# Digital Forecasting: Towards Improving Controllership Effectiveness in Managerial Decision-Making

**Dissertation**

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submitted to:

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**Faculty of Business Administration and Economics**

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# A Research framework

## 1. Motivation and research background

It is consensus that managers need useful business information for decision-making and control purposes and that the effectiveness of decision-making particularly depends on the quality of the underlying "oceans of data" (Zeng et al., 2006). Since the dawn of the internet of 'human' and 'things' as well as a growing digital economy over the past years, 'big data' resulting from a multitude of potential information sources started to play a crucial role in a firm's data environment (Vasarhelyi et al., 2015). Thereby, the amount of data to be processed has grown rapidly over the last few years (e.g., Brown-Liburd et al., 2015) and the number of different data sources scattered across a firms' data infrastructure could easily be more than 100 (Doan et al., 2012). In addition to the resulting volume and velocity of data, an increasing number of data types caused their variety (Appelbaum et al., 2017). In consequence, decision-makers are faced with increasingly large volumes of information (e.g., Luft & Shields, 2010). The terms 'data' and 'information' are frequently used synonymously, referring to relevant as well as irrelevant or redundant information. But in a decision-making context, data is usually denoted as information only when they become relevance to the decision (e.g., Iselin, 1993), i.e., information is extracted from data. Given the potential information gain from today's data environment, businesses not only rely on internal data, but also process external data from various sources (Simons & Masamvu, 2014). Thus, firms are subject to vast technological changes, caused by new information processing demands. While the traditional nucleus of accounting information system (AIS) still consists of internal financial data which are generated by a firm's accounting system, modern business intelligence (BI) – introduced by the Gartner Group in the Mid-1990s (Caserio & Trucco, 2018) – additionally comprises increasingly large database infrastructures as well as advanced applications and analytical tools. Big Data is significantly changing business intelligence, driving new trends in analytics and data science (Kumar et al., 2018; Larson & Chang, 2016) and, therefore, also transforming (management) accounting-based decision-making (e.g., Richins et al., 2017). In order to take advantage of these opportunities, appropriate information systems enabling new capabilities, e.g., predictive and prescriptive analytics, along with aligned decision-making approaches have to be used (Frazzon et al., 2021), allowing for a digitalized planning and forecasting function.

As managers rely on management accountants' involvement in dealing with operational as well as strategic issues (Lambert & Sponem, 2012), using BI to derive appropriate business insights for managerial decision-making is one of the most prominent tasks of highly specialized management accountants which, in German firms, are oftentimes denoted as controllers (Ewert

& Wagenhofer, 2007). In line with the dynamic development of AIS technology, the controllers' role has gradually been shifting over the past few years from being a mere cost recorder, collecting and presenting financial information and analysis, towards becoming a business partner (Goretzki & Strauß, 2017; Wolf et al., 2015). Controllers' business partnering behavior specifically covers the provision of meaningful internal financial reports as informational support for managerial decision-making demands (instrumental information), as well as giving forward-looking structural insights into the firms' business as a whole, to align decision-making with strategic goals and the business environment (conceptual information) (Beyer & Trice, 1982; Rouwelaar et al., 2021; Simon et al., 1954). In consequence, controllers are facing a growing need for information processing capabilities.

In addition, a rapidly changing business environment again requires improved information processing. For example, in times of economic crisis, such as triggered by the COVID-19 pandemic, managerial decision-making becomes increasingly difficult due to radical uncertainty ('unknown unknowns') caused by the growing opaqueness of a firm's information environment (Hopwood, 2009). In a broad sense, uncertainty is an external factor (Widener, 2007) that, according to organizational information-processing theory, determines the level of information that an organization needs to perform a given task. While in situations with low uncertainty, most of the information required to perform managerial decision-making is already available, based on organization's past experiences, in opaque situations with high uncertainty, additional as well as more sophisticated information has to be collected and processed (Galbraith, 1973). Thus, in the wake of the COVID-19 pandemic, underlying assumptions for planning and forecasting have changed significantly, as new economic conditions resulted in the need for radically new judgments (Humphreys & Trotman, 2022).

A more detailed analysis on how BI technologies affect controllership effectiveness in managerial decision-making is the core subject of this dissertation. This is of high interest to (management) accounting research as controllers play a crucial role as information providers to support effective and efficient decision-making. Because data constitute a key input factor for decision-making, the growing volume of data available emphasizes the role of controllers in their decision-support function (Sprinkle, 2003). Selecting relevant data and providing the most relevant information is key to promoting decision quality. Thus, underlying information systems for data acquisition, processing and analysis become increasingly important for accounting research.

The overall research question of this dissertation addresses the challenges formulated above:

How business intelligence technologies make controllers more effective in managerial decision-making?

Despite the continued high importance of digital transformation of business models and processes, research on the advantages of BI technologies on management accounting is still limited (Nespeca & Chiucchi, 2018). Whereas (A)IS research addresses the question of technological benefits of business intelligence per se, the issue whether it makes controllers more effective in decision support has not yet been researched in depth. Even more, a present validity of prior tested relationships cannot be assumed due to the continuous shift towards a digital economy (Wadan et al., 2019), affecting managerial work environments and implying major organizational changes for most companies (Klus & Müller, 2021). Following Newell and Marabelli (2015) who highlight an increasingly data-driven decision-making and control, research on the so called "datification" (Newell & Marabelli, 2015, p. 3) of management accounting and control research is increasingly addressing organizational data infrastructure and tools to effectively collect and prepare information for decision-making (Lycett, 2013). Thus, BI technologies receive a lot of attention from both an academic and practitioner's perspective, facing the benefits that organisations can reach through the use of (big) data analytics (Sharma et al., 2014).

# 2. Research method

## 2.1. Research approach

The three papers of this dissertation employ a survey-based research approach to investigate the underlying research questions, based on a common questionnaire-based online survey. Survey-based research distinguishes four principal types of data collection methods: paper questionnaires, phone questionnaires, questionnaire-based online surveys, and Face-to-Face interviews (Fricker et al., 2005). Questionnaire-based surveys have long been established as a common method of empirical research and are frequently used in the field of management accounting and control (Mahmoudian et al., 2018; Speklé & Widener, 2018; Young, 1996). In particular, surveys are an appropriate approach for theory testing as they are able to investigate even complex relations between various variables, including psychological variables such as an individual respondent's perception (Oppenheim, 1992; Young, 1996). For this reason, surveys usually based on self-reported data collected from certain groups of individuals, providing the most reliable information source with respect to the given research object (Speklé & Widener, 2018; Van der Stede et al., 2005). By means of structured questionnaires, surveys allow for a consistent data collection and, therefore, fulfil the degree of standardization required for statistical analysis (Speklé & Widener, 2018). Furthermore, psychometric effects have not yet been identified for neither paper- nor online-based surveys (Al-Omiri, 2007; Hardré et al., 2010). In consequence, a questionnaire-based online-survey is an appropriate research approach to investigate the controllers' as well as the managers' perception with respect to the impact of technological (Paper 1 and 3) as well as behavioral aspects (Paper 2) on controllership effectiveness in managerial decision-making.

## 2.2. Survey design

The common questionnaire-based online survey underlying each paper consists of two separate questionnaires. The first questionnaire relates to controllers and is structured in three sections. Section 1 contains questions regarding the level of data integration as well as analytical capabilities. Section 2 refers particularly to the context of revenue forecasting and consists of questions regarding, e.g., the use and quality of business intelligence technologies, controllership output quality and influence on management decisions, controllers' role perceptions as well as the impact of the COVID-19 pandemic. Both, Section 1 and 2 refer to a business division perspective. Section 3 consists of additional context questions, e.g., firm size or industry, from an overall firms' perspective. The second questionnaire relates to managers and covers a subset of the questions from Section 2 of the controllers' questionnaire concerning the use of business intelligence technologies, controllership output quality and influence on management decisions, controllers' role perceptions as well as the impact of the COVID-19 pandemic.

The data of the survey was collected in the period between June to October 2020. Based on master data from all German companies which were taken from the trade directory database Markus, only large firms with at least 500 employees were selected, thus excluding small- and medium-sized enterprises (SME), as smaller firms usually do not have a specialized controlling department (e.g., Hiebl et al., 2013). Furthermore, firms of finance and real estate industries were excluded due to their specific business models compared to firms from industrial, service or trading industries. In a final adjustment, duplicate entries were removed, so that in total 5,758 firms were left in the population. For reasons of time and resources, only 20% of the firms were randomly selected and contacted by telephone or, in the case of several missed calls, by e-mail. However, given that the selection of firms was conducted in small batches of 20 to 50 firms, a sample selection biases cannot be fully ruled out. Moreover, our telephone calls were conducted by several parties, which implies further potential selection biases, e.g., due to individual willingness to wait before a call was answered. To capture different aspects of the controllers' tasks in providing revenue forecasts, the controlling manager ('Leiter Controlling'), a functional controller responsible for sales controlling or a similar function of each firm was addressed. As the survey was not limited to controllers, their closest general manager, i.e., a member of upper management such as the CEO, managing director or division manager, was also requested to complete a questionnaire. For that reason, the controlling representatives contacted by phone were asked to forward the separate managers' questionnaire to the respective person. Participants were incentivized by a benchmarking report. Information on participants' individual characteristics was not collected, as it might increase the cancellation rate due to the resulting extent of the questionnaire's length as well as the requirement to provide personal information. Out of the received 156 controller questionnaires, 67 related managers also completed their questionnaire, giving a total of 67 dyadic datasets. This allows for a dyadic research approach, which is useful to counter key informant bias, i.e., to test whether the results might be biased by individuals' subjective views. To ensure that both questionnaires were thorough and comprehensive, they were pre-tested with three executives from business practice, three consultants as well as five academic researchers. The complete questionnaires are shown in Appendix A1 (controllers' questionnaire) and A2 (managers' questionnaire). A descriptive overview of all surveyed items is given in Appendix A3. Appendix 4 provides a code specification of items as used in the individual papers.

# 3. Overview of papers

This dissertation provides insights into three research gaps. First, there is no research that specifically addresses the impact of digital technologies on the effectiveness of controllership in managerial decision-making in the context of forecasting. Second, most empirical research on (A)IS has focused solely on technological features, while neglecting conceptual aspects from an organizational perspective. Third, the impact of economic crises on the controllers' behaviour in managerial decision-making has not yet been analyzed in-depth.

More specifically, three self-contained papers contribute to the overall research question mentioned in Section 1 as follows:

Today's controllers are supposed to rely on a 'single source of truth', i.e., a consistent data base across business units to be able to clearly understand all factors relevant in a given decision-making situation to more effectively achieve operational as well as strategic goals (Cho et al., 2019). In this light, Paper 1 "It's more than just numbers: The impact of data integration on controllership effectiveness" examines the impact of data integration on the effectiveness of controllers in their decision support function and aims to answer the research question: Does an increased level of data integration have a positive effect on controllership effectiveness? Moreover, the paper is intended to examine if the underlying causal inference relate both variables in an instrumental fashion and/or rather in a conceptual way, as data integration strengthens a consistent financial language. The results indicate a positive significant association of data integration with the effectiveness of controlling, which causes directly, i.e., technology-based, as well as a mediated effect instigated by a consistent internal financial language resulting from an increased level of data integration. The paper adds new insights into the discussion on whether data integration is related to the effectiveness of controlling. The findings show that a solely technology-based approach to the controller's tasks ignores the relevance of the consistency of an internal financial language as a driver of controllership effectiveness. Even if the consideration of tailor-made information by the use of customized subsystems can be seen as advantageous from an IS-theoretical perspective, it does not fulfil the controllers' need of an integral view as a 'single source of truth', which is made possible through data integration. From a practical perspective, the results show that data integration not only contributes in an instrumental fashion to the quality of analyses and reports provided by controllers, but also conceptually through its consistency resulting in a better suited financial language for business communication.

In spite of the highlighted research potential (e.g., Van der Stede, 2011), the impact of economic crises on controllers' business partnering activities has not yet been analyzed in-depth. In particular, Hopwood (2009) stated that "… although there have been a number of more general organizational studies, particularly in times of past crises ... management accounting research gives little or no guidance on the modes of organizational response to economic crises", for instance, with respect to the relevant configuration of expertise within the accounting function. Inspired by this research gap, Paper 2 "Controllers as business partners in times of pandemic: The impact of business partnering on controllership effectiveness in revenue forecasting" seeks to investigate how business partnering behavior is linked to controllership effectiveness in managerial decision-making and whether this link changes if the information environment is impaired by the impact of the COVID-19 pandemic, by addressing the research questions: Does an increased level of business partnering activities have a positive impact on controllership effectiveness? Does this impact work in an instrumental fashion by means of providing high-quality output information, or rather conceptually by directly integrating controllers into managerial decision-making processes? And does the instrumental impact become more pronounced in an increasingly opaque information environment, as caused by the COVID-19 pandemic? To counter controllers' key informant bias, the paper conducted a supplementary multi-group analysis using a dyadic controller-manager-dataset. The results suggest that controllers acting as business partners do not in general have an impact on the quality of the information output provided by them. Only in interaction with an opaque information environment which creates an uncertain and volatile decision-making context, it can be observed that business partnering enables controllers to address managerial information needs in a superior manner. The results therefore support the notion that in times of economic crisis, controllers perceive that information quality and – as a result – the influence on managerial decision-making increases if their role as strategic business partners is more pronounced. This suggests that controllers acting as business partners acquire skills enabling them to exploit the information environment in a crisis situation more effectively, thus providing more accurate, reliable and timely information for managerial decision-making. In consequence, adopting the role of a business partner in good times can also be interpreted as building slack and resilience for controllership effectiveness in bad times. Only an established relation as business partner allows for the relevant analytical and technical skills to provide the necessary sophistication to support decision-making under uncertainty. In a similar vein, business partnering can be assumed to reduce uncertainty among controllers with respect to the information needed by management for decision-making. The results of the supplementary analysis provide evidence in two directions. First, they reveal a difference with respect to the conceptual mechanism relating controllers' business partnering to their influence on management decision-making. While the results support a highly significant influence from the controllers' perspective, this influence is not corroborated for the managers' perspective. Such a perception gap between controllers and managers might consequently indicate that controllers overestimate their conceptual influence on management decisions which, in turn, might result from an involvement-independence dilemma. That is, whereas controllers probably feel that they are "strong controller[s]" in the sense of Sathe (1983, p. 34), managers perceive their behavior less as involved but rather as independent, being more of a guardian or a supervisor. This notion is also supported by the results, as under a deteriorating information environment, the main impact on managerial decision-making as perceived by managers, did not relate to business partnering per se, but only to controller abilities to provide high quality information output. In this respect, the results also indicate that research on controllership effectiveness might be subject to misinterpretation due to a key informant bias, if only controllers are surveyed.

As already mentioned, research on the advantages of BI technologies on management accounting is still limited (Nespeca & Chiucchi, 2018). Advanced analytics enable in-depth analyses of (big) data sets (Chen et al., 2012), thus, also wield a particular influence on decision-making (Sharma et al., 2014). In consequence, the use of BI systems to gain business insights as a basis for managerial decision making is one of the most important tasks of highly specialized management accountants. But, on the other hand, Szukits (2022) suggests that the "reliance on analytical information does not replace intuition, but the two are completing and shaping each other". In the light of this situation it is the objective of Paper 3 "From data to insights: How advanced analytical capabilities strengthens the controllers' role in managerial decision-making" to get a better understanding of the impact of advanced analytical capabilities on controllership effectiveness in managerial decision-making in more detail, by answering the following research questions: Does an increased level of advanced analytical capabilities have a positive impact on controllership effectiveness in managerial decision-making? And if so, does the underlying causal inference relate both variables in an instrumental fashion and/or rather in a conceptual way? The results reveal a positive significant association of advanced analytical capabilities with the influence of controllership in managerial decision-making, which causes directly, i.e., instrumental, as well as conceptually, i.e., a mediated effect instigated by the controllers' business partnering behavior resulting from advanced analytical capabilities. Thereby, the results provide insights into the discussion of whether advanced analytical capabilities are related to controllership effectiveness, which at first glance is not necessarily the case, e.g., due to the prevailing opinion that high-value information systems make certain controllers' functions become obsolete. It shows that a solely technology-based approach to the controllers' tasks ignores the relevance of the conceptual contribution in their role as business partners as a driver of controllership effectiveness in managerial decision-making. Even if the information use through reports and analyses is advantageous from an IS-theoretical perspective, it does not fulfil the managers' need of a holistic view on a firm's business to guide and advise managers, which is made possible through supportive controllers' business partnering behavior. Therefore, our results show that advanced analytical capabilities not only contribute in an instrumental fashion by the quality of reports and analyses provided by controllers, but also conceptually through an increased business partnering behavior resulting in a higher controllership influence on management decisions.

The full research framework that links all three papers is presented in Figure 1.

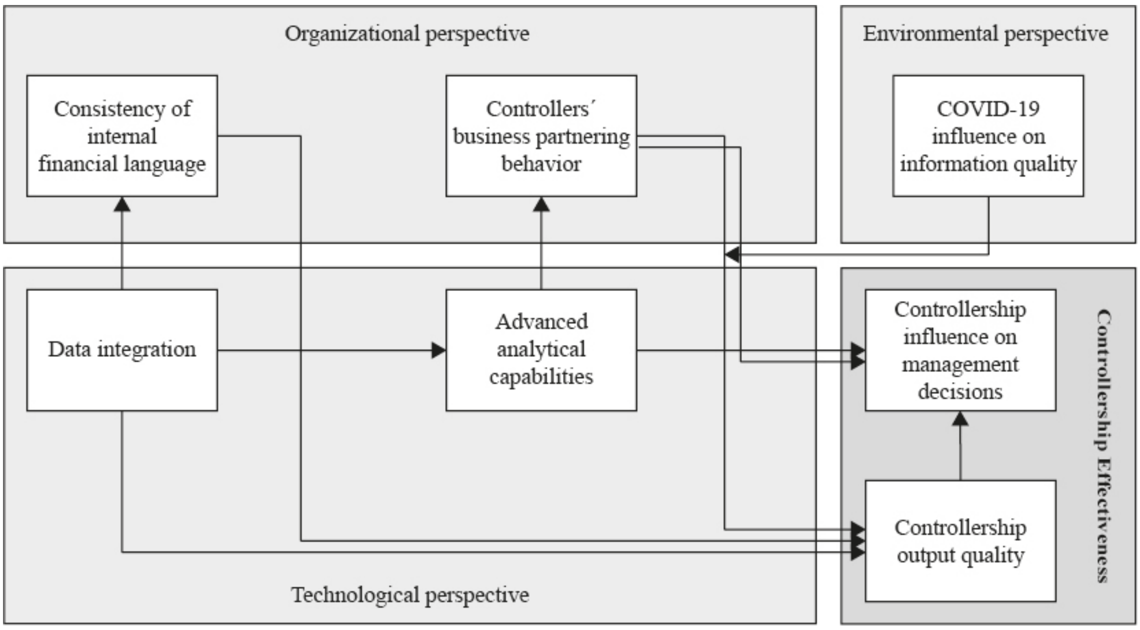


**Fig. 1** Full research framework

The papers have in common that they investigate drivers for controllership effectiveness in managerial decision-making from both technological as well as organizational perspective. Controllership effectiveness is the result of both output and outcome, because only the combination of high output quality and high influence on management decisions contributes to controllers' decision-support function. While Papers 1 and 2 consider output as a distinct variable, Paper 3 solely considers the outcome as a variable, as advanced analytics per se, provide analyses that can be considered directly for managerial decision-making purposes in an instrumental fashion.

The key information of each paper is reported in Table 1, summarizing the title of paper, corresponding research question(s), applied research method, used variables, sample characteristics, research contributions, authors share of contribution, conferences at which the paper was presented, as well as journal to which the paper is submitted.

