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Abstract

Financial decision support has become an important information systems research topic and is also of highest interest to practitioners. Two rapidly emerging trends, the increasing amount of available data and the evolution of data mining methods, pose challenges for researchers. Thus, a review of existing research with the goal to guide future research efforts in this domain is timely. To structure our literature review and future research in this area, we propose a framework in the paper that integrates elements of decision support systems, design theory, and information mining. The framework is then applied in the paper. Our analysis reveals that the focus of existing research can be grouped into three major domain categories. More research is needed in two of the categories for which we found only very few IS studies, despite the high relevance of these topics due to increased turbulences in worldwide financial markets. Furthermore, we discuss the opportunities to make stronger use of heterogeneous data and of combined data mining techniques and to build upon the rich set of available evaluation methods.

Keywords: Literature Review, Financial Decision Support Systems, Structured Data, Unstructured Data, Heterogeneous Data, Information Mining, Text Mining, Data Mining

1 Introduction

The financial services industry belongs to one of the most knowledge- and information-intensive industries. As a result, there are massive amounts of data available, steadily increasing, which may be used as a basis for financial decision making. For example, nowadays a financial investor can draw upon multiple data sources, including news and rating agencies, the trading venues or newer sources of data such as financial twitter feeds, blogs and other social media content. The challenge is to make effective use of this data to improve financial decision making, for which in practice often a combination of different data types is required. Such heterogeneous data includes both unstructured textual data and structured data such as time series with a structure described in a schema (Arasu & Garcia-Molina, 2003). However, both the amounts of data and analytical challenges overwhelm practitioners, motivating further research.

We explore the contribution that information systems (IS) can make to the domain of financial decision making through the lens of Decision Support Systems (DSS), which represents one of the major research streams in IS research (Banker & Kauffman, 2004). Power (2001) defines DSS as an interactive computer-based system developed to support decision makers to identify and solve problems and make decisions. DSS are needed to cope with the massive amount of available data and enable financial decision making. Therefore, the topic of decision support in the financial domain is of highest practical relevance (Manyika, et al., 2011).

From a scientific perspective, a decent amount of research has been published over the last one to two decades that is directed towards understanding how to design effective decision support systems to support financial decision making. Therefore, we argue that it is time to conduct a systematic review of prior research in this important domain and thereby provide guidance for future research. Our research question is: What is the state of the art of knowledge about financial decision support using unstructured and structured data? Despite the high practical relevance of this topic, there are still important gaps in the literature and a synthesis of prior research is needed to guide further research.

The rest of this paper is organized as follows. In the next section we present our research methodology, including the theoretical framework that we developed. The following discussion of results from our literature review is structured according to this framework. The final section of our paper provides suggestions for future research.

2 Methodology

In this section, we first present our analytical framework. The approach of employing such a framework to structure and guide the literature review is an established approach (e.g., Dibbern, Goles, & Hirschheim, 2004). Thereafter, we explain our process of literature identification, selection, and analysis.

2.1 Analytical Framework

As explained by Markus et al. (2002), DSS represent one of the most prominent types of design theories that has driven an entire research stream in IS research. The concept of DSS originates from the work of Scott Morton (1971). While several definitions of IS design theory exist in the literature (Walls, Widmeyer, & El Sawy, 1992), we use the definition of explanatory design theory provided by Baskerville and Pries-Heje (2010), which defines IS design theory as a set of general components that are related to a set of general requirements with the overall goal of solving a class of problems (see Figure 1).

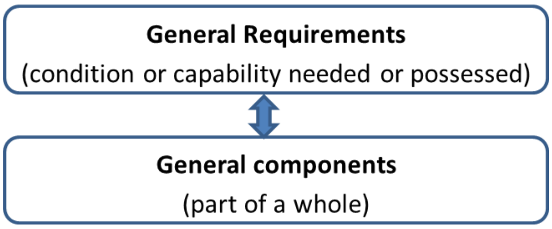

Figure 1: Design theory according to Baskerville and Pries-Heje (2010)

To identify general requirements and components of interest, we utilize the DSS classification framework of Power (2004). We selected Power's extended framework because this is one of the established frameworks to classify DSS Systems. According to this framework, DSS can be first categorised according to their dominant component driver, resulting in five different types of DSS: data-driven, model-driven, knowledge-driven, document-driven, and communication-driven DSS (Power, 2004). In addition to this dominant component driver, there are three additional components in the extended framework: target user (for example individuals, groups and/or departments), the purpose of DSS (for example purpose that helps to support the targeted users) and the enabling technology for the construction of a DSS (see Figure 2).

