The impact of data quality and analytical capabilities on planning performance: insights from the automotive industry

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ABSTRACT

Conventional wisdom suggests that data quality plays a central role for compiling valid and reliable plans to make the right decisions. At the same time, it is acknowledged that planning processes are both data and knowledge intensive and characterized by the human-computer interface. However, there are limited academic investigations on how data quality and analytical capabilities simultaneously impact planning performance. Drawing on the conceptual approach of business analytics, we introduce the notion of analytical capabilities, which is operationalized through three distinct resources: IT-usability, user competence, and analytical execution. To assess the impact of data quality and analytical capabilities on planning performance, we develop a structural equation model, which is then tested using data from the automotive industry. Our results suggest that analytical capabilities are a significant mediator for the effect of data quality on planning performance.

General Terms

Management, Measurement, Performance, Human Factors

Keywords

Data quality, analytical capabilities, corporate planning, business analytics, German automotive industry

1. INTRODUCTION

Ever since the early 1990s, nearly all industries have attempted to establish lean value chain processes that allow for a flexible and fast reaction to changing demand patterns. Just-in-time purchasing initiatives, outsourcing of noncore activities, and the transition from a Build-to-Stock (BTS) to a Build-to-Order (BTO) production environment are just a few examples that document the unbowed striving for highly flexible processes [41].

Additionally, industries oftentimes react to these changing customers needs with an increasing product differentiation and shortenings of product life cycles. For firms to survive in this market environment, the fast adaption to changing demand patterns turns into a key element of their day-to-day operations [3].

A main challenge for management in such an unstable environment is the decision making process [25]. Management needs to be put in the position to quickly decide among several alternative actions [24]. One key aspect regarding decision support is the corporate planning activity [10], which in turn is dependent on the information[1] that it is built upon [24]. The main purpose of planning is to assist in elaborating the better choice among different action alternatives [32]. Due to the size of the problem boundaries (e.g. thousands of products, hundreds of regions, and tens of facilities) and the resulting vast amount of data that needs to be processed, the complexity of planning tasks is substantial [59].

Thereby, Information System (IS) support is vital for a company's decision making by means of reducing costs (e.g. planning costs, procurement costs, or set up costs) and/or realizing benefits (e.g. more accurate information leading to increased decision quality) for the company [11, 36, 58]. The importance of IS for corporate planning is reflected by the approach of fact-based[2] planning [46, 52, 58], which has received legitimate interest over the past few years [63]. Following Davenport, we refer to fact-based planning as the corporate planning activity of a company that is based on hard facts, i.e. on data that is correct, relevant, complete, and accessible to the according decision maker in a timely manner [19]. Thus, corporate planning is closely linked to the data that it is based on.

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1 We will not launch a discussion on the distinction between data and information at this point. Instead, since the terms *data* and *information* are often used synonymously [42, 45], we will use them interchangeably in this paper as well. For a general discussion concerning data and information see [29].

2 Following [52], we will treat the terms *fact-based* and *data-driven* synonymously in this paper.

Previous research has emphasized the relevance of data and its usage for corporate planning processes [30, 59]. As corporate planning is data-intensive and characterized by the insightful analysis of the data available, we state that both the data and the analytical dimension have to be addressed when aiming at the identification of planning performance drivers. For the analytical dimension we draw upon the concept of business analytics [9, 58] and derive the notion of analytical capabilities. In a nutshell, we aim at answering the question as to what extent data quality and analytical capabilities impact planning performance.

To address this research question, we briefly review selected literature that touches upon data quality in the context of planning processes in section two. In section three, we introduce the notion of analytical capabilities which builds on Barney's resource-based view (RBV) [5]. The model is then tested by an empirical study conducted in the automotive industry. After explaining both the sampling and data collection procedure and applied measures we will describe the research results. The paper concludes with a brief discussion section and selected implications.

2. LITERATURE REVIEW

There have been numerous research endeavours that empirically assessed the impact of corporate planning on company's performance. West and Olson, for instance, conducted an empirical study that proved a positive relationship between planning and firm's performance [65].

One of the most critical success factors corporate planners are faced with when aiming at an improved planning performance is that of data [32]. The concept of *data quality* has been defined diversely in literature. Ballou and Pazer divide data quality into different dimensions: accuracy, timeliness, completeness and consistency [4]. In accordance with Ballou and Pazer [4], Wang and Strong argue that data consumers have a broad data quality conceptualization that goes beyond the dimension of data accuracy [62]. Consequently, they developed a framework for organizing data quality dimensions.