**Table 1: Overview of Papers**

| | Paper 1 | Paper 2 | Paper 3 |
|---|---|---|---|
| **Title** | It’s more than just numbers: The impact of data integration on controllership effectiveness | Controllers as business partners in times of pandemic: The impact of business partnering on controllership effectiveness in revenue forecasting | From data to insights: How advanced analytical capabilities strengthens the controllers’ role in managerial decision-making |
| **Research questions** | (1) Does an increased level of data integration have a positive effect on controllership effectiveness?<br>(2) If so, does the underlying causal inference relate both variables in an instrumental fashion and/or rather in a conceptual way? | (1) Does an increased level of business partnering activities have a positive impact on controllership effectiveness, as a combination of controllership information output quality and controllership influence on management decisions?<br>(2) Does the impact work in an instrumental fashion by means of providing high-quality output information, or rather conceptually by directly integrating controllers into managerial decision-making processes?<br>(3) Does the instrumental impact become more pronounced in an increasingly opaque information environment, as caused by the COVID-19 pandemic? | (1) Does an increased level of advanced analytical capabilities have a positive impact on controllership effectiveness in managerial decision-making?<br>(2) If so, does the underlying causal inference relate both variables in an instrumental fashion and/or rather in a conceptual way? |
| **Research method** | Survey | Survey | Survey |
| **Selected variables** | Dependent variable:<br>Controllership Influence on management decisions<br>Indepentent variables:<br>Data Integration<br>Consistency of internal financial language<br>Controllership output quality | Dependent variable:<br>Controllership Influence on management decisions<br>Indepentent variables:<br>Controllers' business partnering behavior<br>Controllership information output quality<br>COVID-19 influence on information quality | Dependent variable:<br>Controllership Influence on management decisions<br>Indepentent variables:<br>Data Integration<br>Advanced analytical capabilities<br>Controllers' business partnering behavior |

(continued on next page)

**Table 1: Overview of Papers**

| | Paper 1 | Paper 2 | Paper 3 |
|---|---|---|---|
| **Research sample** | 156 Controller | 155 Controller<br>67 Manager | 156 Controller<br>67 Manager |
| **Research contribution** | (1) Drawing an explicit connection between data integration as a feature of AIS design and controllership effectiveness<br>(2) No limitation to the instrumental and/or technological features of data integration, but addressing its impact on providing a conceptual perspective<br>(3) Sheding lights on the mechanisms that underlie controllership effectiveness and thus contributing to the discussion on antecedents for controllers' transformation towards becoming business partners | (1) Drawing an explicit connection between controllers' business partnering behaviors and controllership effectiveness<br>(2) No limitation to the conceptual mechanisms relating business partnering behaviors to controllership influence on management decisions, but also include the impact of providing high quality information for fast decision-making and contextualized as well as sophisticated financial analysis, which forms an instrumental part of the business partnering role<br>(3) Examining the impact of the COVID-19 pandemic with respect to information quality on the latter mechanism<br>(4) Sheding lights on the antecedents for controllers becoming (strategic) business partners in times of economic crisis such as the COVID-19 pandemic | (1) Drawing a specific connection between advanced analytical capabilities as a key feature of modern BI systems and controllership effectiveness in managerial decision-making<br>(2) Addressing the impact of advanced analytical capabilities on controllers' business partnering behavior within a conceptual perspective, in addition to their instrumental and/or technological effect<br>(3) Providing insights on the mechanisms underlying the effectiveness of controllership in managerial decision-making, thus contributing to the discussion on the antecedents for controllers becoming (strategic) business partners |
| **Authors share of contribution** | Mark Alexander Sutton (85%)<br>Barbara E. Weißenberger (15%) | Mark Alexander Sutton (85%)<br>Barbara E. Weißenberger (15%) | Mark Alexander Sutton (85%)<br>Barbara E. Weißenberger (15%) |
| **Conference presentations** | 100 Jahre VHB: Jubiläumstagung des Verbands der Hochschullehrer für Betriebswirtschaft, Düsseldorf 2022 | 44th Annual European Accounting Association Congress, Bergen 2022 | |
| **State of publication** | Submitted to:<br>Information & Management | Submitted to:<br>Journal of Accounting & Organizational Change | |

# 4. Contribution

Drawing on the overall research question, how business intelligence technologies make controllers more effective in managerial decision-making, the contributions of this dissertation can be summarized under the following aspects: (1) What is the impact of data integration? (2) What is the impact of business partnering, especially under the economic influence of the COVID-19 pandemic? (3) What is the impact of advanced analytics capabilities?

In terms of data integration, Paper 1 reveals a positive impact of data integration on controllership effectiveness in managerial decision-making. Furthermore, it shows that a solely technology-based approach to the controller's tasks ignores the relevance of the consistency of an internal financial language as a driver of controllership effectiveness. Even if the consideration of tailor-made information using customized subsystems can be seen as advantageous from an IS-theoretical perspective, it does not fulfil the controllers' need for an integral view as a 'single source of truth', which is made possible through data integration. Therefore, Paper 1 points out that not only technological features of business intelligence fostering digital forecasting, but also organizational factors, such as a consistent internal financial language. In their role as business partners, controllers increasingly interact with management and therefore need to speak the language of business in order to provide insights into a (strategic) decision-making. In this direction, Paper 2 suggests that a pronounced controllers' business partnering behavior strengthens the controllership influence in managerial decision-making, since controllers as business partners guide and advise managers by providing insights into how organizational functions or value drivers interact and relate to the firm's strategic goals. Moreover, under the influence of an opaque information environment such as caused by the COVID-19 pandemic, it can be further observed that business partnering behavior enables controllers to address managerial information needs in a superior manner, as business partners acquire skills enabling them to exploit more effectively the information environment in a crisis situation, thus providing more accurate, reliable and timely information for managerial decision-making. The previous findings are strengthened by Paper 3, which shows that advanced analytical capabilities enabled by business intelligence technologies not only enhance the controllership influence on managerial decision- making in an instrumental fashion, but also strengthen the controllers' business partnering behavior through an enhanced information basis, which in turn further reinforces their influence on decision-making.

In sum, the present dissertation provides insights into the discussion of how digital forecasting is related to controllership effectiveness in managerial decision making. The findings show that business intelligence technologies not only improve controllership effectiveness from a technological perspective, but also create value from an organizational perspective by strengthening a consistent internal financial language as well as supporting controllers' business partnering behavior.

## 5. Limitations and opportunities for future research

Obviously, there are some limitations of the papers cited above that call for future research.

Concerning the generalizability, the results concentrate on decision-support in revenue forecasting, which solely addresses one area of the controllers' tasks. Moreover, analyses are based on data drawn from large companies with at least 500 employees, which means that the results must be interpreted carefully with respect to SMEs. Future research could place a specific focus on SMEs, as information systems as well as organizational structures differ from those of large enterprises. As is common in survey-based research, results can be biased by subjectivity and/or a single-respondent bias, given that only controllers' responses were considered for the main analyses. Furthermore, the survey took place during the period of the COVID-19 pandemic. Since the derived sample only covers this specific period, the results might be subject to time-period bias. In order to check for robustness of the results, it requires repeating the survey at a later stage to test for possible time effects, such as, problems of uncertainty or intergroup relations among the decision-making process being improved (Fink et al., 1971). Generally, endogeneity concerns, i.e., unobserved firm characteristics which could affect the results, can only be addressed by repeating the investigation using different designs and analyses (Hill et al., 2021). Furthermore, the study might be affected by unit response bias, as the sample does not cover the entire target population as well as it is likely that for the participants of the study, digitization is of more interest.

Concerning the statistical point of view, results are limited in terms of representativeness due to a non-random sample. However, analyses are based on a sample drawn from a heterogeneous population, which comprises 5,758 of large German firms with more than 500 employees. Because of cross-sectional data, results may not apply to a specific industry type. Alternatively, there is no indication that the subjects discussed in each paper have different relevance with respect to specific industries. A second statistical limitation results from the quasi-formative measurement of the variable *Data integration* by means of an additive index, which is used for the analyses of Paper 1 and 3. As the index is measured as a manifest variable, it ignores an error term that formative latent variables usually have. This error term represents the impact of all remaining causes other than those represented by the indicators included (Diamantopoulos, 2006). Using a composite index assumes that the underlying indicators completely capture the construct, which in most cases is inappropriate (Diamantopoulos, 2008). However, as Diamantopoulos (2006) points out, this approach is legitimate if all possible indicators of a construct can be conceivably specified. Given two key perspectives of data integration derived from IS literature (Popovič et al., 2012), this requirement should be largely fulfilled. Finally, the results of the supplementary analyses of Papers 2 and 3 must be interpreted with caution, given a small sample size of 67 controller-manager-dyads.

The ongoing digital transformation has a tremendous impact on structures and processes within an organization, e.g., communication shifts to digital media, coupled with a wide range of technological changes. However, research on the interaction between new technologies and decision-makers by the use of information is still limited (e.g., Rikhardsson & Yigitbasioglu, 2018). This leaves much space for future research. In addition to the consideration of further organizational factors and new technologies, subcategories of the current technologies as well as individual properties should be investigated in more detail. Moreover, longitudinal studies should be conducted to analyse the impact on variability, e.g., influenced by the proceeding transformation of the digital economy or special periods such as the COVID-19 pandemic, on controllership effectiveness.

# Appendix

## Appendix A1: Controller's questionnaire

Heinrich Heine Universität Düsseldorf

controlling accounting

Lehrstuhl für BWL, insbes. Controlling und Accounting
Prof. Dr. Barbara E. Weißenberger

Forschungsprojekt

### Digital Forecasting

Vor dem Hintergrund der disruptiven Auswirkungen von COVID-19 ist das Bedürfnis nach Planungsfähigkeit für Unternehmen größer denn je. Die vorliegende Umfrage befasst sich deshalb mit der **Digitalisierung von Business Intelligence & Analytics**, um wichtige Einflussfaktoren auf die **Prognosequalität** und damit auch die **Entscheidungsunterstützung** im **Revenue Forecasting** zu identifizieren.

Die Erhebung dient **rein wissenschaftlichen Zwecken** im Rahmen unserer Forschung. Grundsatz unserer wissenschaftlichen Arbeit ist es, konkrete Handlungsempfehlungen für die Praxis zu erarbeiten. Als Dankeschön für Ihre Teilnahme erhalten Sie unsere Ergebnisse in Form eines **exklusiven Benchmarking-Berichts**.

Wir sichern Ihnen ausdrücklich zu, dass alle Angaben in dieser Umfrage **streng vertraulich** behandelt werden. Alle Antworten werden **anonymisiert** ausgewertet.

Die Umfrage ist in verschiedene Themenbereiche unterteilt. Die Vollständigkeit Ihrer Antworten ist für den Erfolg der Studie von großer Bedeutung. Sollten Sie keine bzw. wenig Informationen zur Beantwortung einer Frage haben, so bitten wir Sie bewusst um **Ihre subjektive Einschätzung als Controller (m/w)**. Es gibt keine richtigen oder falschen Antworten.

Das Ausfüllen des Fragebogens dauert **ca. 20 Minuten**.

Für Rückfragen steht Ihnen gerne Herr **Mark Alexander Müller, M.A.** unter der Rufnummer +49-211-81-15418 oder der E-Mail-Adresse mark.mueller@hhu.de zur Verfügung.

Herzlichen Dank für Ihre Zeit und wertvolle Unterstützung!

WEITER

Bitte beantworten Sie die nachfolgenden Fragen aus der **Perspektive Ihres Geschäftsbereichs** (oder Unternehmenseinheit, Sparte, Division etc.) bzw. - falls Sie keinem eigenständig abgegrenzten Unternehmensbereich oder einem Tochterunternehmen zugeordnet sind - aus der Perspektive des Gesamtunternehmens.

ZURÜCK 6% WEITER

## Bitte bewerten Sie das Datenmanagement in Ihrem Geschäftsbereich.

**Durch Klicken auf die Laufleiste oder Skala lässt sich der Schieberegler aktiveren und navigieren.**

Daten sind überall verteilt - auf dem Zentralrechner, in Datenbanken, in Tabellenkalkulationen, Textdateien, in ERP-Anwendungen

Daten sind vollständig integriert - ermöglicht Berichte und Analysen in Echtzeit

Die Daten in der Quelle/den Quellen sind inkonsistent

Die Daten in der Quelle/den Quellen sind konsistent

## Inwieweit können betriebswirtschaftliche Analysen in Ihrem Geschäftsbereich durchgeführt werden?

| | nicht vorhanden | | | | | sehr stark vertreten |
|---|---|---|---|---|---|---|
| Berichte in Papierform | ○ | ○ | ○ | ○ | ○ | ○ |
| Interaktive Berichte (Ad-hoc) | ○ | ○ | ○ | ○ | ○ | ○ |
| On-Line Analytical Processing (OLAP) | ○ | ○ | ○ | ○ | ○ | ○ |
| Analytische Anwendungen, einschließlich Trend- und Szenarioanalysen | ○ | ○ | ○ | ○ | ○ | ○ |
| Data Mining* | ○ | ○ | ○ | ○ | ○ | ○ |
| Dashboards, einschließlich Kennzahlen, Performance-Schlüsselindikatoren (KPI), Warnmeldungen | ○ | ○ | ○ | ○ | ○ | ○ |
| Statistische Prognosemodelle | ○ | ○ | ○ | ○ | ○ | ○ |
| Simulationen, einschließlich Handlungsempfehlungen | ○ | ○ | ○ | ○ | ○ | ○ |

*Data Mining beschreibt die automatische Auswertung großer Datenmengen zur Bestimmung von Regelmäßigkeiten, Gesetzmäßigkeiten sowie verborgener Zusammenhänge.

ZURÜCK 18% WEITER

Bitte beantworten Sie die nachfolgenden Fragen aus der **Perspektive Ihres Geschäftsbereichs** (oder Unternehmenseinheit, Sparte, Division etc.) bzw. - falls Sie keinem eigenständig abgegrenzten Unternehmensbereich oder einem Tochterunternehmen zugeordnet sind - aus der Perspektive des Gesamtunternehmens.

Bitte beziehen Sie Ihre Antworten dabei auf Ihre Tätigkeiten als Controller (m/w) im **Revenue Forecasting**.

ZURÜCK 24% WEITER

Im Folgenden wird der Begriff "Business Intelligence" durch die Abkürzung "BI" ersetzt. Business Intelligence beschreibt dabei die technologiegestützte Umwandlung von Daten in Informationen, die in Entscheidungsprozessen genutzt werden können.

## Welche BI-Systeme kommen im Rahmen des Revenue Forecasting in Ihrem Geschäftsbereich zum Einsatz?

Mehrfachauswähl möglich

- ☐ Microsoft (Power BI, SQL Server Reporting Services, ...)
- ☐ Tableau (Desktop, Online, ...)
- ☐ Qlik (Sense, View, Analytics Platform, ...)
- ☐ IBM (Cognos Analytics, Cognos Mobile, ...)
- ☐ Oracle (Analytics Cloud, Business Intelligence Enterprise, ...)
- ☐ SAS (Enterprise BI Server, Visual Analytics, ...)
- ☐ SAP (Lumira, BusinessObjects BI, ...)
- ☐ Salesforce (Einstein Analytics, Einstein Discovery, ...)
- ☐ Sisense
- ☐ Andere (bitte angeben)

## In welchem Umfang nutzen Sie BI-Systeme im Rahmen des Revenue Forecasting?

| | gar nicht | | | | | sehr oft |
|---|---|---|---|---|---|---|
| Zugriff auf statische Berichte | ○ | ○ | ○ | ○ | ○ | ○ |
| Zugriff auf dynamische Berichte (Drill-Down) | ○ | ○ | ○ | ○ | ○ | ○ |
| Erstellung individueller Berichte | ○ | ○ | ○ | ○ | ○ | ○ |
| Nutzung von Analysefunktionen | ○ | ○ | ○ | ○ | ○ | ○ |
| Verknüpfung vorhandener Daten | ○ | ○ | ○ | ○ | ○ | ○ |
| Erschließung neuer Datenquellen | ○ | ○ | ○ | ○ | ○ | ○ |

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Unser BI-System verbessert meine Fähigkeit, gute Entscheidungen zu treffen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System ermöglicht es mir, meine Arbeit schneller zu erledigen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System ermöglicht es mir, präzisere Arbeitsergebnisse zu erzielen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System erhöht meine Effektivität bei meiner Arbeit. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 35% WEITER

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Unser BI-System liefert mir alle Informationen, die ich benötige. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System liefert mir korrekte Informationen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System liefert mir aktuellste Informationen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Die von unserem BI-System bereitgestellten Informationen sind gut dargestellt. | ○ | ○ | ○ | ○ | ○ | ○ |
| Allgemein liefert mir unser BI-System qualitativ hochwertige Informationen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Ich bin mit den Informationen, die ich von unserem BI-System erhalte, sehr zufrieden. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 41% WEITER

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Unser BI-System arbeitet zuverlässig. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System kann sich flexibel an neue Anforderungen oder Bedingungen anpassen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System kombiniert effektiv Daten aus unterschiedlichen Bereichen des Unternehmens. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System macht Informationen leicht zugänglich. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System reagiert schnell auf meine Abfragen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System ist in unser ERP-System integriert. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System ist ein Self-Service-BI. | ○ | ○ | ○ | ○ | ○ | ○ |
| Allgemein ist unser BI-System von hoher Qualität. | ○ | ○ | ○ | ○ | ○ | ○ |
| Insgesamt bin ich mit unserem BI-System sehr zufrieden. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 47% WEITER

Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Das Zahlenwerk des Controllings steht in einem einfach nachvollziehbaren Zusammenhang mit dem Zahlenwerk des Vertriebs. | ○ | ○ | ○ | ○ | ○ | ○ |
| Informationen aus Controlling und Vertrieb ergeben ein einheitliches Bild der Geschäftssituation. | ○ | ○ | ○ | ○ | ○ | ○ |
| In Diskussionen vertreten Controlling und Vertrieb grundsätzlich einheitliche Meinungen. | ○ | ○ | ○ | ○ | ○ | ○ |

Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Das Controlling spielt eine sehr wichtige Rolle bei der Entscheidungsfindung in unserem Geschäftsbereich. | ○ | ○ | ○ | ○ | ○ | ○ |
| Das Management legt großen Wert auf die Meinung des Controllings bei der Entscheidungsfindung. | ○ | ○ | ○ | ○ | ○ | ○ |
| Das Controlling hat einen starken Einfluss auf die Entscheidungen des Managements in unserem Geschäftsbereich. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 53% WEITER

Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Informationen aus unserem Controlling sind genau. | ○ | ○ | ○ | ○ | ○ | ○ |
| Informationen aus unserem Controlling sind aktuell. | ○ | ○ | ○ | ○ | ○ | ○ |
| Informationen aus unserem Controlling sind fehlerfrei. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser Controlling liefert häufig neue Informationen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser Controlling verwendet geeignete Methoden und Techniken. | ○ | ○ | ○ | ○ | ○ | ○ |
| Die aus unserem Controlling bereitgestellten Berichte sind leicht verständlich. | ○ | ○ | ○ | ○ | ○ | ○ |
| Inhaltlich decken die Berichte aus unserem Controlling alle wichtigen Bereiche unseres Geschäfts ab. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 59% WEITER

Bitte verteilen Sie Ihren tatsächlichen zeitlichen Aufwand prozentual auf die dargestellten Controllerrollen.

Controller in der Rolle als ...

Bitte verteilen Sie Ihren zeitlichen Aufwand so, dass Sie insgesamt 100 % erreichen.

| | | |
|---|---|---|
| ... Kontrolleur / kaufmännisches Gewissen (d.h. operative Überwachung von Leistungsindikatoren) | 0 | % |
| ... Analyst / Informationsspezialist (d.h. Auswertung und empfänger-, respektive führungskräfteorientierte Aufbereitung von Informationen) | 0 | % |
| ... Business Partner / Berater der Führungskräfte (d.h. aktive Unterstützung der Führungskräfte im Entscheidungsprozess) | 0 | % |
| ... Change Agent / Veränderungstreiber (d.h. eigeninitiativer Anstoß von Veränderungsprozessen im Unternehmen) | 0 | % |
| Total | 0 | % |

Bitte verteilen Sie Ihren angestrebten zeitlichen Aufwand prozentual auf die dargestellten Controllerrollen.

