization of the learning process by the additional application of EA seems to be a promising approach. Main advantages of using ML in DSS are better decision results in a faster way. But ML also requires for vast amounts of domain knowledge or training data sets. The predominant evaluation methods for ML-based DSS is simulation. While most work remains technical literature in its current state is silent about organizational and people-related aspects in evaluation. Thus, this gaps in the literature, provide many opportunities to extend iDSS research.

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