In their attempt to measure the effectiveness of planning, Dyson and Foster argue that insufficient data results in unnecessary approximation or complete gaps within the planning process [23]. Other research endeavours have conceptualized and shown that effective planning partially depends on the quality of data and the degree to which it is shared between buyer and supplier firms. Carter and Narasimhan, for instance, predicted that supply management will be more and more characterized by the need for electronic interchange of product and process data [12]. Petersen, Ragatz, and Monczka empirically showed that effective planning processes such as capacity planning, forecasting and inventory positioning are dependent on the quality of data shared between firms [44]. Smunt and Watts demonstrate that detailed production data can be used to predict learning effects, which in turn result in better short-term capacity plans [53].

In spite of the recognition of its relevance for planning processes, data quality remains a major issue on the path to business optimization. Haug et al. analyzed data quality in three Danish corporations and concluded that all three companies face major data quality problems [29]. Vayghan et al. argue that decentralized data management approaches and heterogeneous system architecture, which result in data silos, are the key drivers of poor data quality [60]. In general, researchers estimate that probably 90 per cent of a company's data is not yet explored to its fullest potential and the average employee spends between 15 and 35 per cent of his/her working time on the search for information [9].

In order to leverage the full potential of the company data there is an urgent need for the application of analytical tools that support corporate planners to extract insightful information from its data bases. Both science and several companies such as Harrah's Entertainment or Wal Mart have embossed the term *business analytics*, which describes the extensive use of data as well as statistical and quantitative analyses to provide a solid informational basis for comprising valid and reliable plans and decisions [20]. Business analytics (BA) can be defined as the application of various analytic techniques to data in order to answer questions or solve problems in an organizational setting [9]. Thereby, business analytics is not a technology but a group of approaches, organizational procedures, and analytical tools used in combination with one another to gain information, analyze that information, and predict outcomes of problem solutions [58].

3. ANALYTICAL CAPABILITIES AND DEVELOPMENT OF RESEARCH MODEL

3.1 Analytical capabilities

Rooted in the resource-based view of the firm [5, 39, 61], the IS literature has developed and conceptualized the notion of information technology (IT) capabilities [49, 57] (see [43] for a comprehensive overview). According to Bharadwaj, an IT capability is a firm's ability to acquire, deploy, and leverage its IT resources to shape and support its value chain activities [8]. Thereby, IT capabilities not only refer to the technological infrastructure a company can resort to, but also to the IT competency of its employees [8, 39, 57]. The underlying idea is that various IT- and competence-related resources combine to form analytical capabilities that are valuable, rare, non-imitable, and non-substitutable, thus enhancing the firm's potential to gain competitive advantages [40, 61].

We define analytical capabilities as the organizations ability to consolidate, analyze, and leverage its data resources to support its corporate planning and its decision making activities (in allusion to Mata et al. [39]). Addressing the link between data, user competence, and the usability of IT systems, analytical capabilities form a complex and multi-dimensional construct. In the following, three IT- and competence-related resources will be described that form the notion of analytical capabilities according to our conceptualization: User competence, IT-usability, and analytical execution.

The substantial time spent on the search for information partially results from the fact that business user’s competence in screening data bases and performing complex analyses is less developed than the competence of employees proceeding from the IT department. This fact suggests that BA requires more than mere data access and technological tools [66]. An important aspect often not reflected appropriately in BA research and implementation [37] is the user of the system [1, 13, 27, 28]: professionals using the system need to know what data is available to them and how to make use of that data [21]. In line with literature [47], we refer to this phenomenon as user competence. Following Marcolin et al. we define user competence as the user’s ability to effectively deploy IT functionalities to the highest possible extent in order to maximize performance of a certain job task [38]. The importance of having IT-competent business managers for establishing a close cooperation between business units and the IT department has been demonstrated empirically by Bassellier et al. [6]. Clark et al. postulate the particular relevancy of the capability to exploit, absorb, and utilize information in the context of systems designed to support managerial decision making [16]. Due to its substantial importance for an organization`s BA, we incorporate the user competence construct into our conception of analytical capabilities.