Controller in der Rolle als ...

Bitte verteilen Sie Ihren zeitlichen Aufwand so, dass Sie insgesamt 100 % erreichen.

| | | |
|---|---|---|
| ... Kontrolleur / kaufmännisches Gewissen (d.h. operative Überwachung von Leistungsindikatoren) | 0 | % |
| ... Analyst / Informationsspezialist (d.h. Auswertung und empfänger-, respektive führungskräfteorientierte Aufbereitung von Informationen) | 0 | % |
| ... Business Partner / Berater der Führungskräfte (d.h. aktive Unterstützung der Führungskräfte im Entscheidungsprozess) | 0 | % |
| ... Change Agent / Veränderungstreiber (d.h. eigeninitiativer Anstoß von Veränderungsprozessen im Unternehmen) | 0 | % |
| Total | 0 | % |

ZURÜCK 65% WEITER

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Die Qualität der Controllinginformationen wird von der Corona-Krise beeinträchtigt. | ○ | ○ | ○ | ○ | ○ | ○ |
| Die Qualität unseres Revenue Forecasting wird von der Corona-Krise beeinträchtigt. | ○ | ○ | ○ | ○ | ○ | ○ |
| Für unsere Prognosen im Revenue Forecasting müssen wir während der Corona-Krise auf klassische Excel-Modelle zurückgreifen. | ○ | ○ | ○ | ○ | ○ | ○ |
| In der Corona-Krise sind viele Probleme analytisch nicht zu durchdringen, deswegen müssen Entscheidungen häufig aus unternehmerischer Erfahrung heraus getroffen werden. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 71% WEITER

Bitte beantworten Sie die nachfolgenden Fragen aus der **Perspektive Ihres Gesamtunternehmens**.

ZURÜCK 76% WEITER

## Wie gehen Sie allgemein mit dem Thema Digitalisierung in Ihrem Unternehmen vor?

| |
|---|
| Digitalisierung ist ein fester Bestandteil unserer Unternehmensstrategie. |
| Wir arbeiten an der Umsetzung einzelner Projekte. |
| Wir haben uns noch nicht damit beschäftigt. |

## Das Unternehmen, in dem Sie tätig sind, ist ein(e) ...

| |
|---|
| Holding / Konzernspitze |
| Zwischenholding |
| Tochterunternehmen / Joint Venture |
| Einzelunternehmen ohne Konzernverbund |

## In welcher Branche ist Ihr Unternehmen hauptsächlich tätig?

| |
|---|
| Automobil |
| Bau |
| Chemie, Pharma, Gesundheit |
| Eisen, Stahl |
| Energie, Versorger |
| Handel |
| Konsumgüter |
| Maschinenbau |
| Medien |
| Software, Technologie |
| Telekommunikation |
| Verkehr, Transport |
| Sonstige |

ZURÜCK 82% WEITER

Wie hoch ist der Anteil des im Ausland erzielten Umsatzes am Gesamtumsatz Ihres Unternehmens?

Bitte wählen

Wie hoch ist der Anteil der im Ausland beschäftigten Mitarbeiter an der Gesamtmitarbeiterzahl Ihres Unternehmens?

Bitte wählen

Wie verhält sich der Erfolg Ihres Unternehmens im Vergleich zu dem Ihrer Wettbewerber?

| | sehr schlecht | | | | | sehr gut |
|---|---|---|---|---|---|---|
| Unsere Umsatzrendite war im Durchschnitt der letzten drei Geschäftsjahre im Vergleich zu unseren Wettbewerbern... | ○ | ○ | ○ | ○ | ○ | ○ |

Wie schätzen Sie die Flexibilität Ihres Unternehmens bezüglich der folgenden Kriterien ein?

| | sehr schlecht | | | | | sehr gut |
|---|---|---|---|---|---|---|
| Hohe Anpassungsfähigkeit der Organisation | ○ | ○ | ○ | ○ | ○ | ○ |
| Schnelle Anpassung der Produkte an neue Kundenbedürfnisse | ○ | ○ | ○ | ○ | ○ | ○ |
| Schnelle Reaktion auf neue Entwicklungen am Markt | ○ | ○ | ○ | ○ | ○ | ○ |
| Schnelle Nutzung neuer digitaler Technologien | ○ | ○ | ○ | ○ | ○ | ○ |

Inwieweit treffen die folgenden Aussagen auf das Marktumfeld Ihres Unternehmens zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| In unserem Geschäft ändern sich die Kundenanforderungen stark über die Zeit. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unsere Kunden suchen ständig nach neuen Produkten oder Dienstleistungen. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 88% WEITER

Falls Sie **Ergänzungen und Anmerkungen** zu unserem Forschungsprojekt haben, teilen Sie uns diese gerne mit:

ZURÜCK 94% WEITER

## Unser Dankeschön für Ihre Teilnahme

**Geschafft!** Als Dankeschön für die Unterstützung unseres Forschungsprojekts „Digital Forecasting" bieten wir Ihnen einen exklusiven Benchmarking-Bericht der Studie mit zahlreichen praxisnahen Hinweisen.

### Ihre Kontaktdaten zur Zusendung des Benchmarking-Berichts:

**Angaben freiwillig**

Anrede:

Bitte wählen

Titel:

Vorname:

Name:

Position:

Unternehmen:

Straße / Hausnummer:

PLZ / Ort:

E-Mail:

Telefon:

ZURÜCK 94% WEITER

Unsere Umfrage ist hiermit beendet. **Wir danken Ihnen sehr für Ihre Teilnahme!**

100%

## Appendix A2: Manager's questionnaire

Heinrich Heine Universität Düsseldorf

controlling accounting
Lehrstuhl für BWL, insbes. Controlling und Accounting
Prof. Dr. Barbara E. Weißenberger

Forschungsprojekt

# Digital Forecasting

Vor dem Hintergrund der disruptiven Auswirkungen von COVID-19 ist das Bedürfnis nach Planungsfähigkeit für Unternehmen größer denn je. Die vorliegende Umfrage befasst sich deshalb mit der **Digitalisierung von Business Intelligence & Analytics**, um wichtige Einflussfaktoren auf die **Prognosequalität** und damit auch die **Entscheidungsunterstützung** im **Revenue Forecasting** zu identifizieren.

Die Erhebung dient **rein wissenschaftlichen Zwecken** im Rahmen unserer Forschung. Grundsatz unserer wissenschaftlichen Arbeit ist es, konkrete Handlungsempfehlungen für die Praxis zu erarbeiten. Als Dankeschön für Ihre Teilnahme erhalten Sie unsere Ergebnisse in Form eines **exklusiven Benchmarking-Berichts**.

Wir sichern Ihnen ausdrücklich zu, dass alle Angaben in dieser Umfrage **streng vertraulich** behandelt werden. Alle Antworten werden **anonymisiert** ausgewertet.

Die Umfrage ist in verschiedene Themenbereiche unterteilt. Die Vollständigkeit Ihrer Antworten ist für den Erfolg der Studie von großer Bedeutung. Sollten Sie keine bzw. wenig Informationen zur Beantwortung einer Frage haben, so bitten wir Sie bewusst um **Ihre subjektive Einschätzung als Geschäftsbereichsmanager (m/w)**. Es gibt keine richtigen oder falschen Antworten.

Das Ausfüllen des Fragebogens dauert **ca. 5 Minuten**.

Für Rückfragen steht Ihnen gerne Herr **Mark Alexander Müller, M.A.** unter der Rufnummer +49-211-81-15418 oder der E-Mail-Adresse mark.mueller@hhu.de zur Verfügung.

Herzlichen Dank für Ihre Zeit und wertvolle Unterstützung!

WEITER

Bitte beantworten Sie die nachfolgenden Fragen aus der Perspektive Ihres Geschäftsbereichs (oder Unternehmenseinheit, Sparte, Division etc.) bzw. - falls Sie keinem eigenständig abgegrenzten Unternehmensbereich oder einem Tochterunternehmen zugeordnet sind - aus der Perspektive des Gesamtunternehmens.

Bitte beziehen Sie Ihre Antworten dabei auf Ihre Tätigkeiten als Geschäftsbereichsmanager (m/w) im Revenue Forecasting.

ZURÜCK 10% WEITER

Im Folgenden wird der Begriff "Business Intelligence" durch die Abkürzung "BI" ersetzt. Business Intelligence beschreibt dabei die technologiegestützte Umwandlung von Daten in Informationen, die in Entscheidungsprozessen genutzt werden können.

### In welchem Umfang nutzen Sie BI-Systeme im Rahmen des Revenue Forecasting?

| | gar nicht | | | | | sehr oft |
|---|---|---|---|---|---|---|
| Zugriff auf statische Berichte | ○ | ○ | ○ | ○ | ○ | ○ |
| Zugriff auf dynamische Berichte (Drill-Down) | ○ | ○ | ○ | ○ | ○ | ○ |
| Erstellung individueller Berichte | ○ | ○ | ○ | ○ | ○ | ○ |
| Nutzung von Analysefunktionen | ○ | ○ | ○ | ○ | ○ | ○ |
| Verknüpfung vorhandener Daten | ○ | ○ | ○ | ○ | ○ | ○ |
| Erschließung neuer Datenquellen | ○ | ○ | ○ | ○ | ○ | ○ |

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Unser BI-System verbessert meine Fähigkeit, gute Entscheidungen zu treffen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System ermöglicht es mir, meine Arbeit schneller zu erledigen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System ermöglicht es mir, präzisere Arbeitsergebnisse zu erzielen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser BI-System erhöht meine Effektivität bei meiner Arbeit. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 20% WEITER

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Das Zahlenwerk des Controllings steht in einem einfach nachvollziehbaren Zusammenhang mit dem Zahlenwerk des Vertriebs. | ○ | ○ | ○ | ○ | ○ | ○ |
| Informationen aus Controlling und Vertrieb ergeben ein einheitliches Bild der Geschäftssituation. | ○ | ○ | ○ | ○ | ○ | ○ |
| In Diskussionen vertreten Controlling und Vertrieb grundsätzlich einheitliche Meinungen. | ○ | ○ | ○ | ○ | ○ | ○ |

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Das Controlling spielt eine sehr wichtige Rolle bei der Entscheidungsfindung in unserem Geschäftsbereich. | ○ | ○ | ○ | ○ | ○ | ○ |
| Bei meiner Entscheidungsfindung lege ich großen Wert auf die Meinung des Controllings. | ○ | ○ | ○ | ○ | ○ | ○ |
| Das Controlling hat einen starken Einfluss auf die Entscheidungen in unserem Geschäftsbereich. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 40% WEITER

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Mit unserem Controlling bin ich insgesamt sehr zufrieden. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser Controlling erfüllt meine Erwartungen immer zur vollsten Zufriedenheit. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser Controlling kommt meiner Idealvorstellung von einer perfekten Controlling-Abteilung sehr nahe. | ○ | ○ | ○ | ○ | ○ | ○ |

## Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Informationen aus unserem Controlling sind genau. | ○ | ○ | ○ | ○ | ○ | ○ |
| Informationen aus unserem Controlling sind aktuell. | ○ | ○ | ○ | ○ | ○ | ○ |
| Informationen aus unserem Controlling sind fehlerfrei. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser Controlling liefert häufig neue Informationen. | ○ | ○ | ○ | ○ | ○ | ○ |
| Unser Controlling verwendet geeignete Methoden und Techniken. | ○ | ○ | ○ | ○ | ○ | ○ |
| Die aus unserem Controlling bereitgestellten Berichte sind leicht verständlich. | ○ | ○ | ○ | ○ | ○ | ○ |
| Inhaltlich decken die Berichte aus unserem Controlling alle wichtigen Bereiche unseres Geschäfts ab. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 60% WEITER

Bitte verteilen Sie die von Ihnen wahrgenommene Bedeutung des Controllings prozentual auf die dargestellten Controllerrollen.

Unser Controlling sehe ich in der Rolle als ...

Bitte verteilen Sie die von Ihnen wahrgenommene Bedeutung so, dass Sie insgesamt 100 % erreichen.

| | |
|---|---|
| ... Kontrolleur / kaufmännisches Gewissen (d.h. operative Überwachung von Leistungsindikatoren) | 0 % |
| ... Analyst / Informationsspezialist (d.h. Auswertung und empfänger-, respektive führungskräfteorientierte Aufbereitung von Informationen) | 0 % |
| ... Business Partner / Berater der Führungskräfte (d.h. aktive Unterstützung der Führungskräfte im Entscheidungsprozess) | 0 % |
| ... Change Agent / Veränderungstreiber (d.h. eigeninitiativer Anstoß von Veränderungsprozessen im Unternehmen) | 0 % |
| Total | 0 % |

ZURÜCK 70% WEITER

Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu?

| | trifft gar nicht zu | | | | | trifft voll zu |
|---|---|---|---|---|---|---|
| Die Qualität der Controllinginformationen wird von der Corona-Krise beeinträchtigt. | ○ | ○ | ○ | ○ | ○ | ○ |
| Die Qualität unseres Revenue Forecasting wird von der Corona-Krise beeinträchtigt. | ○ | ○ | ○ | ○ | ○ | ○ |
| Für unsere Prognosen im Revenue Forecasting müssen wir während der Corona-Krise auf klassische Excel-Modelle zurückgreifen. | ○ | ○ | ○ | ○ | ○ | ○ |
| In der Corona-Krise sind viele Probleme analytisch nicht zu durchdringen, deswegen müssen Entscheidungen häufig aus unternehmerischer Erfahrung heraus getroffen werden. | ○ | ○ | ○ | ○ | ○ | ○ |

ZURÜCK 80% WEITER

Falls Sie **Ergänzungen und Anmerkungen** zu unserem Forschungsprojekt haben, teilen Sie uns diese gerne mit:

ZURÜCK 90% WEITER

## Unser Dankeschön für Ihre Teilnahme

**Geschafft!** Als Dankeschön für die Unterstützung unseres Forschungsprojekts „Digital Forecasting" bieten wir Ihnen einen exklusiven Benchmarking-Bericht der Studie mit zahlreichen praxisnahen Hinweisen.

### Ihre Kontaktdaten zur Zusendung des Benchmarking-Berichts:

**Angaben freiwillig**

Anrede:

Bitte wählen

| | |
|---|---|
| Titel: | |
| Vorname: | |
| Name: | |
| Position: | |
| Unternehmen: | |
| Straße / Hausnummer: | |
| PLZ / Ort: | |
| E-Mail: | |
| Telefon: | |

ZURÜCK 90% WEITER

Unsere Umfrage ist hiermit beendet. **Wir danken Ihnen sehr für Ihre Teilnahme!**

100%

**Appendix A3: Descriptive Overview of survey items**

**Datenmanagement**

| **Item** | | **Scale validity** | **Frequency (in %)** | | | | | | **Mean** | **SD** | ***n*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Bitte bewerten Sie das Datenmanagement in Ihrem Geschäftsbereich. | 0 = Daten sind überall verteilt - auf dem Zentralrechner, in Datenbanken, in Tabellenkalkulationen, Textdateien, in ERP-Anwendungen .. 5 = Daten sind vollständig integriert - ermöglicht Berichte und Analysen in Echtzeit | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| DI1 | | | 3.2 | 21.2 | 30.8 | 28.2 | 13.5 | 3.2 | 2.37 | 1.15 | 156 |
| **CO** | Bitte bewerten Sie das Datenmanagement in Ihrem Geschäftsbereich. | 0 = Die Daten in der Quelle / den Quellen sind inkonsistent .. 5 = Die Daten in der Quelle / den Quellen sind konsistent | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| DI2 | | | .6 | 5.1 | 22.4 | 32.1 | 33.3 | 6.4 | 3.12 | 1.04 | 156 |

*SD = Standard deviation*

(continued on next page)

## Appendix A3: Descriptive Overview of survey items

### Qualität und Nutzung von BI-Systemen

| Item | | Scale validity | Frequency (in %) | | | | | | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Inwieweit können betriebswirtschaftliche Analysen in Ihrem Geschäftsbereich durchgeführt werden? | 0 = nicht vorhanden .. 5 = sehr stark vertreten | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| AC1 | Berichte in Papierform ( - ) | | 29.5 | 29.5 | 12.8 | 9.6 | 9.0 | 9.6 | 1.68 | 1.65 | 156 |
| AC2 | Interaktive Berichte (Ad-hoc) | | 4.5 | 11.5 | 15.4 | 28.8 | 30.1 | 9.6 | 2.97 | 1.31 | 156 |
| AC3 | On-Line Analytical Processing (OLAP) | | 19.9 | 14.1 | 16.7 | 18.6 | 16.0 | 14.7 | 2.41 | 1.71 | 156 |
| AC4 | Analytische Anwendungen, einschließlich Trend- und Szenarioanalysen | | 13.5 | 27.6 | 23.1 | 17.9 | 15.4 | 2.6 | 2.02 | 1.36 | 156 |
| AC5 | Data Mining | | 46.2 | 25.0 | 12.8 | 10.9 | 3.8 | 1.3 | 1.05 | 1.26 | 156 |
| AC6 | Dashboards, einschließlich Kennzahlen, Performance-Schlüsselindikatoren (KPI), Warnmeldungen | | 3.8 | 10.9 | 11.5 | 21.8 | 38.5 | 13.5 | 3.21 | 1.34 | 156 |
| AC7 | Statistische Prognosemodelle | | 22.4 | 34.0 | 21.2 | 12.2 | 7.1 | 3.2 | 1.57 | 1.33 | 156 |
| AC8 | Simulationen, einschließlich Handlungsempfehlungen | | 15.4 | 25.0 | 17.3 | 24.4 | 14.7 | 3.2 | 2.08 | 1.41 | 156 |
| **CO** | Welche BI-Systeme kommen im Rahmen des Revenue Forecasting in Ihrem Geschäftsbereich zum Einsatz? | 0 = kommen nicht zum Einsatz .. 1 = kommen zum Einsatz | 0 | 1 | | | | | | | |
| SOFT1 | Microsoft (Power BI, SQL Server Reporting Services, …) | | 51.3 | 48.7 | | | | | .49 | .50 | 156 |
| SOFT2 | Tableau (Desktop, Online, …) | | 88.5 | 11.5 | | | | | .12 | .32 | 156 |
| SOFT3 | Qlik (Sense, View, Analytics Platform, …) | | 85.3 | 14.7 | | | | | .15 | .36 | 156 |
| SOFT4 | IBM (Cognos Analytics, Cognos Mobile, …) | | 89.7 | 10.3 | | | | | .10 | .30 | 156 |
| SOFT5 | Oracle (AnalyticsCloud, BusinessIntelligence Enterprise, …) | | 92.9 | 7.1 | | | | | .07 | .26 | 156 |
| SOFT6 | SAS ( Enterprise BI Server, Visual Analytics, …) | | 99.4 | .6 | | | | | .01 | .08 | 156 |
| SOFT7 | SAP ( Lumira, BusinessObjects BI, …) | | 59.6 | 40.4 | | | | | .40 | .49 | 156 |
| SOFT8 | Salesforce (Einstein Analytics, Einstein Discovery, …) | | 91.7 | 8.3 | | | | | .08 | .28 | 156 |
| SOFT9 | Sisense | | 100.0 | .0 | | | | | .00 | .0 | 156 |
| SOFT10 | Andere (bitte angeben) | | 64.7 | 35.3 | | | | | .35 | .48 | 156 |

*SD = Standard deviation*

(continued on next page)