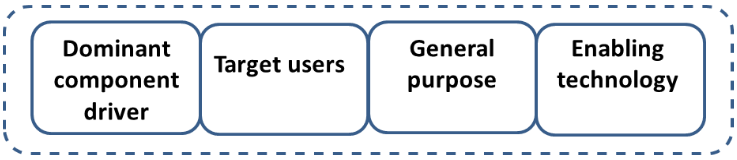

Figure 2: An expanded DSS framework based on Power (2004)

Furthermore, we selected the information mining framework by Gopal et al. (2011), because it presents the state of the art of information mining today. Accordingly, information mining is defined as "the organization and analysis of structured or unstructured data that can be qualitative, textual, and / or pictoral in nature with any set of techniques or methods." (Gopal et al., 2011, p. 728). The framework consists of the following components: data type (for example textual, numerical or graphical data), application area (which could be software engineering, financial engineering, marketing, or other), techniques (for example SVM, neural networks or other data mining techniques), tasks (for example pattern matching and classification) and it consists of the final objective as the output component (e.g., diagnosis, profit) (see Figure 3).

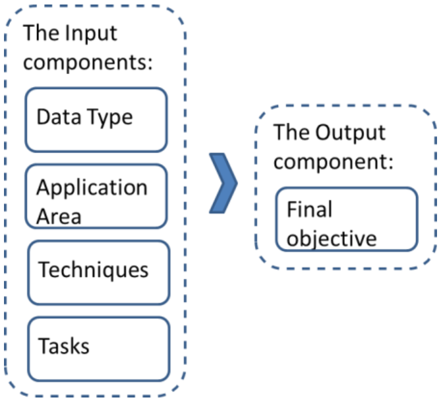

Figure 3: The key components of information mining based on Gopal et al. (2011)

We combined these frameworks (Figure 2 and 3) into a holistic framework by employing the lens of design theory (Figure 1). Accordingly, we structure the components into four categories. First, the problem category (P), which specifies the problem in a domain area and the target user(s), where domain area is taken from the framework of Gopal et al. (2011) and target user is taken from the framework of Power (2004). Second, the requirements category (R), which specifies the purpose(s) according to Power's (2004) framework and the task(s) according to Gopal et al.'s (2011) framework. Finally, the components category (C), which is specified by data and methods according to Gopal et al.'s (2011) framework and by technologies according to Power's (2004) framework. In addition, we complement our framework by an evaluation category (E), based on design science literature that states the importance of evaluating design artefacts and theory (Hevner et al., 2004). Figure 4 summarizes the holistic framework.

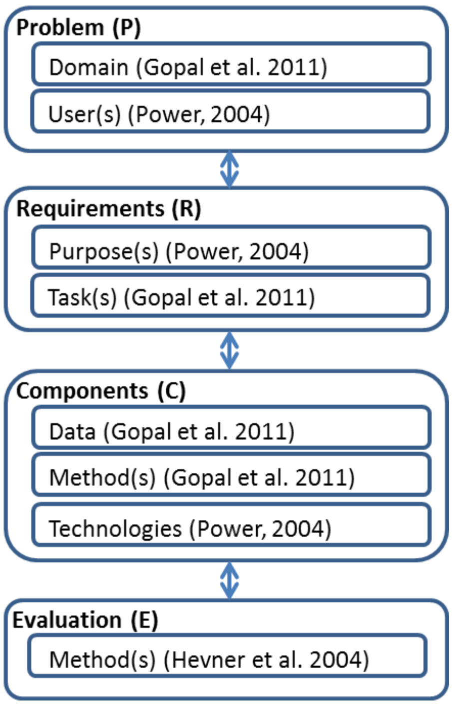

Figure 4: Analytical framework for literature review

Next, we explain our process of literature identification, selection, and analysis.

2.2 Identification Process

As a first step, we identified potentially relevant literature with a structured keyword search in a selection of scientific databases (Brocke et al., 2009; Ferber, 2003). Thereby, we limited our search to international peer-reviewed scientific literature.

To retrieve articles from our keyword search that are potentially relevant for the topic of this literature review, we constructed a Boolean search string based on the components of our framework: 'decision support and financ* and mining'. This search string was used to search in the following databases: EBSCOHOST, ScienceDirect, JSTOR, IEEE Xplore, ACM Digital Library, and AIS Electronic Library. The search yielded 176 articles.