Table 1: Construct definitions

Construct	Definition	Based on
User competence	The user's ability to effectively deploy IT functionalities to the highest possible extent in order to maximize performance of a certain job task	[38]
Data quality	The degree to which data are fit for use by data consumers.	[62]
IT-usability	The capability of IT systems to be used by humans easily and effectively	[51]
Analytical execution	The degree to which analytical methods and tools are applied in practice	own definition
Planning performance	The validity and reliability of planning results in the course of time	[59]

IT researchers agree that the impact of IT resources on corporate performance depends on the actual usage of these resources, while there are ambiguous findings regarding the effects of IT resources and capabilities on firm’s performance [39]. In turn, the actual usage of IT resources is contingent upon the capability of these resources to be used by humans. The International Organization for Standardization (ISO) defines usability as “...the extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use...” [33]. A more IT-specific definition of usability is provided by Shackel who defines IT-usability as the capability of IT systems to be used by humans easily and effectively [51].

We argue that the usage of analytical tools and methods portrays a central element of analytical capabilities. Most commonly used analytical tools comprise a wide range of applications, such as neural networks to anticipate decisions, fuzzy logics, predictive modeling, data mining, and text and web mining. Bose provides a comprehensive overview of analytical methods [9]. Yet, we state the critical success factor is not the availability of analytical tools, but the frequent deployment of analytical tools in order to gain relevant information from distributed data sources. Hence, we further introduce the construct of *analytical execution*, which we define as the degree to which analytical methods and tools are applied in practice.

Together with the concept of data quality and planning performance, we draw on the notion of user competence, IT-usability and analytical execution to elaborate the research model in the next section. Table 1 summarizes the constructs and their definitions.

3.2 Research model and hypotheses

Prior research demonstrates that an insightful data analysis and a seamless planning process are dependent on the ascertainment of the right data and the holistic integration of variable data sources [12, 23, 35, 53, 59]. In line with this literature, we expect data quality to have a positive impact on planning performance and therefore hypothesize:

H1a. Higher levels of data quality result in higher levels of planning performance

As previously stated, IT-usability helps to identify, classify and intelligently analyze data that is stored in various systems across the firm [30]. The content of the user interface is an important measurement dimension when assessing IT-usability [31]. In their study on interactive design and evaluation of entertaining web experiences, Karat et al., for example, ask the participating users about their attitudes towards the content of the interface [34]. Particularly a high degree of data accessibility, which is acknowledged to be a key data quality dimension, can contribute to a more easy-to-use interface [62]. Consolidating customer data from different sources like call centers or online customer portals potentially increases the ease-of-use, as corporate planners do not have to use different systems that are designed against the background of distinct, functional-specific objectives. We therefore hypothesize data quality to have a direct positive impact on IT-usability.

H1b. Higher levels of data quality result in higher levels of IT-usability

Unlike employees proceeding from the IT department, business end-users are in general less skilled in complex analytical methods and thus oftentimes not well versed in the deployment of advanced analytical methods [9]. In many organizations, the analytical skill requirements are comparatively demanding, which leads to a call for more easy-to-use system interfaces [9]. Due to the fact that IT-usability is the central enabler of an enterprise-wide data analysis, it supports business end-users to execute data analysis on a more frequent basis [30]. Consequently, we hypothesize IT-usability to impact analytical execution.

H2a. Higher levels of IT-usability result in higher levels of practicability of analytical executions

In the context of analytical executions, one of the most dominating problems organizations are faced with is a lack of in-house skills required to make optimal use of technology in order to conduct insightful analysis [20]. According to Bose, the hiring of business analyst experts is of paramount importance when it comes to the implementation of analytical executions [9]. Consequently, we hypothesize:

H3. Higher levels of user competence result in higher levels of practicability of analytical executions

Today's information technology offers a broad spectrum of customized analytical applications and methods, ranging from forecasting support applications to data mining techniques. Since information is stored in different systems and formats, a wide range of different analytical applications has to be used in order to gain a complete picture of the data available within the organization. Oftentimes the distinct applications feature potential for complementarities. The systematic screening of stored data (data mining), for instance, is logically complemented by text mining techniques. Both taken together, they provide a more accurate picture of the available data in different sources leading to a fact-based picture of the firm's operational status quo, on which planning processes are based. Consequently, we argue that the practicability of analyses positively affects the validity and reliability of planning results.