## Appendix A3: Descriptive Overview of survey items

### Qualität und Nutzung von BI-Systemen

| Item | | Scale validity | Frequency (in %) | | | | | | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | In welchem Umfang nutzen Sie BI-Systeme im Rahmen des Revenue Forecasting? [Controller] | 0 = gar nicht ..<br>5 = sehr oft | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| SS1 | Zugriff auf statische Berichte | | 17.3 | 13.5 | 9.6 | 12.8 | 17.3 | 29.5 | 2.88 | 1.88 | 156 |
| SS2 | Zugriff auf dynamische Berichte (Drill-Down) | | 16.7 | 8.3 | 9.6 | 12.8 | 23.1 | 29.5 | 3.06 | 1.83 | 156 |
| SS3 | Erstellung individueller Berichte | | 9.6 | 10.9 | 12.2 | 21.8 | 19.9 | 25.6 | 3.08 | 1.63 | 156 |
| SS4 | Nutzung von Analysefunktionen | | 15.4 | 20.5 | 14.7 | 17.3 | 16.0 | 16.0 | 2.46 | 1.70 | 156 |
| SS5 | Verknüpfung vorhandener Daten | | 13.5 | 10.3 | 14.1 | 20.5 | 22.4 | 19.2 | 2.86 | 1.66 | 156 |
| SS6 | Erschließung neuer Datenquellen | | 30.1 | 30.1 | 17.3 | 11.5 | 8.3 | 2.6 | 1.46 | 1.38 | 156 |
| **MGMT** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? [Manager] | 0 = gar nicht ..<br>5 = sehr oft | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| SS1 | Zugriff auf statische Berichte | | 6.0 | 4.5 | 9.0 | 23.9 | 23.9 | 32.8 | 3.54 | 1.45 | 67 |
| SS2 | Zugriff auf dynamische Berichte (Drill-Down) | | 7.5 | 6.0 | 16.4 | 19.4 | 23.9 | 26.9 | 3.27 | 1.53 | 67 |
| SS3 | Erstellung individueller Berichte | | 13.4 | 11.9 | 10.4 | 26.9 | 16.4 | 20.9 | 2.84 | 1.68 | 67 |
| SS4 | Nutzung von Analysefunktionen | | 14.9 | 19.4 | 11.9 | 14.9 | 20.9 | 17.9 | 2.61 | 1.75 | 67 |
| SS5 | Verknüpfung vorhandener Daten | | 14.9 | 9.0 | 7.5 | 26.9 | 23.9 | 17.9 | 2.90 | 1.66 | 67 |
| SS6 | Erschließung neuer Datenquellen | | 17.9 | 32.8 | 17.9 | 13.4 | 9.0 | 9.0 | 1.90 | 1.54 | 67 |

*SD = Standard deviation*

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## Appendix A3: Descriptive Overview of survey items

### Qualität und Nutzung von BI-Systemen

| Item | | Scale validity | Frequency (in %) | | | | | | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | In welchem Umfang nutzen Sie BI-Systeme im Rahmen des Revenue Forecasting? [Controller] | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| USE1 | Unser BI-System verbessert meine Fähigkeit, gute Entscheidungen zu treffen. | | 7.1 | 6.4 | 10.3 | 25.6 | 24.4 | 26.3 | 3.33 | 1.48 | 156 |
| USE2 | Unser BI-System ermöglicht es mir, meine Arbeit schneller zu erledigen. | | 5.8 | 7.1 | 12.8 | 16.0 | 30.1 | 28.2 | 3.42 | 1.48 | 156 |
| USE3 | Unser BI-System ermöglicht es mir, präzisere Arbeitsergebnisse zu erzielen. | | 5.8 | 3.8 | 12.8 | 21.8 | 32.7 | 23.1 | 3.41 | 1.38 | 156 |
| USE4 | Unser BI-System erhöht meine Effektivität bei meiner Arbeit. | | 6.4 | 3.8 | 16.0 | 19.2 | 27.6 | 26.9 | 3.38 | 1.45 | 156 |
| **MGMT** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? [Manager] | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| USE1 | Unser BI-System verbessert meine Fähigkeit, gute Entscheidungen zu treffen. | | 4.5 | 6.0 | 10.4 | 19.4 | 26.9 | 32.8 | 3.57 | 1.43 | 67 |
| USE2 | Unser BI-System ermöglicht es mir, meine Arbeit schneller zu erledigen. | | 4.5 | 7.5 | 11.9 | 13.4 | 31.3 | 31.3 | 3.54 | 1.46 | 67 |
| USE3 | Unser BI-System ermöglicht es mir, präzisere Arbeitsergebnisse zu erzielen. | | 4.5 | 7.5 | 9.0 | 19.4 | 34.3 | 25.4 | 3.48 | 1.40 | 67 |
| USE4 | Unser BI-System erhöht meine Effektivität bei meiner Arbeit. | | 4.5 | 4.5 | 11.9 | 17.9 | 34.3 | 26.9 | 3.54 | 1.36 | 67 |

*SD = Standard deviation*

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## Appendix A3: Descriptive Overview of survey items

### Qualität und Nutzung von BI-Systemen

| Item | | Scale validity | Frequency (in %) | | | | | | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| IQ1 | Unser BI-System liefert mir alle Informationen, die ich benötige. | | 6.4 | 18.6 | 19.9 | 29.5 | 21.2 | 4.5 | 2.54 | 1.31 | 156 |
| IQ2 | Unser BI-System liefert mir korrekte Informationen. | | 5.1 | 1.9 | 9.6 | 20.5 | 39.7 | 23.1 | 3.57 | 1.28 | 156 |
| IQ3 | Unser BI-System liefert mir aktuellste Informationen. | | 5.8 | 10.3 | 11.5 | 17.9 | 37.2 | 17.3 | 3.22 | 1.44 | 156 |
| IQ4 | Die von unserem BI-System bereitgestellten Informationen sind gut dargestellt. | | 7.1 | 10.9 | 14.7 | 27.6 | 30.1 | 9.6 | 2.92 | 1.38 | 156 |
| IQ5 | Allgemein liefert mir unser BI-System qualitativ hochwertige Informationen. | | 5.1 | 5.8 | 10.3 | 21.2 | 46.2 | 11.5 | 3.32 | 1.28 | 156 |
| ISAT1 | Ich bin mit den Informationen, die ich von unserem BI-System erhalte, sehr zufrieden. | | 5.8 | 7.1 | 16.0 | 30.1 | 33.3 | 7.7 | 3.01 | 1.27 | 156 |
| SQ1 | Unser BI-System arbeitet zuverlässig. | | 5.8 | 2.6 | 8.3 | 23.1 | 43.6 | 16.7 | 3.46 | 1.27 | 156 |
| SQ2 | Unser BI-System kann sich flexibel an neue Anforderungen oder Bedingungen anpassen. | | 8.3 | 16.7 | 26.3 | 18.6 | 23.1 | 7.1 | 2.53 | 1.41 | 156 |
| SQ3 | Unser BI-System kombiniert effektiv Daten aus unterschiedlichen Bereichen des Unternehmens. | | 8.3 | 17.3 | 19.2 | 28.2 | 19.2 | 7.7 | 2.56 | 1.40 | 156 |
| SQ4 | Unser BI-System macht Informationen leicht zugänglich. | | 5.1 | 8.3 | 14.1 | 31.4 | 28.8 | 12.2 | 3.07 | 1.31 | 156 |
| SQ5 | Unser BI-System reagiert schnell auf meine Abfragen. | | 6.4 | 7.7 | 15.4 | 30.8 | 29.5 | 10.3 | 3.00 | 1.32 | 156 |
| ERP1 | Unser BI-System ist in unser ERP-System integriert. | | 26.9 | 13.5 | 10.9 | 13.5 | 19.9 | 15.4 | 2.32 | 1.86 | 156 |
| SS7 | Unser BI-System ist ein Self-Service-BI. | | 19.9 | 11.5 | 18.6 | 20.5 | 19.2 | 10.3 | 2.38 | 1.64 | 156 |
| SQ6 | Allgemein ist unser BI-System von hoher Qualität. | | 6.4 | 7.7 | 13.5 | 32.7 | 32.1 | 7.7 | 2.99 | 1.29 | 156 |
| SSAT1 | Insgesamt bin ich mit unserem BI-System sehr zufrieden. | | 6.4 | 7.7 | 14.7 | 35.3 | 29.5 | 6.4 | 2.93 | 1.26 | 156 |

*SD = Standard deviation*

(continued on next page)

## Appendix A3: Descriptive Overview of survey items

### Ergebnisqualität und Rollenverständnis des Controllings

| Item | | Scale validity | Frequency (in %) | | | | | | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? [Controller] | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| CQ1 | Informationen aus unserem Controlling sind genau. | | .0 | .0 | 4.5 | 14.1 | 53.8 | 27.6 | 4.04 | .77 | 156 |
| CQ2 | Informationen aus unserem Controlling sind aktuell. | | .0 | 1.3 | 8.3 | 21.8 | 42.3 | 26.3 | 3.84 | .95 | 156 |
| CQ3 | Informationen aus unserem Controlling sind fehlerfrei. | | .0 | 1.3 | 9.6 | 29.5 | 46.8 | 12.8 | 3.60 | .88 | 156 |
| CQ4 | Unser Controlling liefert häufig neue Informationen. | | .6 | 4.5 | 21.2 | 34.0 | 31.4 | 8.3 | 3.16 | 1.04 | 156 |
| CQ5 | Unser Controlling verwendet geeignete Methoden und Techniken. | | .6 | 4.5 | 17.9 | 32.1 | 35.3 | 9.6 | 3.26 | 1.05 | 156 |
| CQ6 | Die aus unserem Controlling bereitgestellten Berichte sind leicht verständlich. | | .0 | 3.2 | 12.2 | 35.9 | 37.8 | 10.9 | 3.41 | .95 | 156 |
| CQ7 | Inhaltlich decken die Berichte aus unserem Controlling alle wichtigen Bereiche unseres Geschäfts ab. | | .0 | 3.8 | 7.1 | 30.8 | 42.3 | 16.0 | 3.60 | .97 | 156 |
| **MGMT** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? [Manager] | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| CQ1 | Informationen aus unserem Controlling sind genau. | | 1.5 | .0 | 4.5 | 10.4 | 62.7 | 20.9 | 3.96 | .86 | 67 |
| CQ2 | Informationen aus unserem Controlling sind aktuell. | | 1.5 | 3.0 | 7.5 | 16.4 | 47.8 | 23.9 | 3.78 | 1.08 | 67 |
| CQ3 | Informationen aus unserem Controlling sind fehlerfrei. | | 1.5 | 1.5 | 9.0 | 25.4 | 53.7 | 9.0 | 3.55 | .94 | 67 |
| CQ4 | Unser Controlling liefert häufig neue Informationen. | | 3.0 | 3.0 | 17.9 | 29.9 | 35.8 | 10.4 | 3.24 | 1.14 | 67 |
| CQ5 | Unser Controlling verwendet geeignete Methoden und Techniken. | | 3.0 | 1.5 | 13.4 | 29.9 | 34.3 | 17.9 | 3.45 | 1.16 | 67 |
| CQ6 | Die aus unserem Controlling bereitgestellten Berichte sind leicht verständlich. | | 3.0 | 1.5 | 9.0 | 26.9 | 49.3 | 10.4 | 3.49 | 1.05 | 67 |
| CQ7 | Inhaltlich decken die Berichte aus unserem Controlling alle wichtigen Bereiche unseres Geschäfts ab. | | 4.5 | 7.5 | 7.5 | 16.4 | 47.8 | 16.4 | 3.76 | 1.18 | 67 |

*SD = Standard deviation*

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## Appendix A3: Descriptive Overview of survey items

### Ergebnisqualität und Rollenverständnis des Controllings

| Item | | Scale validity | Frequency (in %) | | | | | | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? [Controller] | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| UNI1 | Das Zahlenwerk des Controllings steht in einem einfach nachvollziehbaren Zusammenhang mit dem Zahlenwerk des Vertriebs. | | 2.6 | 7.1 | 13.5 | 23.1 | 37.8 | 16.0 | 3.35 | 1.25 | 156 |
| UNI2 | Informationen aus Controlling und Vertrieb ergeben ein einheitliches Bild der Geschäftssituation. | | 2.6 | 6.4 | 9.6 | 20.5 | 41.0 | 19.9 | 3.51 | 1.24 | 156 |
| UNI3 | In Diskussionen vertreten Controlling und Vertrieb grundsätzlich einheitliche Meinungen. | | 4.5 | 18.6 | 23.1 | 27.6 | 23.1 | 3.2 | 2.56 | 1.25 | 156 |
| **MGMT** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? [Manager] | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| UNI1 | Das Zahlenwerk des Controllings steht in einem einfach nachvollziehbaren Zusammenhang mit dem Zahlenwerk des Vertriebs. | | 4.5 | 7.5 | 7.5 | 16.4 | 47.8 | 16.4 | 3.45 | 1.32 | 67 |
| UNI2 | Informationen aus Controlling und Vertrieb ergeben ein einheitliches Bild der Geschäftssituation. | | 4.5 | 3.0 | 7.5 | 16.4 | 44.8 | 23.9 | 3.66 | 1.26 | 67 |
| UNI3 | In Diskussionen vertreten Controlling und Vertrieb grundsätzlich einheitliche Meinungen. | | 4.5 | 16.4 | 28.4 | 28.4 | 16.4 | 6.0 | 2.54 | 1.25 | 67 |

*SD = Standard deviation*

(continued on next page)

## Appendix A3: Descriptive Overview of survey items

**Ergebnisqualität und Rollenverständnis des Controllings**

| Item | | Scale validity | Frequency (in %) | | | | | | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? | 0 = trifft gar nicht zu ..<br>5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| INF1 | Das Controlling spielt eine sehr wichtige Rolle bei der Entscheidungsfindung in unserem Geschäftsbereich. | | .0 | 5.1 | 10.3 | 20.5 | 34.6 | 29.5 | 3.73 | 1.14 | 156 |
| INF2 | Das Management legt großen Wert auf die Meinung des Controllings bei der Entscheidungsfindung. | | .0 | 6.4 | 12.8 | 19.9 | 35.3 | 25.6 | 3.61 | 1.18 | 156 |
| INF3 | Das Controlling hat einen starken Einfluss auf die Entscheidungen des Managements in unserem Geschäftsbereich. | | .0 | 8.3 | 12.2 | 24.4 | 37.2 | 17.9 | 3.44 | 1.17 | 156 |
| **MGMT** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? | 0 = trifft gar nicht zu ..<br>5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| INF1 | Das Controlling spielt eine sehr wichtige Rolle bei der Entscheidungsfindung in unserem Geschäftsbereich. | | .0 | 4.5 | 3.0 | 14.9 | 47.8 | 29.9 | 3.96 | .99 | 67 |
| INF2 | Das Management legt großen Wert auf die Meinung des Controllings bei der Entscheidungsfindung. | | 1.5 | .0 | 4.5 | 17.9 | 47.8 | 28.4 | 3.96 | .94 | 67 |
| INF3 | Das Controlling hat einen starken Einfluss auf die Entscheidungen des Managements in unserem Geschäftsbereich. | | .0 | .0 | 10.4 | 32.8 | 35.8 | 20.9 | 3.67 | .93 | 67 |

*SD = Standard deviation*

(continued on next page)

## Appendix A3: Descriptive Overview of survey items

### Ergebnisqualität und Rollenverständnis des Controllings

| Item | | Scale validity | Min. | Max. | Median | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|
| **CO** | Bitte verteilen Sie Ihren tatsächlichen zeitlichen Aufwand prozentual auf die dargestellten Controllerrollen. | Controller in der Rolle als ... 0 .. 100 % | | | | | | |
| ROL11 | … Kontrolleur / kaufmännisches Gewissen (d.h. operative Überwachung von Leistungsindikatoren) | | 0 | 85 | 20 | 26.83 | 15.45 | 156 |
| ROL12 | … Analyst / Informationsspezialist (d.h. Auswertung und empfänger-, respektive führungskräfteorientierte Aufbereitung von Informationen) | | 0 | 80 | 40 | 36.58 | 14.17 | 156 |
| ROL13 | … Business Partner / Berater der Führungskräfte (d.h. aktive Unterstützung der Führungskräfte im Entscheidungsprozess) | | 0 | 55 | 20 | 22.70 | 10.84 | 156 |
| ROL14 | … Change Agent / Veränderungstreiber (d.h. eigeninitiativer Anstoß von Veränderungsprozessen im Unternehmen) | | 0 | 85 | 10 | 13.89 | 12.37 | 156 |
| **CO** | Bitte verteilen Sie Ihren angestrebten zeitlichen Aufwand prozentual auf die dargestellten Controllerrollen. | Controller in der Rolle als ... 0 .. 100 % | | | | | | |
| ROL21 | … Kontrolleur / kaufmännisches Gewissen (d.h. operative Überwachung von Leistungsindikatoren) | | 0 | 85 | 10 | 15.99 | 11.46 | 156 |
| ROL22 | … Analyst / Informationsspezialist (d.h. Auswertung und empfänger-, respektive führungskräfteorientierte Aufbereitung von Informationen) | | 0 | 60 | 30 | 27.15 | 12.92 | 156 |
| ROL23 | … Business Partner / Berater der Führungskräfte (d.h. aktive Unterstützung der Führungskräfte im Entscheidungsprozess) | | 4 | 90 | 30 | 34.47 | 12.42 | 156 |
| ROL24 | … Change Agent / Veränderungstreiber (d.h. eigeninitiativer Anstoß von Veränderungsprozessen im Unternehmen) | | 0 | 70 | 20 | 22.39 | 11.60 | 156 |

*SD = Standard deviation*

(continued on next page)

**Appendix A3: Descriptive Overview of survey items**

**Ergebnisqualität und Rollenverständnis des Controllings**

| Item | | Scale validity | Min. | Max. | Median | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|
| **MGMT** | Bitte verteilen Sie Ihren <u>angestrebten</u> zeitlichen Aufwand prozentual auf die dargestellten Controllerrollen. | Controller in der Rolle als ...<br>0 .. 100 % | | | | | | |
| ROL31 | … Kontrolleur / kaufmännisches Gewissen (d.h. operative Überwachung von Leistungsindikatoren) | | 0 | 80 | 30 | 30.42 | 16.75 | 67 |
| ROL32 | … Analyst / Informationsspezialist (d.h. Auswertung und empfänger-, respektive führungskräfteorientierte Aufbereitung von Informationen) | | 0 | 80 | 30 | 30.61 | 13.80 | 67 |
| ROL33 | … Business Partner / Berater der Führungskräfte (d.h. aktive Unterstützung der Führungskräfte im Entscheidungsprozess) | | 4 | 90 | 25 | 26.24 | 13.46 | 67 |
| ROL34 | … Change Agent / Veränderungstreiber (d.h. eigeninitiativer Anstoß von Veränderungsprozessen im Unternehmen) | | 0 | 45 | 10 | 12.73 | 9.04 | 67 |

| Item | | Scale validity | Frequency (in %) | | | | | | Mean | SD | *n* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **MGMT** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? | 0 = trifft gar nicht zu ..<br>5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| CSAT1 | Mit unserem Controlling bin ich insgesamt sehr zufrieden. | | 1.5 | 3.0 | 3.0 | 16.4 | 58.2 | 17.9 | 3.81 | .97 | 67 |
| CSAT2 | Unser Controlling erfüllt meine Erwartungen immer zur vollsten Zufriedenheit. | | 1.5 | 4.5 | 7.5 | 31.3 | 49.3 | 6.0 | 3.40 | .99 | 67 |
| CSAT3 | Unser Controlling kommt meiner Idealvorstellung von einer perfekten Controlling-Abteilung sehr nahe. | | 4.5 | 7.5 | 17.9 | 40.3 | 22.4 | 7.5 | 2.91 | 1.19 | 67 |

*SD = Standard deviation*

(continued on next page)