2.3 Selection Process

In the next step of our research process, we reduced the number of articles from 176 to 18. First, we carefully read the titles, abstracts, and selectively the introductory and conclusions sections of the 176 identified papers and removed papers from our list that did not deal with the defined topic, resulting in 17 articles after two iterations. Second, we carefully reviewed the remaining studies and conducted a forward and backward search based on Webster and Watson's (2002) recommendations. The database Web of Science was used for the forward search. The final sample consisted of 18 articles.

2.4 Classification and Analysis Process

To apply and use our framework (Figure 4) for our literature review, we first selectively coded each article. The coding scheme derived from our framework, together with sample quotations from our data, is summarized in the following Table 1:

Code derived from the framework	**Sample quotation from literature analysis**
P_user	P_user: individual investors "…where individual investors represent the target user group of the system…" (Muntermann, 2009, page 83)
P_domain	P_domain: corporate credit rating "Company credit ratings are typically very costly…" (Huang, Hsinchun, Hsu, Chen, & Wu, 2004, page 543)
R_purpose	R_purpose: portfolio selection "We formulate the winner and loser portfolio selection as two binary classification problems." (Huang, Lai, & Tai, 2011, page 20:7)
R_task	R_task: time series forecasting "…provides another promising tool in financial time series forecasting…" (Tay & Cao, 2001, page 340)
C_data	C_data: unstructured "…based on empirical dataset that comprises 425 company announcements…" (Muntermann, 2009, page 84)
C_method	C_method: single and multiple SVM "For each region, one SVM expert is constructed." (Tay & Cao, 2001, page 349)

C_technology	C_technology: "mobile devices and messaging services provide the enabling technology that provide flexible information supply and decision support on the basis of wireless communication technologies." (Muntermann, 2009, page 84)
Evaluation	Evaluation: Evaluation metric "We conduct an experiment to measure the performance of our approach ... the rate of degeneration is slow, and the total overall accuracy drops gradually from 89.09% to 71.34%." (Chan & Franklin, 2011, page 8)

Table 1: Coding scheme, together with examples from our analysis

Coding reliability was achieved through a control of the first author's coding by the co-authors, following by intensive group discussions.

3 Results of Literature Review

In this section, we present the results of our literature review. Table 2 summarizes our coding of the literature. We discuss our analysis results according to the elements of our framework. For example, from our problem domain coding we identified three generic problem domains, which are financial analysis (Table 2, reference number 1 to 12), risk management (Table 2, reference number 13 to 17), and fraud detection (Table 2, reference number 18). Since the problem domain is strongly related to requirements category, we discuss these two together.

Reference	Problem	Requirements	Components	Evaluation
1. Wüthrich, Leung, Permunetillek e, Sankaran, Zhang, & Lam (1998)	P_Domain: Financial analysis P_User: Investors	R_Task(s): Prediction of stock market daily movements of five stock indices R_Purpose(s): Support investment decision	C_Data: Unstructured (articles downloaded from Web) C_Method(s): Probabilistic rules	Evaluation metric: Accuracy between 40-46.7%. (for periods of 3 months) and over 60% (for few weeks)
2. Tay & Cao (2001)	P_Domain: Financial analysis P_User: Investors	R_Task(s): Prediction (currency exchange rates) R_Purpose(s): Support investment decision	C_Data: Structured financial time series (stock index futures, 10/30-year government bonds , given as daily closing prices) C_Method(s): Multiple SVM, single SVM	Evaluation metrics and statistical analysis: Comparison between multiple SVM and single SVM. The multiple SMV method outperforms the single SVM
3. Gidófalvi & Elkan (2003)	P_Domain: Financial analysis P_User: Investors	R_Task(s): Prediction of stock price R_Purpose(s): (Performance) portfolio management	C_Data: Unstructured C_Method(s): Naïve Bayes	Simulation and domain evaluation metric: Average profit per trade
4. Peramunetille ke & Wong (2001)	P_Domain: Financial analysis P_User: Currency traders	R_Task(s): Prediction of intraday currency exchange rate movements R_Purpose(s): Buying of one currency and selling of another-decision	C_Data: Unstructured (market news headlines) C_Method(s): Rule-based algorithm (based on 400 keyword delivered by domain experts)	Simulation and evaluation metric: Accuracy 53% for DEM/US and 3 hours