H4. Higher levels of practicability of analytical executions result in higher levels of planning performance

The construct of IT-usability, besides others, refers to the planning options that are included in the information systems supporting the BA activity. Thereby, the planning options feature both a temporal distinction (short-, medium-, and long-term) and a typological differentiation (e.g. simultaneous and/or successive planning). Furthermore, the planning options can be classified with respect to the number of planners that use them with the purpose of compiling collaborative plans. In line with Van Landeghem and Vanmaele [59] we argue that planning performance is partially dependent on the re-planning frequency. The more planning options are available and the more planners resort to these options, the higher the validity and reliability of planning results. Thus, we argue that IT-usability has a positive impact on planning performance.

H2b. Higher levels of IT-usability result in higher levels of planning performance

The proposed research model is shown in Figure 1.

4. METHODOLOGY

The following section deals with the procedure of sampling and data collection. Before addressing the results in greater depth, the measures applied to the research model will be presented and analyzed against the background of validity and reliability.

4.1 Instrument development

For the development of the instrument (a survey questionnaire) we used the guidelines and examples provided in the general IS literature (e.g. [50, 56]). The measures were developed on the basis of an extensive literature review following the recommendations of Webster and Watson [64] to obtain measures that adequately reflect the belonging constructs and have minimal overlap among constructs. Since the measures were firstly developed in the context of this study, content validity was assessed. First, items were generated and evaluated independently by each of the researchers. In a second step, each construct and its according items were discussed in joint meetings. This resulted in an agreed set of measures per construct. Following the advice of Cronbach, an expert panel was conducted by means of a workshop with two academics and two practitioners [17]. This expert panel feedback helped us in refining existing measures [56]. By following this approach for the selection and development of the initial set of items, a high degree of content validity was achieved. The measures of the instrument were designed to be formative [22] and reflective [15].

After the first draft of the instrument was developed, a pre-test with researchers in the IS field and with industry representatives was carried out. We kindly asked the participants for comments and suggestions on the measures as well as on the instructions of the questionnaire itself. On the basis of this instrument evaluation, the instrument was altered slightly. The resulting set of items was then included in the final instrument. The items were measured using a 5-point Likert-type scale where respondents were asked to state to what extent they agreed or disagreed with the given statements.

4.2 Sampling and data collection

The target group of the survey at hand was the automotive industry, addressing both Original Equipment Manufacturers (OEMs) and 1st and 2nd-tier suppliers located in Germany. The automotive industry was selected because of its highly competitive and lean business environment, requiring short-term planning and adaptive operations structures. Even though there was no specific business unit focus, it was decided to exclude IT professionals from the study, since business users who are responsible for planning activities were in the centre of the study at hand. Moreover, a revenue threshold of EUR 15 million was set in order to exclude small niche players that feature centralized and single-layer planning processes.

The automotive companies addressed were randomly selected from the German Association of the Automotive Industry (VDA). In total, a sample of 1,200 was chosen. The questionnaire was sent both via mail and via electronic mail to automobile managers in charge of planning procedures. In total, an overall return rate of 5.25% was achieved. Of the total sample size, approximately 60% of the participants worked for OEMs while the remaining 40% were managers responsible for planning in large and medium-sized automotive suppliers. The list of participants consistently features extensive professional experience, with over 60% having a minimum of ten years of experience in the automotive sector. Regarding the departmental representation, the panel covers a broad spectrum of different departments, ranging from logistics and procurement to strategy and marketing.

To account for non-response bias, the test developed by marketing researchers Armstrong and Overton was applied [2]. According to this technique, responses of early and late respondents should be compared, assuming that late respondents inherit similar characteristics as non-respondents. In case of substantial differences between both groups, the presence of non-response bias is likely. For the research at hand, some respondents sent the questionnaire back within a period of four weeks after the roll-out. These respondents were designated as non-hesitant respondents. In contrast, most automotive mangers were contacted at least twice before they participated in the study. Hence, the latter ones were designated as late respondents. As a result of the comparison of both participant groups, no substantial differences between non-hesitant respondents and late respondents was observable.

As a measurement for sample representativeness, we compared the average annual sales volumes of the respondent firms with the average sales volumes of all members of the German Association of the Automotive Industry for the year 2008. While industry average amounts to approximately 541 million EUR, the sample size features an average sales volume of 577 million EUR, exceeding the industry average by 6.73 per cent. Hence we can presume that the non-response had no significant influence on the results of the paper at hand and that the panel represents the German automotive industry adequately.