**Appendix A3: Descriptive Overview of survey items**

**Einfluss von COVID-19**

| **Item** | | **Scale validity** | **Frequency (in %)** | | | | | | **Mean** | **SD** | ***n*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| COV1 | Die Qualität der Controllinginformationen wird von der Corona-Krise beeinträchtigt. | | 39.7 | 29.5 | 7.1 | 10.9 | 10.3 | 2.6 | 1.30 | 1.47 | 156 |
| COV2 | Die Qualität unseres Revenue Forecasting wird von der Corona-Krise beeinträchtigt. | | 17.9 | 18.6 | 14.1 | 8.3 | 26.9 | 14.1 | 2.50 | 1.76 | 156 |
| COV3 | Für unsere Prognosen im Revenue Forecasting müssen wir während der Corona-Krise auf klassische Excel-Modelle zurückgreifen. | | 15.4 | 17.9 | 15.4 | 12.8 | 20.5 | 17.9 | 2.59 | 1.74 | 156 |
| COV4 | In der Corona-Krise sind viele Probleme analytisch nicht zu durchdringen, deswegen müssen Entscheidungen häufig aus unternehmerischer Erfahrung heraus getroffen werden. | | 9.0 | 19.9 | 14.1 | 15.4 | 31.4 | 10.3 | 2.71 | 1.55 | 156 |
| **MGMT** | Inwieweit treffen die folgenden Aussagen auf Ihren Geschäftsbereich zu? | 0 = trifft gar nicht zu .. 5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| COV1 | Die Qualität der Controllinginformationen wird von der Corona-Krise beeinträchtigt. | | 34.3 | 29.9 | 10.4 | 14.9 | 4.5 | 6.0 | 1.43 | 1.50 | 67 |
| COV2 | Die Qualität unseres Revenue Forecasting wird von der Corona-Krise beeinträchtigt. | | 19.4 | 17.9 | 14.9 | 16.4 | 19.4 | 11.9 | 2.34 | 1.70 | 67 |
| COV3 | Für unsere Prognosen im Revenue Forecasting müssen wir während der Corona-Krise auf klassische Excel-Modelle zurückgreifen. | | 28.4 | 11.9 | 14.9 | 17.9 | 13.4 | 13.4 | 2.16 | 1.79 | 67 |
| COV4 | In der Corona-Krise sind viele Probleme analytisch nicht zu durchdringen, deswegen müssen Entscheidungen häufig aus unternehmerischer Erfahrung heraus getroffen werden. | | 14.9 | 22.4 | 13.4 | 20.9 | 17.9 | 10.4 | 2.36 | 1.61 | 67 |

*SD = Standard deviation*

(continued on next page)

## Appendix A3: Descriptive Overview of survey items

### Allgemeine Angaben zum Unternehmen

| Item | | Scale validity | Frequency (in %) | | | | | | | | | | | | | n |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CO | Das Unternehmen, in dem Sie tätig sind ist ein(e) ... | 1 = Holding / Konzernspitze<br>2 = Zwischenholding<br>3 = Tochterunternehmen / Joint Venture<br>4 = Einzelunternehmen ohne Konzernverbund | 1 | 2 | 3 | 4 | | | | | | | | | | |
| LEVEL | | | 41.7 | 10.3 | 34.6 | 13.5 | | | | | | | | | | 156 |
| CO | In welcher Branche ist Ihr Unternehmen hauptsächlich tätig? | 1 = Automobil<br>2 = Bau<br>3 = Chemie, Pharma, Gesundheit<br>4 = Eisen, Stahl<br>5 = Energie, Versorger<br>6 = Handel<br>7 = Konsumgüter<br>8 = Maschinenbau<br>9 = Medien<br>10 = Software, Technologie<br>11 = Telekommunikation<br>12 = Verkehr, Transport<br>13 = Sonstige | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | |
| BRANCH | | | 13.5 | 5.8 | 11.5 | 4.5 | 11.5 | 9.0 | 9.6 | 12.8 | .0 | 3.2 | 1.3 | 4.5 | 12.8 | 156 |

(continued on next page)

**Appendix A3: Descriptive Overview of survey items**

**Allgemeine Angaben zum Unternehmen**

| **Item** | | **Scale validity** | **Frequency (in %)** | | | | | | **Mean** | **SD** | ***n*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Wie hoch ist der Anteil des im Ausland erzielten Umsatzes am Gesamtumsatz Ihres Unternehmens? | 1 = 0 - 20 %<br>2 = 21 - 40 %<br>3 = 41 - 60 %<br>4 = 61 - 80 %<br>5 = 81 - 100 % | 1 | 2 | 3 | 4 | 5 | | | | |
| INT_REV | | | 40.4 | 10.9 | 19.2 | 18.6 | 10.9 | | 2.49 | 1.45 | 156 |
| **CO** | Wie hoch ist der Anteil der im Ausland beschäftigten Mitarbeiter an der Gesamtmitarbeiterzahl Ihres Unternehmens? | 1 = 0 - 20 %<br>2 = 21 - 40 %<br>3 = 41 - 60 %<br>4 = 61 - 80 %<br>5 = 81 - 100 % | 1 | 2 | 3 | 4 | 5 | | | | |
| INT_FTE | | | 55.1 | 10.9 | 16.7 | 12.8 | 4.5 | | 2.01 | 1.28 | 156 |
| **CO** | Wie verhält sich der Erfolg Ihres Unternehmens im Vergleich zu dem Ihrer Wettbewerber? | 0 = sehr schlecht<br>5 = sehr gut | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| RETURN | | | 1.3 | 5.1 | 18.6 | 38.5 | 28.2 | 8.3 | 3.12 | 1.06 | 156 |
| **CO** | Wie schätzen Sie die Flexibilität Ihres Unternehmens bezüglich der folgenden Kriterien ein? | 0 = sehr schlecht<br>5 = sehr gut | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| FLEX1 | Hohe Anpassungsfähigkeit der Organisation | | 4.5 | 23.1 | 32.1 | 24.4 | 12.8 | 3.2 | 2.28 | 1.18 | 156 |
| FLEX2 | Schnelle Anpassung der Produkte an neue | | .6 | 19.9 | 29.5 | 22.4 | 21.8 | 5.8 | 2.62 | 1.21 | 156 |
| FLEX3 | Schnelle Reaktion auf neue Entwicklungen am Markt | | 1.9 | 26.3 | 24.4 | 26.3 | 15.4 | 5.8 | 2.44 | 1.25 | 156 |
| FLEX4 | Schnelle Nutzung neuer digitaler Technologien | | 8.3 | 25.0 | 25.6 | 25.0 | 12.2 | 3.8 | 2.19 | 1.28 | 156 |

*SD = Standard deviation*

(continued on next page)

**Appendix A3: Descriptive Overview of survey items**

**Allgemeine Angaben zum Unternehmen**

| **Item** | | **Scale validity** | **Frequency (in %)** | | | | | | **Mean** | **SD** | ***n*** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **CO** | Wie gehen Sie allgemein mit dem Thema Digitalisierung in Ihrem Unternehmen um? | 1 = Digitalisierung ist ein fester Bestandteil unserer Unternehmensstrategie.<br>2 = Wir arbeiten an der Umsetzung einzelner Projekte.<br>3 = Wir haben uns noch nicht damit beschäftigt. | 1 | 2 | 3 | | | | | | |
| DIGITAL | | | 55.8 | 43.6 | .6 | | | | 1.45 | .51 | 156 |
| **CO** | Inwieweit treffen die folgenden Aussagen auf das Marktumfeld Ihres Unternehmens zu? | 0 = trifft gar nicht zu ..<br>5 = trifft voll zu | 0 | 1 | 2 | 3 | 4 | 5 | | | |
| DYN1 | In unserem Geschäft ändern sich die Kundenanfoderungen stark über die Zeit. | | 1.9 | 26.9 | 24.4 | 23.1 | 19.2 | 4.5 | 2.44 | 1.25 | 156 |
| DYN2 | Unsere Kunden suchen ständig nach neuen Produkten oder Dienstleistungen. | | 3.2 | 32.7 | 27.6 | 19.9 | 11.5 | 5.1 | 2.19 | 1.24 | 156 |

| **Item** | | **Scale validity** | **Min.** | **Max.** | **Median** | **Mean** | **SD** | ***n*** |
|---|---|---|---|---|---|---|---|---|
| **CO** | | #; mEUR | | | | | | |
| EMP | Anzahl Mitarbeiter (#) | | 518 | 544,282 | 4,477 | 22,474 | 65,646 | 156 |
| REV | Umsatz (mEUR) | | 13,574 | 80,531 | 1,129 | 6,089 | 13,618 | 155 |
| ASSET | Bilanzsumme (mEUR) | | 1 | 297,500 | 754 | 11,103 | 33,899 | 148 |

*SD = Standard deviation*

**Appendix A4: Coding of survey items**

| | Coding | | |
|---|---|---|---|
| **Survey items** | **Paper 1** | **Paper 2** | **Paper 3** |
| DI1 | DI1 | | DI1 |
| DI2 | DI2 | | DI2 |
| AC4 | | | AC1 |
| AC5 | | | AC2 |
| AC7 | | | AC3 |
| AC8 | | | AC4 |
| UNI1 | CL1 | | |
| UNI2 | CL2 | | |
| INF1 | CI1 | CI1 | CI1 |
| INF2 | CI2 | CI2 | CI2 |
| INF3 | CI3 | CI3 | CI3 |
| CQ1 | CQ1 | CQ1 | |
| CQ2 | CQ2 | CQ2 | |
| CQ3 | CQ3 | CQ3 | |
| ROL13 | | CBP | CBP |
| COV1 | | COV | |

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# B It’s more than just numbers: The impact of data integration on controllership effectiveness

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# It’s more than just numbers: The impact of data integration on controllership effectiveness

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# Abstract

In the digital economy, technologically advanced business intelligence systems use high volumes of data from a broad range of different internal or external sources which makes data integration an increasingly relevant, but also ambiguous issue for management accounting and control. Our paper contributes to this field by empirically analyzing (1) whether the level of data integration has a direct, i.e., instrumental, influence on controllership effectiveness, and (2) whether the consistency of internal financial language mediates the influence of data integration on controllership effectiveness from a conceptual information use perspective. We supplement our findings by means of two explorative analyses to address potential moderating effects due to technological as well as organizational criteria. Our analysis is based on covariance-based structural equation modelling using a sample of 156 management accountants surveyed from large German companies. We find a significant direct effect of data integration on controllership effectiveness as well as a significant indirect mediating effect of a consistent internal financial language on controllership effectiveness. Our results contribute by showing that data integration not only has a beneficial impact on controllership effectiveness from an instrumental point of view, but also increases organizational validity by providing conceptually a coherent view on the business.


**Keywords**: data integration; business intelligence; controllership effectiveness; financial language; structural equation modelling (SEM)

**JEL code**: M15, M41

# 1. Introduction

It is a commonly accepted fact that managers need useful business information for decision-making and control and that the effectiveness of their decision-making depends on the quality of the underlying “oceans of data” (Zeng et al., 2006) that are generated as well as provided by a broad set of constantly evolving accounting information system (AIS) technologies. While the traditional nucleus of these systems still consists of internal financial databases which are generated by a firm’s accounting system, modern business intelligence (BI) – a concept that was introduced by the Gartner Group in the Mid-1990s (Caserio & Trucco, 2018) – additionally comprises increasingly large database infrastructures as well as advanced applications and analytics tools for managerial decision-making. Furthermore, as levels of BI maturity had been progressing over the years, the underlying databases extended their scope, to include not only transactional accounting data from enterprise resource planning (ERP) systems, but increasingly operative, non-financial data from corporate and business units (Marx et al., 2012), a development that has been fuelled since the last decade by the increasing need of sustainability information (Dao et al., 2011). Besides, with the advent of the internet – not only the internet of ‘humans’, but also of ‘things’ – and the digital economy, ‘big data’ resulting from a multitude of different information sources started to play a key supplementary role as data source within BI technology (Vasarhelyi et al., 2015) and thus became a major issue in AIS research (Cho et al., 2019), addressing not only the increasing volume or velocity of data, but also their rapidly increasing heterogeneity, resulting from a growing number of data types (Appelbaum et al., 2017) as well as uncertain veracity (Zhang et al., 2015).

Since companies are grappling with the growing volume, velocity, and variety of data from different sources (Işık et al., 2013), the use of BI to derive appropriate business insights to provide managerial decision-making support is one of the most prominent tasks of highly specialized management accountants which, in German firms, are oftentimes denoted as controllers (Ewert & Wagenhofer, 2007). In line with the dynamic development of AIS technology, controllers’ role for several years has gradually been shifting from being a mere cost recorder collecting and presenting mainly financial information and analysis towards becoming a business partner proactively participating in managerial operative and strategic decision-making (Goretzki & Strauß, 2017; Wolf et al., 2015).

Still, to become such “trusted advisors” or “consultants” (McNally, 2002), controllers have to ensure high data quality within their BI systems. Issues of data quality had been discussed in early accounting research with respect to formal criteria addressing the impact of single data regarding on decision-making, e.g., sufficiency, relevance, significance, reliability, understandability, or practicality of data (e.g., Snavely, 1967). With increasingly complex data architectures within so-called BI data warehouses (i.e., repositories for structured data) or data lakes (i.e., large pools of unstructured data) (Romero et al., 2012), data integration has been considered increasingly relevant to provide a unified perspective on the nature and flow of operations and resources (Chapman & Kihn, 2009). In other words, today’s controllers are supposed to rely on a ‘single source of truth’, i.e., a common data base across business units to be able to clearly understand all factors relevant in a given decision-making situation to more effectively achieve operational as well as strategic goals (Cho et al., 2019).

Data integration prevents data inconsistency. Traditionally, data consistency refers to interdependent data between systems (Goodhue et al., 1992; Sheth & Larson, 1990): As the volume of disparate data sources continues to grow, the problem of data conflicts inevitably increase, which in turn may cause seriously hamper data use for analytical and/or decision-making purposes. Essentially, three types of inconsistency can be distinguished: (1) With respect to data format, i.e., structural differences such as definitions between different data sources, e.g., business units or regions, (2) with respect to data synchronization, i.e., the time of availability between the different sources, e.g., if some data still have to be entered manually, if inter-firm consolidation of data is necessary, or if data privacy and/or security hurdles prevent timely access, and (3) with respect to data contradictions, i.e., data from different sources that do not fit to each other or even provide equivocal information (Zhang et al., 2015).

It follows, that data integration and the resulting data consistency comes at an economic price, as firms have to make tremendous efforts to harmonize business structures and processes as well as master data, data definitions or data collection procedures. In some cases, consistency may even become unachievable, e.g., in the course of major business transformations, in situations of crises or after non-organic growth and the resulting necessity to integrate newly acquired ventures, which all may impair intertemporal comparison of data or even render it impossible (Granlund & Malmi, 2002; Scapens & Jazayeri, 2003). Furthermore, data integration may in some cases even lead to detrimental effects in decision-making, if relevant data properties become lost within the integration process due to standardization, reconciliations, or offsetting – a problem that was discussed in accounting literature until the 1990s under the label of ‘different costs for different purposes’ (Gjesdal, 1981; Nilsson & Stockenstrand, 2015) as a gold standard for accounting system design (Weißenberger & Angelkort, 2011).

In the light of this dilemma situation and the growing relevance of data integration due to an increasing heterogeneity of data sources, it is the objective of our paper to get a better understanding of the impact of data integration on controllership effectiveness in more detail. Specifically, two potential mechanisms may link both constructs in a beneficial way. First, there may be an instrumental relation, as AIS research has been suggesting in earlier studies (DeLone

& McLean, 1992; Melville et al., 2004). If a given decision problem at hand has to be solved, a high level of data integration facilitates and speeds up information collection, preparation of management accounting reports and analyses or even policy adherence to operational standards and procedures (Granlund & Malmi, 2002). The increasing use of external big data sources as well as of non-financial sustainability information adds to the relevance of this instrumental dimension. Second, the underlying mechanism linking data integration and controllership effectiveness may also be found in an organizational context (Beyer & Trice, 1982; DeLone & McLean, 2003), as data integration allows for a conceptual information use by facilitating a consistent financial language to understand and communicate business information and analyses. In this vein, we draw on the research on convergence of financial and managerial accounting systems (e.g., Nilsson & Stockenstrand, 2015; Weißenberger & Angelkort, 2011) that emphasizes the need for a consistent financial language for business communication (Belkaoui, 1980; Boland & Pondy, 1983) to foster a general knowledge-base of the business structures and processes for general enlightenment without comprehensively or directly being applicable to a specified decision-making problem at hand (Menon & Varadarajan, 1992). The notion of conceptual information use is also supported by earlier studies in AIS research which indicate that organizational and behavioral implications are highly relevant in the course of BI implementation (Lodh & Gaffikin, 2003). Thus, our work extends the existing body of research by addressing the following research questions:

- Does an increased level of data integration have a positive effect on controllership effectiveness?
- If so, does the underlying causal inference relate both variables in an instrumental fashion and/or rather in a conceptual way?

Our research contribution is threefold. First, with our analysis, we draw an explicit connection between data integration as a feature of AIS design and controllership effectiveness, which has not yet been done in previous research. Second, we do not limit our analysis to the instrumental and rather technological impact of data integration, but address its influence on providing a conceptual view on the organization in the sense of a consistent financial language. Third, our research is distinctive, as it sheds lights on the mechanisms that underlie controllership effectiveness and thus contributes to the discussion on antecedents for controllers’ transformation towards becoming business partners.

For our empirical investigation, we chose revenue forecasting as a specific anchoring point as it is not only common in virtually all firms, but also an accounting and control issue of highest relevance. We can therefore assume that controllers use all accessible systems at hand to provide as accurate and meaningful revenue forecasts as possible, and that their performance is an appropriate indicator of the overall quality of their work and their influence on management decision-making. Although we conduct our investigation in a national context by surveying large German companies, our contributions are also of interest to an international discussion on IS success for management accounting and control purposes.

Our paper is structured as follows. Section 2 provides a review of the underlying literature of our study. Section 3 presents the research model and identifies the four derived hypotheses. Section 4 describes the empirical method of our study, including information on the measurement of the variables used in our model. Section 5 shows the results of our study, and adds two exploratory multi-group analyses based on our baseline model. Finally, Section 6 discusses the results and outline implications for future research.

## 2. Literature review

Our research draws on three different literature streams, using (1) literature on the technological advancement in AIS technology of recent decades in conjunction with (2) information systems (IS) literature discussing data integration as an antecedent for BI success and (3) management accounting literature referring to the theoretical grounding of information use for controllership effectiveness.

AIS research links accounting and IS research as it deals with technologies, for e.g., processing business transaction, recording and storing business data in financial accounting ledgers or other databases, as well as with auditing these systems (e.g., Romney & Steinbart, 2018). The use of AIS technology started in the early 1970s with the introduction of computerized Management Information Systems (MIS) for storing, organizing, and processing information from different sources in order to improve business (Azvine et al., 2006; Roetzel & Fehrenbacher, 2019). Being first dubbed as decision support systems (DSS), MIS were designed to help managers make key decisions at different levels within an organization (Power, 2007). In the 1980s, new technologies came along and more functionalities were added, e.g., dashboards as well as graphical user interfaces that facilitated a customized visualization of key figures, or drill down functions to allow detailed level of data views (Watson & Frolick, 1993).

At the same time, modern ERP systems evolved from traditional operational data technologies called Material Requirements Planning (MRP) or Manufacturing Resource Planning (MRP II), which were used to record transactional data for the main business functions and processes in a firm’s supply chain. In the 1990s, supplementary tools, e.g., Customer Relationship Management (CRM) systems allowed to align such supply information systems with customer demand, thus comprehensively grasping the firm’s value chain (Caserio & Trucco, 2018).