5. Huang, Nakamori, & Wang) (2004)	P_Domain: Financial analysis P_User: Investors	R_Task(s): Prediction of Index quote R_Purpose(s): Supporting investment decision	C_Data: Structured (NIKKEI 225 Index) C_Method(s): SVM combined with other methods	Evaluation metric: Hit ratio of combined model 75%
6. Pui, Fung, Yu, & Lu (2005)	P_Domain: Financial analysis P_User: Investors	R_Task(s): Prediction of stock price movement R_Purpose(s): Supporting investment decision	C_Data: Unstructured and structured (intraday stock prices and news stories) C_Method(s): SVM	Simulation: Buy and sell decision based on trend forecast Correct prediction if m=5 days is 65.4%
7. Brandl & Keber (2006)	P_Domain: Financial analysis in FX market P_User: Foreign exchange market brokers	R_Task(s): Prediction of EUR/USD-exchange rates R_Purpose(s): Supporting investment decision	C_Data: Structured C_Method(s): Genetic algorithm	Simulation: Outperforms a defined benchmark
8. Muntermann (2009)	P_Domain: Financial analysis P_User: Private investor	R_Task(s): Prediction of stock price movement R_Purpose(s): Supporting investment decision	Unstructured (425 company announcements and corresponding intraday stock prices) C_Method(s): OLS regression, machine learning proposed	Simulation and evaluation metric: Statistical tests to compare supported trader with a random trader
9. Schumaker & Chen (2009)	P_Domain: Financial analysis P_User: Trading professionals	R_Task(s): Prediction of stock price movement R_Purpose(s): Supporting investment decision	C_Data: Unstructured (financial news) C_Method(s): Support vector regression (SVR)	Simulation and statistical analysis: F-measure 85%
10. Tsai & Hsiao (2010)	P_Domain: Financial analysis P_User: Investors	R_Task(s): Prediction of stock price movement R_Purpose(s): Supporting investment decision	C_Data: Structured (financial and macroeconomic variables from the Taiwan Economic Journal Database) C_Method(s): Genetic Algorithm, Decision Tree and Neural Net	Simulation and evaluation metrics: Average accuracy 75.34%
11. Huang, Lai, & Tai (2011)	P_Domain: Financial analysis P_User: Investors, analysts	R_Task(s): Prediction of stock price movement R_Purpose(s): Supporting investment decision	C_Data: Structured (historical stock prices of leading U.S. companies of S&P100 Index) C_Method(s): SVM, AdaBoost	Simulation and evaluation metrics: Accuracy 66.41%
12. Chan & Franklin (2011)	P_Domain: Financial analysis P_User: Investors	R_Task(s): Prediction of financial trend or behaviour R_Purpose(s): Supporting investment decision	C_Data: Unstructured (2000 financial reports) C_Method(s): Decision Tree	Evaluation metrics: Accuracy between 71.34% and 89.1%

13. Huang, Hsinchun, Hsu, Chen, & Wu (2004)	P_Domain: Credit rating P_User: Bond raters	R_Task(s): Prediction of bond rating R_Purpose(s): Supporting Credit rating decision	C_Data: Structured (bond-rating data sets from the US and Taiwan markets) C_Method(s): SVM and Neural Net	Simulation and evaluation metric: Accuracy ~80%
14. Sinha & Zhao (2008)	P_Domain: Credit rating P_User: Domain experts	R_Task(s): Credit rating classification R_Purpose(s): Performance comparison of data mining classification methods incorporating domain experts knowledge	C_Data: Structured (given as years of previous residence, monthly income and payments) C_Method(s): Naïve Bayes, Decision Tree, Neural Net, k-Nearest Neighbour, SVM	Simulation, comparison of methods: Neural net 84.8%, kNN 77.8%, SVM 78.2%
15. Ruggieri, Pedreschi, & Turini (2010)	P_Domain: Credit scoring P_User: Manager	R_Task(s): Classification of potential discriminatory risks R_Purpose(s): Discover and measure discrimination in credit scoring model	C_Data: Structured (transactions representing the good/bad credit class of bank account holders and beneficiary demographics) C_Method(s): Rule-based algorithms	Simulation: Comparison of two inference models on the basis of historical data
16. Groth & Muntermann (2011)	P_Domain: Market risk management P_User: Risk manager	R_Task(s): Prediction or intraday stock price volatilities R_Purpose(s): Trading decision	C_Data: Unstructured and structured (news stories and related stock prices) C_Method(s): Naïve Bayes, kNN, Neural Net, SVM	Simulation and evaluation metric: Best results with SVM 78.49% accuracy
17. Huang & Li (2011)	P_Domain: Market risk management P_User: Investors, accountants	R_Task(s): Extraction of risk factors R_Purpose(s): Risk management	C_Data: Unstructured (risk factors reported in SEC 10-K form) C_Method(s): k-Nearest Neighbour	Simulation and evaluation metric: Accuracy (74.94%) and four metrics for multi-label classifications, search for optimal kNN parameters
18. Kirkos, Spathis, & Manolopoulos (2007)	P_Domain: Fraud detection P_User: Compliance officers	R_Task(s): Analysis of financial statements R_Purpose(s): Detection of fraudulent statements	C_Data: Structured (financial ratios extracted from financial statements of 76 Greek manufacturing firms) C_Method(s): Decision Trees, Neural Net and Bayesian Belief Network	Evaluation metric: classification performance (decision tree 73.6%, neural network 80%, Bayesian belief network 90.3%)