4.3 Measures

All five constructs introduced in chapter three are latent variables requiring indirect measurement [15]. In the following, the measures of each construct will be explained briefly.

The notion of planning performance in the context of analytical capabilities has not been addressed empirically in previous research, resulting in an explorative operationalization approach. Yet, the concept of planning robustness, which refers to the validity of plans in the course of time and in the event of demand pattern changes, has been proposed in literature as a means to express planning performance [59]. Sridharan and Berry support this view when arguing that an increase in re-planning frequency decreases the planning stability and should therefore be obviated [55]. Another dimension of planning performance refers to the timeliness of the planning results. The statement Ewing made almost four decades ago: "The utterly essential dimension of planning is time." [26, p. 439] is even more valid in today's flexible and uncertain business environment than ever before. Thus, we regard the timely availability of planning outcomes to the according decision maker (planning timeliness) as crucial for effectively conducting corporate planning [18] and thereby apply planning timeliness as an indicator of planning performance. Additionally, an important aspect of corporate planning is the usability of planning outcomes, i.e., the question whether the planning outcomes are indeed being utilized in decision making by the according executive. Consequently, planning performance features three distinct measurement dimensions: (1) planning robustness, (2) planning timeliness, and (3) usability of planning outcomes.

By conducting a 2-stage survey, Wang and Strong developed a conceptual framework to capture major data quality dimensions [62]. They identified the following four main quality dimensions: (1) intrinsic data quality (2) contextual data quality (3) representational data quality and (4) accessibility data quality. Batini et al. [7] define a basic set of data quality dimensions which includes accuracy, completeness, consistency, and timeliness. In line with Wang and Strong [62] and Batini et al. [7], we utilize the following dimensions in order to measure data quality: (1) data accessibility, (2) data completeness, (3) data timeliness, (4) data reliability, (5) data consistency, and (6) data accuracy.

Given the fact that the construct of analytical execution has not been measured in previous research, we draw on rather general business intelligence-(BI) literature to derive appropriate measures for this construct in an explorative manner. According to Kohavi et al. [35], current analytical execution systems are characterized by a long cycle time, where the cycle time is defined as the time it takes a business user to ascertain, integrate, and evaluate data for better decision making. For the conduction of short-term planning processes, reducing cycle-time is considered to be a prerequisite. We therefore distinguish the short-term practicability of analysis from the general practicability of analysis for measuring analytical execution. Additionally, the dimension of analysis robustness is taken into account.

The question as how to measure usability is a central question in user interface evaluation. The difficulties of elaborating valid measures primarily results from the fact that usability is a psychological construct [31]. Hornbaek classifies usability measures along three outcome-oriented dimensions [31]: (1) effectiveness (2) efficiency and (3) satisfaction. Since the outcome of usability measures is reflected through the endogenous construct of planning performance in our model and given the fact that exogenous constructs are measured in a reflective manner due to lacking validation criteria, we utilize three reflective usability measures: (1) ease-of-use, (2) transparency of data base, and (3) planning options. The measures applied refer to the usability of IT systems that were designed for analysis by business users.

According to Marcolin et al., user competence can legitimately be operationalized and measured in a number of ways [38]. In the field of IS research, previous studies have addressed the importance of a user being informed about IT assets and opportunities [6, 13, 57]. Previous research has highlighted that many professionals still do not use IT in an efficient and effective way [38]. Therefore, we resort to the measure of *Technical IT-skills*, which has been conceptualized by Mata et al. [39]. Furthermore, the measure of methodical competence is taken into account for the study at hand since the growing complexity of planning tasks and the customization of queries demand advanced methodical skills such as forecasting and scenario development knowledge [16, 20]. In addition, the user`s knowledge of analytical tools (e.g. forecasting options or scenario techniques) is included into our model as an indicator of user competence since it is crucial for a user who is to efficiently conduct business analytics to know what features the available IT systems offer [21].