Storing data resulting from such transactional systems in large databases as well as making them accessible for analyses, planning, decision-making and control purposes called for technologically advanced MIS architectures, which were denoted as Business Intelligence (BI) and in some cases also Strategic Enterprise Management Systems (SEMS) (Brignall & Ballantine, 2004; Frolick & Ariyachandra, 2006). BI systems therefore combine operating applications, e.g., ERP or CRM, tools for data acquisition and storage as well as a set of different platforms, suites, and solution tiers for data usage (Zeng et al., 2006). From a technological point of view, BI systems contribute in several ways, e.g., by facilitating access to business information, by making querying and analysis easier, by allowing for interactivity across the organization, and by improving data consistency due to data integration as well as other related data management activities (Popovič et al., 2009).

A major challenge that BI technology has to address since its introduction is that firms mostly stored data in various sources and under different definitions or formats, which requires substantial data management techniques to allow a coherent view of the data. A major tool developed in this vein is online analytical processing (OLAP) which allows to perform complex statistical analyses over the data provided, e.g., regression, segmentation, or clustering for scorecarding, predictive modeling or even data mining (Chen et al., 2012). Still, data analytics and data infrastructure represent not only two different technology areas, but also constitute two separated AIS research areas, as data analytics are rather of technological nature, whereas the impact of data infrastructure is also analyzed with respect to organizational factors (Popovič et al., 2012).

The resulting challenge has been amplified not only with the emergence of the digital economy over the last years, but also with the rapidly growing need of non-financial sustainability information, e.g., on water consumption or greenhouse gas emissions within the overall business ecosystems. As a result, firms’ data environments have become increasingly broad, since they are collecting and analyzing large volumes of data from both non-formal structures as well as from existing MIS (Bhimani, 2020). In a similar vein, big data has become not only a key issue that is strongly addressed and well discussed in corporate practice, but also most prominent in AIS research (Cho et al., 2019). Integrating big data into AIS technology facilitates the use new information sources and extends the use of information generated from internal accounting or operative records to an unprecedented extent. As a result, organizations must deal with a multitude of potential data sources to gain information (Johns, 2017) with categories ranging from (internal) operational data collected from different organizational units (e.g., Finance, Sales, Operations, or Human Resources) to external data from third parties (i.e., competitive, industry or economic data) or even private data such as individual analyses (Moss & Atre, 2003). Still, despite its potential, the information value of big data may be limited, as organizations using them must overcome restraining factor, such as technical deficiencies in acquiring big data, the involuntary use of irrelevant or questionable data sources or even employees’ insufficient expertise in extracting information (Warren et al., 2015).

Whether AIS technology can be implemented successfully, e.g., with respect to data integration, is a major issue in the second stream of literature reviewed for our research project, which addresses data integration as an antecedent for IS success and which has received much attention over the past decades. However, there is a differentiated understanding of IS success and its measurement (Glass, 2005; Linberg, 1999). Based on the concepts of Shannon and Weaver (1963) and Mason (1978), DeLone and McLean (1992) identified six success impact factors that are still an integral part of IS success research, i.e., system quality, information quality, usage, user satisfaction, individual influence, and organizational influence. Over the past years, the origin model has been conceptually developed, i.e., modified or extended by various researchers (e.g., DeLone & McLean, 2003; Lowry et al., 2007), but still validate these underlying factors as good predictors for IS success in several studies (e.g., McKinney et al., 2002; Petter et al., 2013; Rai et al., 2002).

As a result, with the increasing volumes of data-sourcing and analytics, data integration as “consolidation of dispersed silos of data” (Frolick & Ariyachandra, 2006, p. 47) has gained relevance for IS success as a cross-system key issue (Lenzerini, 2002). Data integration comprises standardizing data in terms of its definitions and structures by the use of a common conceptual schema in one or more data sources (Heimbigner & McLeod, 1985; Litwin et al., 1990), but also data harmonizing, by, e.g., providing definitions and measurement standards, data cleansing or master data management (Halevy, 2001; Popovič et al., 2009). Even in today’s rich data ecosystems, data integration cannot simply be replaced by using larger volumes of data, as big data are typically messy, include too many variables or inherent biases that must be addressed as well (Bhimani & Willcocks, 2014). Overall, IS literature assume data integration to be one of the key factors contributing to long-term benefits of all IS systems (Seddon et al., 2010). For example, Elbashir et al. (2008) find in their study on the relationship between BI and organizational performance data integration to be a relevant issue.

From a technical point of view data integration is therefore pervasive and a key challenge whenever groups of individuals collect data independently while trying to collaborate with each other. The number of different data sources scattered across a company could easily more than 100 (Doan et al., 2012). The benefits of integrated and standardized data are positively affected by the strength of which organizational units need to share information among each other (McCann & Ferry, 1979).

Still, IS literature also addresses several issues that limit data integration efforts. For example, the more heterogeneous a firm's business units, the more nuanced and differentiated are their information needs for accounting and control purposes (Gjesdal, 1981; Weißenberger & Angelkort, 2011). Thus, costs of integrating and standardizing data increase with the heterogeneity of organizational units (Lawrence & Lorsch, 1986), e.g., by the amount of individual information as well as information systems that need to be integrated, even though the cost of communications, information storage, and required hardware have been decreasing over time (Amankwah-Amoah et al., 2021). But in addition to expenditures for hardware and software, as well as integration costs for developing common definitions and standards, creating information system designs as well as database structures, trade-off costs occur when individual needs and requirements of organizational units, are not fully covered, resulting in a lower quality or data usefulness (Goodhue et al., 1992). In addition, changing processes can also be costly due to a lack of individuals' motivation or abilities to adopt new methods (Leonard, 1992). This particularly occurs in organizations that are dominated by long-established processes, structures, or legacy systems. Finally, the implementation of new technologies can also cause employee resistance due to increasing pressures, e.g., IT-related uncertainties and challenges, or growing control system tightness resulting from stronger surveillance (Amankwah-Amoah et al., 2021). For example, data owners may be prone to avoid collaboration on data integration as a result of intra-organizational competition or business problems within a department may become more transparent in the wake of data integration, thus reducing managerial discretion (Doan et al., 2012). In sum, data integration, i.e., enabling a uniform language that satisfies all information needs of all organizational units, is costly and associated with trade-offs (Goodhue et al., 1992).

An important link between a firm's BI use and its performance on an organizational level within managerial decision-making and control is the controllers' function. According to the International Association of Controllers, controlling as a function "encompasses the entire process, from setting the target, to planning, to management in the area of finance and performance management", with taking "the responsibility for the results transparency." (International Association of Controllers, 2021). Thus, digital transformation to date has instigated changes in the work and function of controllers, which have a lasting impact, one of them being data management. As already noted, consistent data are necessary for enabling analytics and providing relevant information to achieve transparency and to support managerial decision-making. In this context, data used by controllers are only useful if they are connected to each other (Appelbaum et al., 2017), or – to put it in the words of Russell L. Ackoff – management's need is not more relevant information, but less irrelevant information (Ackoff, 1989, p. 3).

Whereas IS research addresses the question of technological benefits of data integration per se, the issue whether data integration makes controllers more effective in decision support has not yet been researched in depth. Even more so, a continuing validity of prior tested relationships cannot be assumed due to the continuous shift towards a digital economy (Wadan et al., 2019), affecting managerial work environments and implying major organizational changes for most companies (Klus & Müller, 2021). Following the call for research by Newell and Marabelli (2015) who highlight an increasingly data-driven decision-making and control, research on the so called “datification” (Newell & Marabelli, 2015, p. 3) of management accounting and control research is increasingly addressing organizational data infrastructure to effectively collect and prepare information (Lycett, 2013).

In this vein, a third literature stream in management accounting and control research supports a behavioral information theory approach by introducing the idea of conceptual information use of data, i.e., to provide general enlightenment and understanding of the business at hand (Burchell et al., 1980; Menon & Varadarajan, 1992). In contrast to the instrumental use of information which refers to the immediate use of data for solving a given decision problem at hand, conceptual information use is rather seen as influencing a decision-makers thinking about an issue without putting it to a specific or documentable use (Pelz, 1978). In the accounting literature, conceptual information use is closely related to accounting as a language for business communication in the cross-functional exchange between controllers and managers (Boland & Pondy, 1983; Otley & Berry, 1980). Weißenberger and Angelkort (2011) have used this approach to analyze the impact of convergent accounting systems, i.e., the use of the same database for financial and managerial accounting purposes, on controllership effectiveness. They found a significant and positive impact which is not triggered by the technical issues underlying the integration of accounting systems, but rather by an indirect effect drawing on the resulting consistency of financial language. Pierce and O'Dea (2003, p. 258) denote this effect as “organizational validity” and show in a case study based on 11 firms that it drives managerial satisfaction with accounting information to a much higher extent than its mere technical validity.

This approach is also valid for our research question. Whereas the technological purpose of data integration is to provide high quality information for decision-making, it facilitates in an organizational context the communication of business information by having a consistent financial language to provide an integral view on the firm’s business (Islam & Sharif, 2017). Our research therefore draws on all these strands of literature, combining the technological advancement in AIS technology of the recent decades with data integration as an antecedent for IS success and the use of BI by controllers to provide meaningful business information as well as understanding and insights for management accounting and control purposes.

# 3. Background and hypotheses

In our study, we want to address whether an increased level of data integration has a positive effect on controllership effectiveness and to which extent this effect is based rather on technical features of data integration influencing controllership effectiveness in an instrumental fashion or whether both constructs are – at least to some extent – linked in a conceptual way as data integration increases the consistency of internal financial language for business communication.

Following these research questions, the first hypothesis in our research model relates to technical impact of data integration within a firm’s BI, thus examining the technical inference between an increasing level of data integration and controllership output quality. Previous research of IS success evaluates the quality of data on a holistic level, even though quality constructs are fundamentally multidimensional (Rai et al., 2002). The evaluation of data quality can be made from an intrinsic or contextual perspective (Nelson et al., 2005). From an intrinsic point of view, the properties of data are independent of the context (e.g., user or task) and measured by evaluating the degree of correspondence between data values and the real world (Lee et al., 2002; Seddon, 1997). Consistency is a frequently used quality dimension to evaluate whether the representations of the real world within the data differ or even contradict or not (Fisher & Kingma, 2001). The contextual perspective extends the notion of data quality by evaluating whether data are valid from the perspective of certain users or related to a particular task (Wang & Strong, 1996). For example, the subjective data quality provided by a BI system and perceived by a controller can be evaluated in the context of a given decision or control task at hand. If data are disparate and from various sources, a need for consistency arises (Daft & Lengel, 1986).

Data integration reduces inconsistency of the data provided, it prevents delays and enables a higher availability as well (Huber, 1982). In consequence, data integration makes the collection, comparison, and aggregation of data easier (Gattiker & Goodhue, 2004), as it allows to harmonizes multiple data sources to expand the body of available data and to enable correct as well as efficient queries across individuals, because the more independently data is processed, the more error-prone the extracted information (Doan et al., 2012). Particularly in situations in which the organizational environment is affected by increased uncertainty, e.g., in times of economic crisis, and therefore a firm’s existing data ecosystem is more likely to be subject to errors or irregularities, it can be beneficial for management accounting to work in a more decentralized manner in order to be able to access and understand data more flexible. In such a situation, it is important to know where data comes from and how it is generated. Furthermore, from a management accounting perspective, data integration allows to discover new relations or to test new assumptions (Davenport, 1998). Even though the process of data integration in itself is costly and associated with trade-offs (e.g., Orlikowski, 1991), we assume with Gattiker and Goodhue

(2004) that in the long run the advantages of taking a set of heterogeneous sources and transforming as well as combining the resulting data to achieve a uniform perspective on the business at hand exceed the potential costs, following that controllers should be able provide to high quality analyses and reports to management in an accurate and more timely manner than when using non-integrated data sources. We therefore hypothesize:

*H1: An increased level of data integration leads to an increased controllership output quality.*

As already shown in (A)IS research as well as the large body of technology acceptance modeling (Venkatesh et al., 2003), technical system quality from an instrumental perspective does not guarantee its use due to other, e.g., organizational or behavioral factors (Elbanna, 2007; Jasperson et al., 2002). In this vein, a relevant issue is that data integration supports consistency of internal financial language as a core element of the controlling function.

As controllers’ roles have been constantly evolving towards being a business partner for several decades now, their work has been changing towards setting their analyses, reports, and recommendations in a broader context, relating them to operating activities as well as strategic decision-making (Burns et al., 1999). As a result, controllers must be able to reconcile different types of data from various sources. But only if the underlying data are integrated, they represent the required common source of knowledge providing an unambiguous and coherent view on a firms’ business, processes, and structures, resulting in a consistent financial language as a fundamental basis for communication within firms (Galbraith, 1973; Huber, 1982). Consistency of financial language describes, similar to consistency of data, a common use of terms and their meaning. We therefore hypothesize:

*H2: An increased level of data integration leads to an increased consistency of internal financial language.*

The need for consistent information is in accordance with behavioral research that address the pursuit for consistency in a human’s individual decision-making process. Establishing the social psychological theory of cognitive dissonance, Festinger (1957) points out that dissonance, being psychologically uncomfortable, motivates people to try to reduce it to achieve consonance by actively avoiding situations as well as information which would probably increase the dissonance. Thus, when information is inconsistent, theory of cognitive dissonance suggests, that controllers will avoid using the comprehensive set of information which in turn hamper the quality of their analyses and reports. In a similar vein, organizational information processing theory (Galbraith, 1973) suggests that inconsistent information on an organizational level causes uncertainty and, as a result, reduces the subjective judgement on information quality as well as the inclination to use this information for decision-making purposes (Daft & Lengel, 1986; Tushman & Nadler, 1978).

We therefore hypothesize:

*H3: An increased consistency of internal financial language leads to an increased controllership output quality.*

Both H2 and H3 link data integration to controllership output quality in an indirect fashion, using the pertinent role of internal financial language as a conceptual tool to provide a general understanding on a firm’s business situation and to allow for a meaningful communication between controllers and managers as business partners in operational as well as strategic matters.

To provide a comprehensive view on controllership effectiveness, it is not only necessary to capture controllership output quality, but also the resulting influence on managerial decision-making as an outcome variable, i.e., the degree to which the controllers’ output is in effect used by management for decision-making and control. Controllership effectiveness is the result of both output and outcome, because only the combination of high output quality and high influence on management decisions contributes to controllers’ decision-support function as well as their business partnering role. In accordance with the basic assumptions of rational choice theory (Hedström & Swedberg, 1996), but also in line with empirical results in the accounting and control literature (e.g., Bauer, 2002; Weißenberger & Angelkort, 2011) we assume that an increased controllership output quality will cause an increased use of it, i.e., higher influence on management decisions. We therefore finally hypothesize:

*H4: An increased controllership output quality leads to an increased controlling influence on management decisions.*

The full research design is presented in Figure 1.

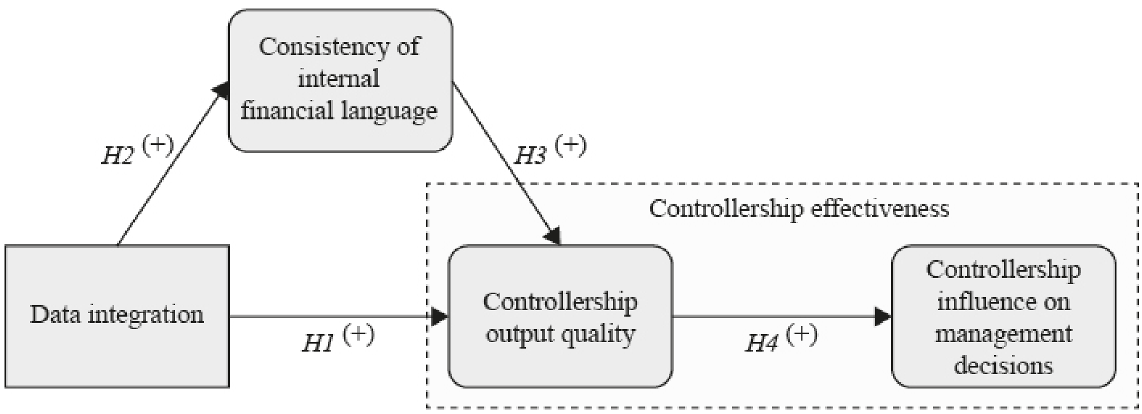


**Fig. 1** Full research design

# 4. Method

## 4.1. Sample and survey design

Data for our study were collected from June to October 2020 by means of a questionnaire-based online survey. Our starting point was the database Markus with contact data of all German companies. We exclusively selected companies with at least 500 employees which are supposed to have a separate controller department, thus excluding small- and medium-sized enterprises (SME). In addition, we excluded finance as well as real estate industries due to their divergent business models compared to industrial, or trading industries. After eliminating duplicate entries, a finally number of 5,758 companies were left in our population. Of these, for reasons of time and resources, 20% were contacted by telephone or, in the case of several missed calls, by e-mail.

To capture the aspects of the controllers’ tasks in providing information for decision-making and control purposes, we addressed the controlling manager or in case of absence, a functional controller responsible for sales controlling or a similar function. If several controlling departments exists, we asked for the hierarchical most highly ranked controller.

To ensure ex ante completeness and understandability of our questionnaire, we followed the recommendations of Dillman (2007) and pre-tested our online-questionnaire with three executives from business practice, three consultants and five academic researchers. In total, we received 159 completed questionnaires of which three questionnaires had to be excluded for reasons of non-fulfilled requirements for the number of employees. The final sample of 156 questionnaires correspond to return rates of 13.3% to the participant population, of which 89% had been contacted by telephone and the remaining 11% by e-mail. Our sample is composed of 65 holding companies, 16 intermediate holding companies, 54 subsidiaries, and 21 individual companies, and is balanced between companies where digitization is part of the corporate strategy (55.6%) and companies which implement individual digitization projects unrelated to their strategy (43.8%). Just one company stated that it had not yet addressed the issue of digitization (0.6%). As Table 1 shows, our sample covers a broad range of industry affiliations.

**Table 1: Surveyed firms by industry**

| Variable | Frequency | Percentage |
|---|---|---|
| Automotive | 21 | 13,5% |
| Construction | 9 | 5,8% |
| Chemicals/Pharma/Health care | 18 | 11,5% |
| Industrial Goods | 7 | 4,5% |
| Energy/Utility | 18 | 11,5% |
| Wholesale/Retail | 14 | 9,0% |
| Consumer goods | 15 | 9,6% |
| Engineering | 20 | 12,8% |
| Software/Technology | 5 | 3,2% |
| Telecommunication | 2 | 1,3% |
| Transport/Logistics | 7 | 4,5% |
| Others | 20 | 12,8% |
| n | 156 | |

Summary statistics of the company size are shown in Table 2.

**Table 2: Summary statistics on company size measures of surveyed firms**

| Variable | n | Mean | SD | Median |
|---|---|---|---|---|
| Number of employees | 156 | 22,474 | 65,646 | 4,477 |
| Sales (Million EUR) | 155 | 6,089 | 13,618 | 1,129 |
| Assets (Million EUR) | 148 | 11,103 | 33,899 | 754 |

## 4.2. Measures

Our research model consists of one exogenous variable *Data integration* as well as three endogenous variables *Consistency of internal financial language*, *Controllership output quality* and *Influence of controllership on management decisions*. The measurement of all variables is based on scales derived from the relevant literature, thus being validated by prior research. All survey items are measured on a 6-point rating scale with a translated range from 0 to 5. An item summary is provided in Table A1 (see appendix).

### 4.2.1. Exogenous variable

Different BI maturity models have been identified in literature (Chuah & Wong, 2011; Rajterič, 2010). Although models widely vary in terms of their individual dimensions, most models either isolate the perspective of data management activities, or consider it separately from analytical capabilities (e.g., Cates et al., 2005; Glancy & Yadav, 2011). Thus, common literature supports the theoretical understanding that data as well as analytics are disparate parameters for evaluating BI systems maturity. Empirical studies confirm that data integration is not only a key success factor for an organization's IS, but also a fundamental quality of BI systems (Seddon et al., 2010).