Table 2: Classification of articles

3.1 Problem Domain and related Requirements

We find that past research has addressed three different problem domains, which we discuss separately in the following.

Domain of financial analysis. Research in this domain covers the following tasks: Prediction of stock price movement (eight studies), prediction of exchange rate movements (three studies), prediction of index movement (one study) and prediction of bond ratings (one study). We found that the observed articles focus mostly on unstructured data (eight studies of thirteen). With regards to applied methods, we found that there is no coherency between unstructured data and applied methodology in this problem domain. The reason for this may be situated in the computational complexity of natural language, causing researchers to evaluate different methods in order to find the most appropriate one for the particular task. We also find that coherence between structured data and applied method exist. The most popular method here is the SVM, reasonably because it achieves very good prediction performance when applied to structured data (Huang, Nakamori, & Wang, 2004; Huang, Hsinchun, Hsu, Chen, & Wu, 2004).

Domain of risk management. This domain comprises research of market and credit risk management. Four studies cover one of the following tasks: discriminatory risks detection, extraction of risk factors from disclosures, credit rating, and credit scoring. Two studies are based on structured and two studies on unstructured data. Further, we found no coherency between data and applied methods. This may be explained by the small number of research studies.

Domain of fraud detection. This domain has a focus on the detection of fraudulent financial statements. Since we found only one research study, it is safe to say that research in this category is still in its infants. This finding is noteworthy because of the following reason: Manipulated financial statements are attributed to market abuse and subsequently cause improper/inadequate behaviour of investors (Financial Services Authority, 2012). Despite the financial crisis in the last years, there is lack of academic research about fraud detection and market surveillance. Apparently, there is a lack of understanding of how to detect fraudulent information circulated in the financial domain.

User. Target users of a DSS can either be a member or customer of an organization, including both individuals and groups (Power, 2004). Present studies primarily investigate requirement aspects of financial DSS without explicit involvement of these users. It appears that target user is mostly only mentioned in the present studies and requirements and problem statements have been derived from the literature only.

In the following, we discuss cross-domain findings, according to the components and evaluation categories of our framework.

3.2 Components

Data. The evidence of types of data analysed in the studies shows that recent studies on DSS in finance tend to use unstructured data in form of company announcements, news stories, or text data downloaded from internet sources, including user-generated contents. Including unstructured data into the analysis for improving decision support in finance domains becomes more popular.

	1998	2001	2004	2005	2006	2007	2008	2009	2010	2011
Structured		1	1	1	1	1	1		2	1
Unstructured	1	2		1				2		3

Table 3: Classification of articles by data

Since the beginning of the year 1998, we observe the regular publication of financial DSS related research studies. While between 1998 and 2007 nine relevant articles are published, for the years 2008 to 2011 we count also 9 relevant publications. This finding affirms increased relevance of financial DSS.

Method(s). Our analysis of the applied methods reveals that 11 different data mining techniques have been used in the reviewed research articles. In the next paragraph we briefly discuss the three most frequently applied techniques.

Support Vector Machine (SVM): SVM is the most frequently used data mining technique in our sample. SVM is an algorithm where the classifier is a hyperplane, which separates the feature space into different categories (Witten & Frank, 2005; Feldman & Sanger, 2007). SVM is a supervised learning method, which has been developed by Vapnik and Chervonenkis (1974).