Table 2: Indicator and construct validity and reliability

	Loading / Weight			
	lower bound	upper bound	point estimation	t value
Planning Performance [PPerf]. (R^2 = .51)				
1.1 Planning robustness	.136	.159	.129	.796
1.2 Planning timeliness	.212	.236	.268	1.653
1.3 Usability of planning outcomes	.864	.877	.882	9.539
Data Quality [DataQual] (AVE = .58; CR = .89;α = .85)				
2.1 Data accessibility			.700	16.29
2.2 Data completeness			.879	27.48
2.3 Data timeliness			.659	6.160
2.4 Data reliability			.674	7.045
2.5 Data consistency			.809	16.14
2.6 Data accuracy			.822	15.14
Analytical Execution [AnalExe] (R^2 = .27; AVE = .73; CR = .89; α = .81)				
3.1 Analysis practicability			.927	50.05
3.2 Short-term analysis practicability			.844	12.31
3.3 Analysis robustness			.781	13.34
IT-usability [ITuse] (R^2 = .32; AVE = .70; CR = .88; α ,= .79)				
4.1 Ease-of-use			.817	12.89
4.2 Transparency of data base			.888	30.03
4.3 Planning options			.806	10.87
User Competence [UserComp] (AVE = .62; CR = .83; α = .71)				
5.1 Technical IT-skills			.768	4.441
5.2 Methodical competence			.890	17.37
5.3 Knowledge of analytical tools			.702	7.219

Table 2 shows the quality measures for indicator and construct validity and reliability of the research model. The t-values were conducted using the partial least squares (PLS)-bootstrapping-procedure (n = 500). Since all t-values exceed the threshold of 1.643 it can be concluded that all loadings differ significantly (.95, one-tailed) from zero. The only exception has to be made regarding (formative) weights of the planning performance item 1.1, which does not reach the threshold. However, as the 95%-confidence-interval does not include zero we adjudicate the item to be reliable. Average Variances Extracted (AVE), Construct Reliabilities (CR), and Cronbach's Alphas (α) exceed the required threshold of .60.

In total, the overall research model, which combines both formative and reflective constructs, can be regarded appropriate for hypothesis testing and further analysis of the relationships between conceptualized constructs.

5. DATA ANALYSIS

For the purpose of analyzing the research model, we prefer the Partial Least Squares (PLS) structural equation modeling techniques to traditional covariance-based techniques such as LISREL. The use of PLS countervails small sample size problems and provides conservative estimates of the path coefficients in comparison to covariance-based techniques [14]. Several software packages support PLS, of which we utilized SmartPLS version 2.0 [48].

Table 3 shows the construct scores and their correlations with the square root of AVE in bold. None of the correlations (column wise) exceeds the square root of AVE for the specific construct. Hence, discriminant validity of the constructs is given.

Table 4 shows the estimated path coefficients with t-values (500 PLS-Blindfolding runs) in brackets for the research model. Total effects of the exogenous constructs on planning performance and analytical execution are also shown taking all direct and indirect influences into account.

Cross validated redundancies for the endogenous constructs were calculated to further asses the quality of the estimated model. Thereby, we use the PLS-Blindfolding-procedure for different omission ranging from 3-17. Analytical execution reveals a mean of .156 for cross validated redundancies, IT-usability of .178, and planning performance of .142. All redundancies exceed the threshold of zero. Hence, the model constitutes a relevant possibility to predict data as evidenced through data collection. Finally, the Stone-Geisser-Criterion is applied to address the quality of the model at hand (Table 5).

Except data quality and analytical execution, all exogenous construct have a positive impact of the explained variance of the endogenous constructs. Including data quality in the model "vanish" a per mill of the explained variance of analytical execution. As data quality is essential to the model we decided to go with this flaw. In a nutshell, Figure 1 illustrates the path coefficients and R-squares graphically. The asterisk symbol indicates path significance on a 90% level (*).

Table 3: Construct scores and correlation

	Construct Scores				Construct Correlations				
	Mean	S.D.	l.b.*	u.b.**	AnalExe	DataQual	ITuse	PPerf	UserComp
AnalExe	3.54	.94	3.47	3.61	**.853**				
DataQual	3.65	.74	3.59	3.70	.561	**.762**			
ITuse	2.97	.85	2.91	3.04	.230	.563	**.838**		
PPerf	3.74	.78	3.69	3.80	.514	.526	.601	***	
UserComp	3.65	.90	3.58	3.71	.450	.200	-.047	.127	**.790**

* lower bound for 95%-confidence-interval; ** upper bound;*** Planning Performance is measured formatively and therefore no AVE is retrieved , S.D. = Standard Deviation.