Since the aim of data integration is to enables a uniform access to a set of autonomous and heterogeneous data sources, it faces two key challenges, the quantity of sources as well as the heterogeneous of data. First, data integration is challenging with each increase in data sources, even at a small number of sources. Second, the design of data sources typically varies as they cover different user purposes or based on different application, so that different data systems as well as data types exists in practice. While some sources are fully structured, e.g., relational databases, others are unstructured or semi-structured, e.g., containing XML or text (Doan et al., 2012).

The conceptualization of our exogenous variable *Data integration* is therefore based on the measurements of Popovič et al. (2012). According to the extant literature they identify data integration as an autonomous dimension of BI system maturity, measured by two indicators with respect to the number of sources, i.e., the centrality of data sources, as well as the consistency of data. We adopt these two items as they cover both key challenges of data integration. Thus, our exogenous variable, labeled as *Data integration*, represents the extent to which data used by controllers for revenue forecasting are integrated and consistent within an organization. We assume that its underlying character is continuous, as partial integration can be observed in practice.

Latent variables can be operationalized by a formative or reflective measurement, depending on whether indicators are influence (formative) or influenced by (reflective) latent variables (Bollen, 1989). In CB-SEM research, reflective measurement is used in most cases, which, in line with the underlying test theory implying that the observed variables (i.e., indicators) are dependable manifestations of the latent variable. In consequence, changes in the latent variable leads to changes in all related indicators as well (Bollen & Lennox, 1991; Diamantopoulos, 2008; Diamantopoulos & Winklhofer, 2001). On the other hand, in a formative measurement approach it is assumed that a latent variable is formed by its indicators. In that case, it is the changes in the indicators that lead to changes in the latent variable. A formative variable is therefore also referred to as a composite variable (MacKenzie et al., 2005).

Formative measurement received more attention over time, but its key issues concerning its properties, advantages and limitations are not clearly understood so far, so that its application in empirical studies is still rare (Diamantopoulos et al., 2008; Diamantopoulos, 2008). As a consequence, measurement models are often concerned with misspecification: by adopting reflective indicators where formative indicators, and thus index formations, would be appropriate (Diamantopoulos, 2008) as shown by several studies (e.g., Jarvis et al., 2003). A variety of guidelines on the trade-off between reflective and formative measurement can be found in the literature (Jarvis et al., 2003), but a key aspect to consider is whether if one of the indicators suddenly changes in a particular direction, the other items necessarily change in the same direction. If this case is not present, the construct is of a formative nature (Chin, 1998).

Our variable *Data integration* consists of two items that represent the centralization as well as consistency of data (see Table A1 in the appendix). As both indicators influence data integration, we use a formative measurement approach for our exogenous variable. Because of the direction of causality in formative models, a simultaneous increase of all indicators is not required, i.e., a high correlation between indicators is not expected, but may be observed (Bollen & Lennox, 1991). Thus, since from a theoretical perspective, a greater centralization of data leads to an increase in data integration even if consistency remains the same, it also supports our use of a formative measurement.

Diamantopoulos and Winklhofer (2001) affirm that formative measurement can be used in CB-SEM. However, for a formative latent variable it is necessary that at least two paths toward dependent variables are uncorrelated to be statistically identifiable (Bollen & Lennox, 1991; MacCallum & Browne, 1993). Our model does not meet this condition as both variables *Consistency of internal financial language* as well as *Controllership output quality* are linked to *Data integration* by our hypotheses *H1* and *H2*. To address this issue, we measure the variable *Data integration* by building an additive index. The use of a pre-summed composite index approximates a special case for the formative indicator model in which all items are equally weighted and the residual variance of the composite index is limited to zero (Bollen & Lennox, 1991).

### 4.2.2. Endogenous variable

For the three endogenous latent variables *Consistency of internal financial language*, *Controllership output quality* and *Controlling influence on management decisions* we adopt a reflective measurement approach, since the underlying items in each case are intended to be interchangeable and dependent on the latent variables (Bollen & Lennox, 1991; Diamantopoulos & Winklhofer, 2001; see Table A1 in the appendix).

*Consistency of internal financial language* measures the extent to which information is consistent between controllers and sales operatives, i.e., if information serves as a financial language within an organization. It represents a modified version of a scale developed by Weißenberger and Angelkort (2011) and is derived by measuring two manifest indicators (see Table A1 in the appendix).

A main function of controllership is to provide business information that supports managers in their decision-making and control processes (Bhimani, 2020). Therefore, the effectiveness of controlling is particularly depending on the quality of information provided (Bauer, 2002). We therefore capture *Controllership output quality* by measuring its informational quality, i.e., correctness, accuracy and timeliness of information provided. These three reflective indicators were adopted as a modified version of a scale developed by Bauer (2002) originally consisting of eight indicators on a seven-point Likert scale. All items are shown in Table A1 (see appendix).

Finally, the variable *Influence of controllership on management decisions* reflects the perceived influence of controllership in management decision-making through its output quality. It is measured by a modified version of a measurement model developed by Spillecke (2006) and consists of three reflective indicators originally measured on a five-point Likert scale. The last item was formerly taken from Bauer (2002). All items are provided in the appendix in Table A1.

### 4.2.3. Reliability and validity measures

Before testing the effects between variables, the conditions of reliability and validity of each latent variable have to be ensured. Reliability tests the internal consistency of a scale, which is required for measurement validity and refers to the conceptual accuracy of a scale (Bagozzi & Yi, 1988; Schäffer, 2007).

As one of the most common measures of reliability, Cronbach's alpha (CA) consistently exceeds the critical value of .70 (Nunnally & Bernstein, 1995). Because CA is positively related to the number of items, factor reliability (FR) and average variance extracted (AVE) must also be substantiated. All variables exceed the critical values of .60 for factor reliability (FR) and .50 for average variance extracted (AVE) (Bagozzi & Yi, 1988). Table 3 summarizes the descriptive statistics for all variables and the respective reliability and validity measures.

**Table 3: Summary statistics, reliability and validity measures**

| Item | Indicator | Min | Max | Mean | SD | SMC | CA | FR | AVE |
|---|---|---|---|---|---|---|---|---|---|
| Data integration | DI | 0.00 | 10.00 | 5.48 | 1.956 | | | | |
| Consistency of internal financial language | CL1 | 0.00 | 5.00 | 3.35 | 1.248 | .703 | .877 | .865 | .615 |
| | CL2 | 0.00 | 5.00 | 3.51 | 1.242 | .869 | | | |
| Controllership output quality | CQ1 | 2.00 | 5.00 | 4.04 | .773 | .635 | .808 | .910 | .517 |
| | CQ2 | 1.00 | 5.00 | 3.84 | .954 | .574 | | | |
| | CQ3 | 1.00 | 5.00 | 3.60 | .878 | .573 | | | |
| Controllership influence on management decisions | CI1 | 1.00 | 5.00 | 3.73 | 1.144 | .733 | .939 | .974 | .837 |
| | CI2 | 1.00 | 5.00 | 3.61 | 1.184 | .913 | | | |
| | CI3 | 1.00 | 5.00 | 3.44 | 1.165 | .874 | | | |

*n = 156; SD = Standard Deviation; SMC = Squared Multiple Correlation; CA = Cronbach’s Alpha; FR = Factor Reliability; AVE = Average Variance Explained*

To test for discriminant validity, we use the Fornell-Larcker (1981) criterion, showing that AVE of each of our variables exceeds any squared correlation of that variable as is required (see Table 4).

**Table 4: Discriminant validity according to the Fornell-Larcker criterion**

| Variable | AVE | Squared correlation with variable | |
|---|---|---|---|
| | | Consistency of internal financial language | Controllership output quality |
| Consistency of internal financial language | .615 | | |
| Controllership output quality | .517 | .368 | |
| Controllership influence on management decisions | .837 | .108 | .292 |

Finally, we conducted Harman’s (1967) single-factor test to examine for possible indication of common method bias. As shown in Table 5 there is no evidence of the existence of a common factor underlying our measurement, as the eigenvalues of all variables indicating that no single factor emerged, and the first factor accounts for less than 50% of the variance among variables. Although the first factor is close to the threshold of 50%, data simulations indicate that a high level of common method variance (70% or greater) must be present to sufficiently affect relationships between variables. Therefore, values below 50% do not pose a serious threat to the validity of research results (Fuller et al., 2016).

**Table 5: Harman's single-factor test**

| Factor | Initial eigenvalues | | | Extraction sums of squared loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of variance | Cumulative % | Total | % of variance | Cumulative % |
| 1 | 4.418 | 49.092 | 49.092 | 3.885 | 43.163 | 43.163 |
| 2 | 1.563 | 17.368 | 66.460 | | | |
| 3 | 1.014 | 11.271 | 77.732 | | | |
| 4 | .701 | 7.791 | 85.523 | | | |
| 5 | .438 | 4.869 | 90.391 | | | |
| 6 | .343 | 3.811 | 94.202 | | | |
| 7 | .213 | 2.367 | 96.569 | | | |
| 8 | .209 | 2.317 | 98.886 | | | |
| 9 | .100 | 1.114 | 100.000 | | | |

*Extraction Method: Principal Component Analysis*

## 4.3. Method of analysis

To test our hypotheses, we use a covariance-based structural equation modelling (CB-SEM) with maximum likelihood (ML) estimation, applying the software AMOS 28. It allows (1) to include both manifest (observed) and latent (unobserved) variables, (2) to take a holistic approach to model building that also considers indirect effects, (3) to take a confirmatory (rather than an exploratory) approach to data analysis and – in comparison to, e.g., variance-based approaches, (4) to provide metrics for evaluating whole models (Byrne, 2016; Smith & Langfield-Smith, 2004). A critical assumption of CB-SEM is multivariate normality of the underlying data (Byrne, 2016). Even if several simulation studies (e.g., Boomsma & Hoogland, 2001; Lei & Lomax, 2005) have shown that the method is quite robust to violation of the normality assumption, we use bootstrapping as an accepted technique to counter the problem of non-normally distributed data (Byrne, 2016; Cheung & Lau, 2008; Shrout & Bolger, 2002). A recommended sample size of ≥ 100 (Smith & Langfield-Smith, 2004) is also met by our sample of 156 firms.

# 5. Results

## 5.1. Outcome of hypotheses testing

As shown in Table 6, all global criteria of model fit perform the required thresholds, i.e., the hypothesized model fits the empirical data.

**Table 6: Goodness-of-fit indices for confirmatory factor analysis**

| Index | Estimate | Critical Value | References |
|---|---|---|---|
| $X^2/df$ | 1.16 | ≤ 2 | Byrne (1989) |
| $p$-value | .264 | ≥ .05 | Bagozzi and Yi (1988) |
| RMSEA | .032 | ≤ .05 | Browne and Cudeck (1993) |
| GFI | .958 | ≥ .90 | Homburg and Baumgartner (1995) |
| CFI | .995 | ≥ .97 | Schermelleh-Engel et al. (2003) |
| TLI | .993 | ≥ .97 | Schermelleh-Engel et al. (2003) |

*$X^2/df$ = chi-square / degrees of freedom; p-value = probability value; RMSEA = root mean square error of approximation; GFI = goodness of fit index; CFI = comparative fit index; TLI = Tucker-Lewis index*

Specifically, we estimate the following goodness-of-fit indices for each confirmatory factor analysis: The ratio of chi-squared ($X^2$) and degrees of freedom ($df$) refers to the null hypothesis that the specification of factor loadings, factor variances, covariances, and error variances are valid with respect to an overall model fit, i.e., that the hypothesized model fits the empirical data (Bollen, 1989). The closer the fit of the hypothesized model is to a perfect fit, the higher the probability value (p-value) associated to $X^2/df$, so that the null hypothesis cannot be rejected. However, the $X^2$-test has some limitations with respect to its dependence on sample size and model complexity. With large samples, the $X^2$-test tends to reject models falsely (type-1-error), while with small samples it tends to accept poor models (type-2-error). Furthermore, the $X^2$-test is subject to model size, i.e., the more variables are included, the higher the risk of a type-1-error. Because of the limitations of the $X^2$-test, additional goodness-of-fit indices have been developed. However, the $X^2$-test is the basis for most alternative fit indices (Backhaus et al., 2015). The root mean square error of approximation (RMSEA) index considers the error of approximation in the population and compares it to optimally chosen parameter values (Browne & Cudeck, 1992), i.e, accounts for whether the hypothesized model provides a close approximation of the empirical reality, instead of an exact fit. Comparison goodeness-of-fit indices compare the fit of a hypothesized model with fit of a baseline model, which is particularly appropriate for nested models. Their measures are commonly range between 0 (no fit) and 1 (perfect fit) (Hu & Bentler, 1995). Three indicies out of this category are widely used in practice. The absolute goodness-of-fit index (GFI) compares the hypothesized model with no model at all by measuring the explained amount of variance and covariance in the data (Hu & Bentler, 1995). In contrast, the comparative fit index (CFI) as well as the Tucker-Lewis index (TLI) are additional incremental fit measures that compare the hypothesized model to a so-called null model, which allows all variables in the model to have variation but no correlation (Byrne, 2016).

Figure 2 presents the coefficient values of the causal paths connecting the four variables as well as the explained variance ($R^2$) obtained from the empirical data.

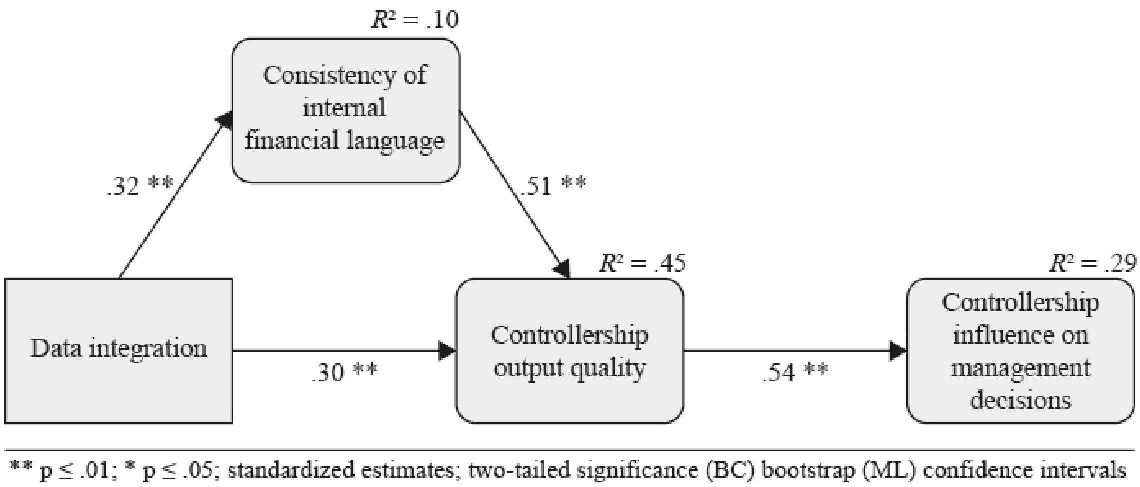


**Fig. 2** Empirical results of CB-SEM

The results reveal a positive direct association of *Data integration* with *Controllership output quality*. Thus, our first hypothesis *H1* is supported. Furthermore, as assumed in our hypothesis *H2*, *Consistency of internal financial language* is positively associated with *Data integration*, which explains 10% of the variance of the variable *Consistency of internal financial language*. As assumed in hypothesis *H3*, this variable has a further positive association with *Controllership output quality*. *Data integration* together with *Consistency of internal financial language* explain 45% of the variance of the variable *Controllership output quality*. Moreover, as assumed in hypothesis *H4*, *Controllership influence on management decisions* is positively associated with *Controllership output quality*, explaining 29% of the variance of the dependent variable *Controllership influence on management decisions*.

Even though our structural model is based on data surveyed at a single timeframe and does not allow for causal inference, our empirical data support our theoretical model of data integration underlying the work of controllers having a direct effect on the assessment of controllership effectiveness. In addition, our empirical results are also in line with the assumption that the direct effect on controllership effectiveness can be enhanced by a consistent internal financial language between controllers and sales operatives. From a methodological perspective, the empirical results therefore suggest that the model structure we hypothesized in Figure 1 is fully supported. It maps the empirical data and confirms the understanding of data integration in the context of a controller's effectiveness. To examine the relations between the four variables included in our model we consider the direct, indirect (i.e., mediating), and total effects. We tested the statistical significance of the effects using bias-corrected bootstrap confidence intervals (Cheung & Lau, 2008).

*Consistency of internal financial language* mediates the relation between the *Data integration* and *Controllership output quality* with a combined path coefficient of .165. The direct effect of *Data integration* on *Controllership output quality* (.302) is also statistically significant. Thus, resulting from the significant effect of *Controllership output quality* on *Controllership influence on management decisions* (.541), the total effect of *Data integration* on *Controllership influence on management decisions* is .253. All standardized effects are reported in Table 7.

**Table 7: Standardized direct, indirect and total effects**

| Independent variables | Dependent variables | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Direct effects** | | | **Indirect effects** | | | **Total effects** | | |
| | Consistency of internal financial language | Controllership output quality | Controllership influence on managemen decisions | Consistency of internal financial language | Controllership output quality | Controllership influence on managemen decisions | Consistency of internal financial language | Controllership output quality | Controllership influence on managemen decisions |
| Data integration | .324** | .302** | | | .165** | .253*** | .324** | .467** | .253*** |
| Consistency of internal financial language | | .510** | | | | .276*** | | .510** | .276** |
| Controllership output quality | | | .541** | | | | | | .541** |

***** $p \leq .001$; ** $p \leq .01$; * $p \leq .05$; two-tailed significance (BC) bootstrap (ML) confidence intervals*

Our data suggest a positive association of data integration with controllership effectiveness based on both a direct effect as well as a mediating effect of a consistent internal financial language, supporting our notion that data integration has an impact both in an instrumental way as well as with respect to conceptual information use, as consistency of internal financial language plays a significant role in the association between data integration and controllership effectiveness.

## 5.2. Supplementary analysis

To examine our findings for possible moderating effects, we compare the results of our analysis for different sub-groups within our sample by conducting a multi-group causal analysis, thus testing the sub-groups for the equality of the estimated path coefficients (Steenkamp & Baumgartner, 1998). This involves testing a series of nested models (Bagozzi & Yi, 1988; Steinmetz et al., 2009), which each nested model (one for each group) consisting of a set of sub-models of which the parameters are estimated simultaneously. Throughout the test series, certain sets of parameters are constrained to the extent that they are equal in all sub-models across the groups. This allows us to test for differences in path coefficients between the groups. As the parameter sets become equal over the test series, each model is subject to more stringent constraints than its predecessor. Evaluating the change in model fit as well as individual model parameters can then be performed by a $X^2$-difference test for each step in the nested models (Reinecke, 2014). If differences can be observed, the resulting deterioration of the model fit leads to a higher value for $X^2$. However, the model gains one degree of freedom with each constraint, so the increase in $X^2$ has to be compared to the degrees of freedom gained. If the deterioration of the model fit is significant, it indicates that the last set of constrained parameters is not equal with respect to the compared groups. Furthermore, the groups must be classified in accordance to the variable assumed to have a moderating influence on the model parameters. However, dichotomization also produce disadvantages, as information about the variation among some individuals get lost (MacCallum et al., 2002). We use multi-group analysis following the approach recommended by Byrne (2016) and test for two potential moderating effects within our model.