Neural Networks (NN): NN emulate human pattern recognition. It consists of connected neurons, which are able to receive and send impulses to and from its neighbours.

Decision Trees (DT): DT's classifier consists of nodes, where internal nodes are labelled by the features, each having its own weight (Witten & Frank, 2005). The documents are categorized starting by the root node and moving to the leaves, which are the classes of the document (Feldman & Sanger, 2007). The following Table 4 summarises all methods applied in the studies with Probabilistic Rules (PR), Rule Based (RB), Mean Absolute Abnormal Return (MAAR), Naïve Bayes (NB), Bayesian Belief Networks (BBN), Genetic Algorithm (GA), k Nearest Neighbour (kNN), and Support Vector Regression (SVR), apart from the above discussed SVM, NN, and DT.

	1998	2001	2004	2005	2006	2007	2008	2009	2010	2011
Method(s)	PR	NB, RB, Multiple SVM, Single SVM	SVM, NN	SVM, SVM Combined	GA	DT, NN, BBN	NB, DT, NN, kNN, SVM	MAAR,SVR	RB, combination of NN, DT, and GA	SVM, DT, kNN, NB, NN

Table 4: Classification of articles by applied data mining techniques

Our analysis reveals that for decision support in financial analysis, the combined methods applied on structured data delivers promising results. In the research of Tay & Cao (2001) it was shown that a SVM combined with a self-organizing feature map (SOM) outperforms a single SVM by 0.25%. These research findings are consistent with the results of another study (Huang, Nakamori, & Wang, 2004), in which increased accuracy is reached by applying SVM with other methods including a neural networks.

Technologies. We find that a great majority of the selected papers do not provide information regarding the underlying technologies. This observation can be explained by the fact that most studies do not present an artefact instantiation (i.e. prototype), but mainly forecasting on classification models.

3.3 Evaluation Methods

All reviewed papers present an evaluation that has been conducted either on the basis of evaluation metrics (e.g. accuracy, precision and recall) or on the basis of a simulation (which may incorporate evaluation metrics allowing comparisons with alternative designs). This observation is noteworthy since the design science literature presents a rich set of design evaluation methods, including both qualitative (e.g. case studies and controlled experiments) and quantitative methods (e.g. optimization or simulation). Consequently, none of the papers observed the contribution's performance within its original organisational context.

4 Implications for Further Research and Conclusion

In this study we analysed the state of the art of financial decision support systems. As a conceptual basis for this, we developed a framework, which consists of four major categories. The analysis results confirm the applicability of our framework and suggest directions for future research along the examined categories:

Problem and related requirements. Future research might focus on those domains that remain underexplored. Compared to the field of financial analysis we found only a very limited number of studies in the risk management and fraud detection domains. Considering the financial crises of recent years, these two domains appear highly relevant. Future research in these fields could also build upon domain expert knowledge or the increasing amount of unstructured user-generated contents.

Components. While the use of structured data in DSS in the financial analysis domain has been extensively utilised, the exploitation of unstructured data in order to provide decision support is still very limited. The reason may be situated in the complexity of natural language as a computational problem (Burger & Du Plessis, 2011). Accordingly, more research in computational intelligence is needed. Next, we found that the decision support of risk management might need more research in order to refit the organisations in the endeavours of managing the risk using both structured and unstructured data available to the company. These findings relate to those found by Geva and Zahavi (2010) confirming that using both kinds of data could enable better decision making in diverse financial domains. Next, it might be interesting for practice to strengthen the organisational compliance offices by providing information that is useful for decision making. This information could be for example derived from unstructured data like financial tweets or blogs, providing the insights into current mood states in the market.

Evaluation. In general, it appears that the evaluation from the organisational and/or user perspective has been excluded so far. This might be an opportunity for IS researchers to explore and apply the rich set of different evaluation methods, e.g. in order to receive valuable feedback from domain experts. It is widely accepted in the literature that engaging those who are experiencing and know the addressed domain problem can be very beneficial (Van de Ven, 2007). Those focusing solely on generic evaluation metrics and simulation will definitely miss this research opportunity.

In conclusion, in this study we analysed the current state of the art of financial DSS by developing and applying an analytical framework that may also serve future researchers in this domain to structure their investigations.

Acknowledgement

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