Table 4: Path coefficients, t-values and total effects

	ITuse	AnalExe	AnalExe(total)	PPerf	PPerf total
DataQual	**.563** (7.519)		**.141** (1.625)	.034 (.198)	**.366** (2.247)
UserComp		**.462** (4.896)			**.176** (2.040)
ITuse		**.251** (1.851)		**.494** (3.872)	**.590** (4.745)
AnalExe				**.381** (2.199)	

Significant (.90, two-tailed) paths are marked bold.

Table 5: Stone-Geisser-Criterion

	ITUse			AnalExe			PPerf		
	incl.	excl.	f²	incl.	excl.	f²	incl.	excl.	f²
DataQual	.3172	.0000	.4646	.2655	.2652	.0004	.5103	.5100	.0006
UserComp				.2655	.0570	.2839	.5103	.5090	.0027
ITuse				.26455	.2050	.0824	.5103	.3720	.2824
AnalExe							.5103	.4140	.1967

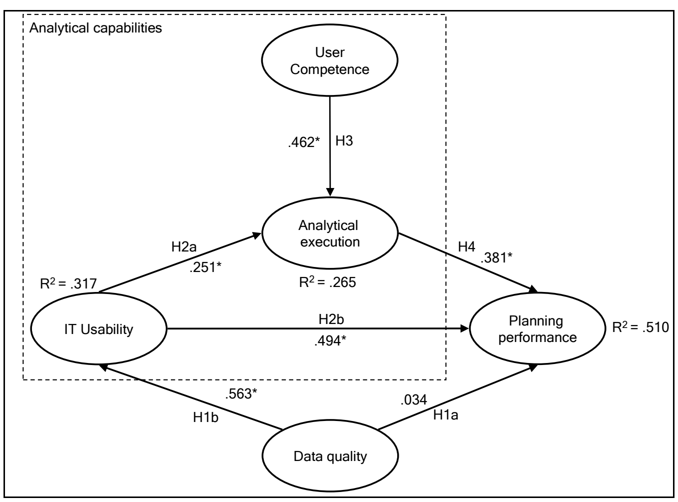

Figure 1: Standardized parameter estimates for the research model

Hypothesis 1a (.034) is not supported by the research model. In contrast, the data reveals support for hypothesis 1b, which links data quality and IT-usability. The path coefficient of .563 is significant, and the R-square of IT-usability (.317) can be regarded substantial. Furthermore, hypothesis 2a (.251) is significant. The construct of analytical execution is not only impacted by hypothesis 2a, but also by hypothesis 3 (.462). The total difference between the impact of IT-usability and user competence on analytical execution (.224) is not significant (t = 1.145, one-tailed, .90). With a path coefficient of .381, hypothesis 4 is supported, providing evidence for the sustentative role of analytical execution for planning performance. Finally, hypothesis 2b is significant at a 90% level.

Data quality has a significant total effect of .141 on analytical execution, being significantly (t = 1.949 resp. 2.181) smaller than IT-usability's (difference = .107) and the user competence's impact (difference = .330).

In total, IT-usability and user competence together explain more than one quarter (26.5%) of the total variance of analytical execution. In turn, the construct analytical execution exerts a significant, positive influence (.381) on planning performance. Likewise, the direct, positive influence of IT-usability on planning performance is significant (.494). In contrast, the absolute difference (.113) of both influences is not significant (t = .4456; one-tailed, 90).

User competence has a significant total impact (.176) on planning performance and so have IT-usability (.590) and data quality (.366). Thereby, merely the difference between user competence and IT-usability (.409) is significantly different (t = 2.532). We observe no significant difference between the total impact of IT-usability and data quality. In total, analytical capabilities (IT-usability, user competence, and analytical execution) and data quality together explain more 50 per cent of the observed variance of planning performance.

We also checked for robustness of data using a clustering approach. In relation to planning performance we clustered the dataset in a poor performing sub-sample (n = 32; construct score below 3.87; *mean* = 3.15; *S.D.* = .60) and a high performing sub-sample (n = 32; construct score above 3.86; *mean* = 4.34; *S.D.* = .35). The distribution of analytical execution's construct scores differs significantly (poor = 3.14, high = 3.94; U = 232.5; p = .000) between both sub-samples and so do the distribution of data quality (poor = 3.36, high = 4.07; U = 235.5; p = .000) and IT usability (poor = 2.60, high = 3.35; U = 255.5; p = .005). In line with the small total effect the distribution of user competence does not differ significantly (poor = 3.61, high = 3.68; U = 262.0; p = .502) between both sub-samples. Therefore, the relationships between the constructs can be considered robust.

Figure 2 depicts the total effect of the exogenous constructs on planning performance and the mean construct scores. The total effect of IT-usability is the highest among the four total effects on planning performance. At the same time, IT-usability features the lowest mean score (2.97) among the four constructs. With a mean construct score of 3.65, user competence and data quality feature the highest score.

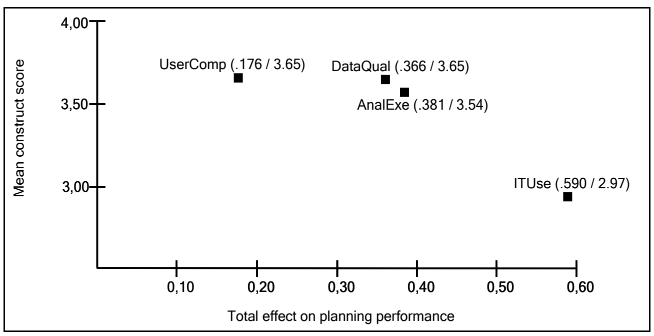

Figure 2: Total effects on planning performance and mean construct score

As can be depicted from Figure 1, IT-usability is a significant mediator (z = 21.292) for the impact of data quality on planning performance, thus 89.11% of the effect of data quality on planning performance are due to the impact of data quality on IT-usability [54]. In addition, analytical execution is a significant mediator (z = 15.844) for the total effect of data quality on planning performance. 61.32% of the total effect of data quality on planning performance is due to the total effect of data quality on analytical execution. In contrast, analytical execution is not a significant mediator (z = 1.416) of the impact of IT-usability on planning performance (16.23%) due to the strong direct impact of IT-usability on planning performance.

The final chapter of the paper at hand concludes the main findings described in chapter five, answers the research question and briefly deals with selected implications and limitations.

6. CONCLUSION

The research findings of the paper at hand cast doubt on the unconstraint and direct impact of data quality on planning performance. While reliable and valid plans might result from a high data quality base in partial, high data quality does not necessarily result in a high planning performance. The data collected from the automotive industry indicates that data quality primarily affects planning performance in an indirect manner through the mediator of analytical capabilities. In particular, IT-usability mediates the impact of data quality, indicating that the ease-of-use of operational systems serves as a catalyst for data's impact on planning performance. Furthermore, it can be concluded that the direct impact of IT-usability on planning performance shows that the ease-of-use of IT systems fosters planning managers to use applications on a more frequent basis. Overall, the research results indicate that IT-usability is not being paid attention to an adequate extent, as its total effect on planning performance in relation to its construct score illustrates (see Figure 2).

The results regarding the user competence's high impact on both analytical execution and planning performance confirm conceptual BI literature, which emphasizes employees' high skill level required to make optimal use of analytical methods and tools [16, 20]. Given the high variance of planning performance explained (R^2=.510), it can be concluded that both data quality and analytical capabilities impact planning performance to a large extent. This is particularly true when taking into account that numerous influencing factors such as volatile demand patterns, cross-functional barriers, and data ownership structures were kept aside. Since the influence of user competence on analytical execution is comparatively higher than the impact of IT-usability on analytical execution, automotive companies ought to invest in human resource development as opposed to the usability of the technological infrastructure when aiming at the improvement of analytical capabilities. Yet, when aiming at an increased planning performance, IT-usability might be the focus of resource allocation.

As with every research endeavor, the study at hand has clear limitations that need to be kept in mind when evaluating the results. First and foremost, all data obtained is self-reported, potentially biasing the results. For instance, the self-reported usage of IT systems might diverge from actual usage. Secondly, the constructs of user competence and IT-usability can be legitimately operationalized in different ways, given their complex character. Furthermore, the model was tested using data from the automotive industry which possibly impacts cross-industrial comparability. In addition, there may be differences regarding the necessity of the degree of data integration between big and medium-sized firms.

Previous research has shown that planning positively affects corporate performance [65]. Against this background, future research is needed which focuses on the investigation as to how data quality and analytical capabilities together with planning performance exerts influence on the corporate performance of companies proceeding from the automotive industry. Furthermore, the questionnaire should be applied at different industrial levels to support or challenge the results presented in this paper. Finally, we believe further research to be necessary regarding the threshold of the impact of data quality and analytical capabilities on planning performance since both are not cost-free.

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