The first supplementary analysis concerns organizational firm size as a moderating variable, which is already a subject of discourse in BI research (e.g., Ifinedo, 2007). In other words, we test if differences in path coefficients can be observed between a group consisting of smaller firms and a group covering larger firms. In the second supplementary analysis, we examine technological influence as a moderator. As noted in Section 2, On-Line Analytical Processing (OLAP) is a key software technology for structuring data. In our examination of data integration, we exclude analytic tools as a separate dimension of BI. However, OLAP is used for structuring data and thus a relevant software for data management. Therefore, it is of interest whether the intensity of OLAP use as a core element of a modern BI architecture has an impact on e.g., communication levels. Both analyses should serve as possible drivers for further research. Summary statistics of organizational size is presented in Table 2 as well as of OLAP is given in Table A2 (see Appendix).

### 5.2.1. Organizational size

Based on the literature review, organizational factors as company size attain a great importance in IS research. For example, Ein-Dor and Segev (1978) test the influence of company size and other organizational characteristics on the success of IS, which suggest that findings related to larger companies do not necessarily apply to smaller companies. They posit that firm size is moderates IS success, because larger firms tend to be more organizationally mature and have more resources to allocate for IS. However, they also find that company size is inversely related to the centralization of some IS functions (Ein-Dor & Segev, 1982). Moreover, Raymond (1985) noted that larger companies implement a greater number of administrative applications and IS are used more in such companies. We therefore analyze our model with respect to the question whether firm size has a moderating effect on the results of our baseline model, i.e., differences between smaller and larger organizations can be observed.

To test whether organizational company size affects the results of our baseline model, we divided the underlying sample into two subsamples, companies with less than 5,000 employees (group 1) and companies with at least 5,000 employees (group 2). Instead of common financial criteria, e.g., sales or sum of assets, we use number of employees to reflect the organizational firm size. We use the threshold of 5,000 employees because 5000 employees are a common threshold in business statistics to classify large companies (Applegate & Lampert, 2021). For both groups, the global criteria of model fit perform the required thresholds very well, i.e., the hypothesized model fits the empirical data, as shown in Table 8.

**Table 8: Goodness-of-fit indices for confirmatory factor analysis**

| Index | SIZE | OLAP | Critical Value | References |
|---|---|---|---|---|
| $X^2/df$ | 1.040 | 1.193 | ≤ 2 | Byrne (1989) |
| *p* -value | .397 | .169 | ≥ .05 | Bagozzi and Yi (1988) |
| RMSEA | .016 | .035 | ≤ .05 | Browne and Cudeck (1993) |
| GFI | .932 | .930 | ≥ .90 | Homburg and Baumgartner (1995) |
| CFI | .998 | .989 | ≥ .97 | Schermelleh-Engel et al. (2003) |
| TLI | .997 | .983 | ≥ .97 | Schermelleh-Engel et al. (2003) |

*$X^2/df$ = chi-square / degrees of freedom; p-value = probability value; RMSEA = root mean square error of approximation; GFI = goodness of fit index; CFI = comparative fit index; TLI = Tucker-Lewis index*

It must be noted that our analysis does not focus on the absolute values of our observed variables, but on the covariances which reflect the associations. If differences can be observed with respect to the direct or indirect effects, this indicates different associations between group 1 and group 2. Our test approach is illustrated in Figure 3. We test for significant differences concerning the direct (*b1_1* and *b1_2*) and the indirect effects (*b2_1* * *b3_1* and *b2_2* * *b3_2*) between the variables *Data integration* and *Controllership output quality* across the groups in a test series of four models.

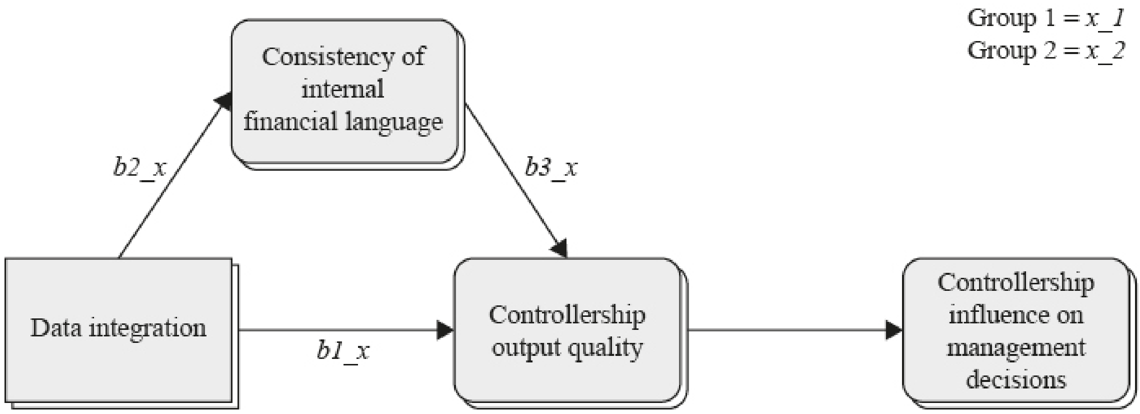


**Fig. 3** Multi-group analysis

Model A tests for configurational invariance by estimating an unconstrained model for both groups. In this model, all model parameters (e.g., factor loadings) are freely estimated for both groups. That is, the model is constrained only to the extent that it is the same in structure and design between groups. As shown in Table 8, the fit measures ($X^2/df = 1.040$) of the unconstrained model indicate that the same model structure applies to both groups, i.e., we measure the same variables, items, and paths for both groups. The results for each model of the following test series are shown in Table 9.

**Table 9: Results of multi-group analysis - SIZE**

| **Model** | **Compared Model** | $X^2$ ($df$) | $\Delta X^2$ ($\Delta df$) | **RMSEA** | **CFI** |
|---|---|---|---|---|---|
| A: Configural invariance | - | 49.927 (48) | - | .016 | .998 |
| B: Full metric invariance | A | 52.844 (53) | 2.917 (5) | .000 | 1.000 |
| C: Invariance of direct effect | B | 54.978 (54) | 2.134 (1) | .011 | .999 |
| D: Invariance of indirect effect | B | 54.023 (55) | 1.179 (2) | .000 | 1.000 |

*$X^2$ = chi-square; df = degrees of freedom; p-value = probability value; RMSEA = root mean square error of approximation*

Model B tests for full metric invariance, i.e., the manifest indicators measure the same in the different groups, or the same indicators can be used for measuring the different groups. In this model, all factor loadings of the measurement constructs are constrained to be the same in both groups, i.e., all indicators underlying a related construct are appropriate to measure the latent variable in a similar way. Although these restrictions result in an increase in $X^2$ of 2.917, the decrease in model fit is not significant as 5 degrees of freedom are gained. Thus, full metric invariance can be assumed. This allows us to test for structural invariance, i.e., if the structural relationships of both groups are also valid. Thus, we compare in separate steps the direct and indirect effects between the two groups.

Model C tests for invariance of the direct effects. Thus, in addition to the constraints from Model B, the direct effects between the variable *Data integration* and *Controllership output quality* are set equal in both groups. That means we fix the effect *b1_1* identical to *b1_2*. As Table 9 shows, the equalization of the direct effects leads to a deterioration of the model fit, as $X^2$ increases by 2.134 compared to Model B. However, the deterioration in model fit is below the threshold of 3.84 (for 1 degree of freedom gained). Therefore, different direct effects between the two groups cannot be established, i.e., there is no strong deviation between the controllers’ and managers’ perceptions on the influence of *Data integration* on *Controllership output quality*.

Model D finally tests for invariance of the indirect effects, i.e., we test whether significant differences for the perceptions of controllers and managers can be observed for the indirect influence of *Data integration* on *Controllership output quality*. In addition to the constraints from Model B the indirect effects between the variable *Data integration* and *Controllership output quality* are set equal in both groups. In other words, we constrain the effect *b2_1* is equal to *b2_2* as well as the effect *b3_1* is equal to *b3_2*. As in Model C, the equalization of the indirect effects leads to a deterioration of the model fit, as $X^2$ increases by 1.179 compared to Model B. However, the deterioration in model fit is far below the threshold of 5.99 (for 2 degrees of freedom gained).

Therefore, our multi-group comparison does not support the notion of different indirect effects between the two groups. Obviously, the technical as well as conceptual impact of data integration on controllership effectiveness holds for larger and smaller firms in the same way. In conclusion, our results show that no moderating effect of group membership on the direct and indirect relations between our variables *Data integration* and *Controllership output quality* can be assumed. Since a moderating effect is not supported by the test statistics, it is not feasible to compare the factor loadings of both groups.

### 5.2.2. OLAP as a core technology

BIS consist of different interconnected technologies, which can be distinguished into tools and technologies of data management as well as analytics (e.g., Cates et al., 2005; Glancy & Yadav, 2011). A most common type of data management tools is OLAP, which allows to transform large amounts of opaque data from heterogeneous data sources into useful information, and is therefore closely linked to effective data integration (Jaklič, 2008). In case of well-integrated data, OLAP allows different users to interactively create an individual perspective on data (Kelidbari & Rayat, 2017; Schwarz et al., 1998). OLAP is therefore also an essential part of AIS technology, allowing faster access to information as well as to interact and communicate within an organization more easily. This leads us to consider whether OLAP might have a moderating effect on the results of our study, i.e., the impact of data integration in organizations with low versus high use of OLAP.

To test that OLAP affects the results of the baseline research, our sample was once again divided into two subsamples using a median split, which represent the two different levels of use, companies with a lower use (group 1) and companies with a higher use (group 2) of OLAP. We use a median split as because it is the most common method for testing moderation effects. For both groups, the global criteria of model fit perform the required thresholds well, i.e., the hypothesized model fits the empirical data, as shown in Table 8.

As in the previous multi-group analysis in Section 5.2.1, we test for significant differences concerning the direct (*b1_1* and *b1_2*) and the indirect effects (*b2_1* * *b3_1* and *b2_2* * *b3_2*) between the variable *Data integration* and *Controllership output quality* across the groups in a test series of four models as indicated in Figure 3.

Model A tests for configurational invariance by estimating an unconstrained model for both groups. As shown in Table 8, the fit measures ($X^2/df$ = 1.193) of the unconstrained model indicate that the same model structure applies to both groups. The results for each model of the following test series are shown in Table 10.

**Table 10: Results of multi-group analysis - OLAP**

| Model | Compared Model | $X^2$ ($df$) | $\Delta X^2$ ($\Delta df$) | RMSEA | CFI |
|---|---|---|---|---|---|
| A: Configural invariance | - | 57.263 (48) | - | .035 | .989 |
| B: Full metric invariance | A | 62.429 (53) | 5.166 (5) | .034 | .989 |
| C: Invariance of direct effect | B | 64.672 (54) | 2.243 (1) | .036 | .987 |
| D: Invariance of indirect effect | B | 73.282 (55) | 10.853 (2) | .046 | .978 |

*$X^2$ = chi-square; df = degrees of freedom; p-value = probability value; RMSEA = root mean square error of approximation*

Model B tests for full metric invariance. Although these restrictions result in an increase in $X^2$ of 5.166, the decrease in model fit is not significant as 5 degrees of freedom are gained. Thus, full metric invariance can be assumed. This allows us to test for structural invariance, i.e., whether the structural relationships are also valid between both groups. Therefore, we compare separately the direct and indirect effects.

Model C tests for invariance of the direct effects between the variables *Data integration* and *Controllership output quality*, i.e., in addition to the constraints from Model B, we set the effect *b1_1* equal to *b1_2*. As Table 10 shows, the equalization of the direct effects leads to a deterioration of the model fit, as $X^2$ increases by 2.243 compared to Model B. However, the deterioration in model fit is below the threshold of 3.84 (for 1 degree of freedom gained). Therefore, different direct effects between the two groups cannot be identified.

Model D finally tests for invariance of the indirect effects between the variable *Data integration* and *Controllership output quality*, i.e., in addition to the constraints from Model B, we constrain that the effect *b2_1* is equal to *b2_2* and the effect *b3_1* is equal to *b3_2*. As figured in Table 10, the equalization of the direct effects leads to a deterioration of the model fit, as $X^2$ increases by 10.853 compared to Model B. In contrast to Model C, the deterioration of the model fit is significant, as the threshold of 5.99 (for 2 degrees of freedom) is exceeded. Therefore, it can be assumed that group membership has a moderating effect on the indirect effects between the variables *Data integration* and *Controllership output quality*. For a more precise insight into the differences between the two groups, we consider the results of Model B with full metric invariance. As shown in Figure 4, the indirect effect for group 1 is not significant, whereas it shows significance for group 2. Moreover, the direct effect is not significant for group 1 whereas it becomes slightly significant for group 2. This might indicate that the effects of *Data integration* on *Consistency of internal financial language* are influenced by the use of OLAP. Moreover, the results could indicate that capabilities of an individual structuring, analysis or visualization of data influence the contribution of an internal financial language as a means of communication.

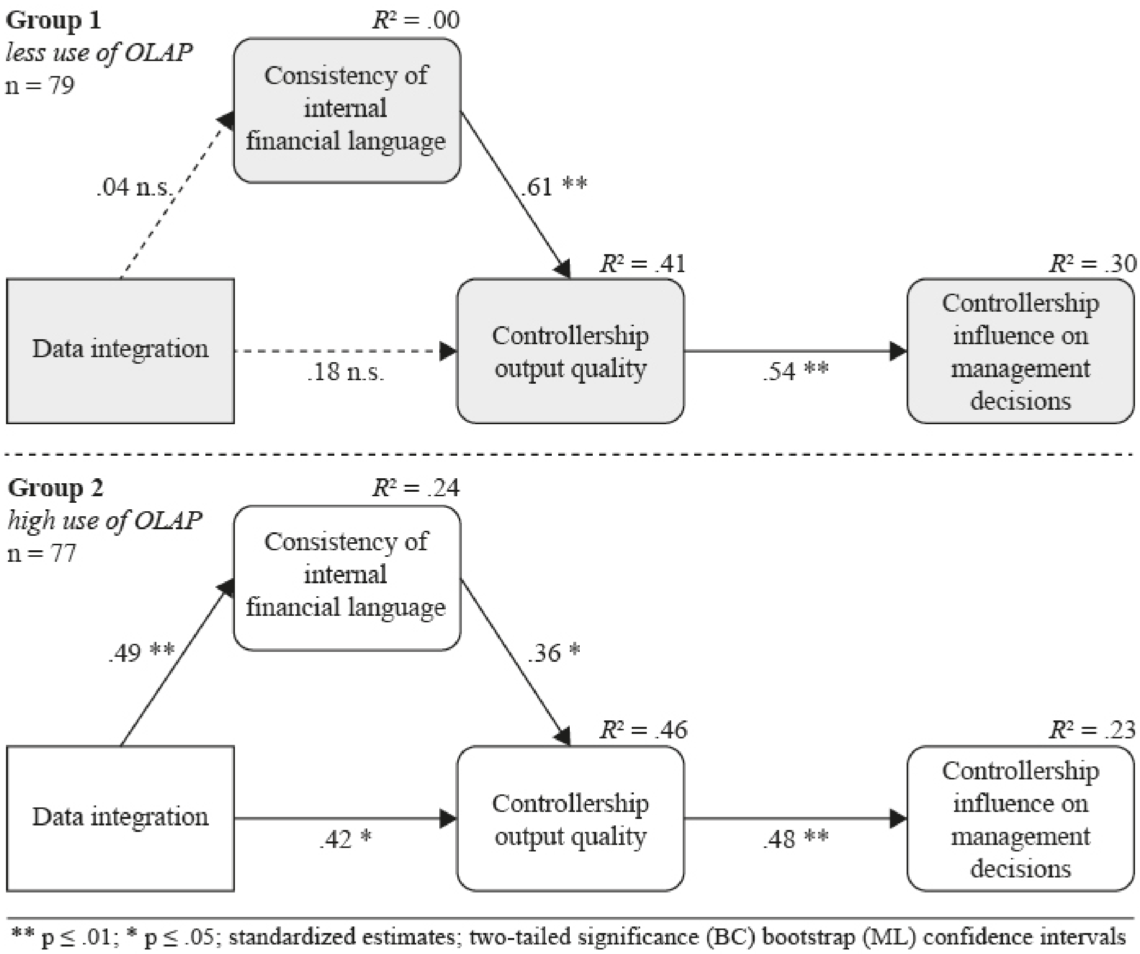


**Fig. 4** Empirical results of Model B with full metric invariance

## 6. Discussion

Our study was motivated by the increasing digital transformation of accounting information technology and the changing role of controllers towards business partnering demanding effective support in operational as well as strategic managerial decision-making and control. In this vein, our interest has been focused on data integration, which is significantly affected by increased volumes of heterogeneous data as well as by technology-based organizational complexity. Our research contributes to the clarification of whether data integration has a positive impact on controllership effectiveness, and whether the underlying association between the two variables is direct, i.e., technology-driven, or indirect, i.e., via conceptual use within an internal financial language for business communication. The results of our research which is based on 156 controller responses from large German companies with at least 500 employees, indicate that there is a positive significant association of data integration with the effectiveness of controlling, which causes directly, i.e., technology-based, as well as a mediated effect instigated by a consistent internal financial language resulting from an increased level of data integration. Our findings add new insights into the discussion on whether data integration is related to the effectiveness of controlling which on first sight is not necessarily the case, e.g., due to loss of information due to standardization or business units’ resistance against the control system tightness induced by transparency resulting from data integration.

We show that a solely technology-based approach to the controller's tasks ignores the relevance of the consistency of an internal financial language as a driver of controllership effectiveness. Even if the consideration of tailor-made information using customized subsystems can be seen as advantageous from an IS-theoretical perspective, it does not fulfil the controllers’ need of an integral view as a 'single source of truth', which is made possible through data integration.

Therefore, our results show that data integration not only contributes in an instrumental fashion to the quality of analyses and reports provided by controllers, but also conceptually through its consistency resulting in a better suited financial language for business communication. Although not explicitly addressed in our study, consistency could also be interpreted as a mechanism that prevents the emergence of uncertainty among controllers in terms of the information provided to management for decision-making.

Although our exploratory complementary analysis on a moderating effect of organizational size does not provide evidence of an influence, consistency with respect to data integration should be of importance, especially for large companies. This notion is supported by the idea that the number of subsystems and thus the risk of inconsistent information tends to increase with the organizational company size. Communication within organizations also shifts to digital media due to an increasing organizational company size as well as, in general, the digital transformation.

This implication could be the subject of further research, as our second supplementary analysis on the moderating influence of OLAP shows that specific properties of data integration may have an impact on the consistency of the information and thus, e.g., on internal financial language. One reason might be that consistent information serves as a financial language only if the information can be interactively structured and visualized according to the individual needs of various users.

Obviously, there are some limitations to the generalizability of our results. First, our results concentrate on decision support in revenue forecasting, which solely address the consistency of information in one area of the controllers’ tasks. Moreover, our analysis is based on data drawn from large companies with at least 500 employees, which means that our results must be interpreted carefully with respect to SMEs, even if our supplementary analysis does not initially suggest a contradictory size effect on our results. As common in survey-based research, our results could be biased by subjectivity and/or a single-respondent bias, especially given that we surveyed only representatives of the controlling function. Furthermore, our survey took place during the period of the COVID-19 pandemic. Since our sample only covers this specific period, our results might be a subject of time-period bias. In order to check for robustness of our results, it requires repeating the survey at a later stage to test for possible time effects, such as, problems of uncertainty or intergroup relations among the decision-making process being improved (Fink et al., 1971). In general, endogeneity concerns, i.e., unobserved firm characteristics which could affect our results, can only be addressed by repeating the investigation using different designs and analyses (Hill et al., 2021).

Although the total effect between the variables *Data integration* and *Controllership influence on management decisions*, which is mediated by the variable *Consistency of internal financial language*, is highly significant and the path coefficient between *Data integration* and *Consistency of internal financial language* indicates a strong (.32) significant effect, *Data integration* explains only 10% of the variance in *Consistency of internal financial language*. This leaves much space for the question which additional causes could explain this variable. This should be another subject of further research.

Related to the statistical point of view, our results are limited in terms of representativeness due to our non-random sample of companies. However, our analysis is based on a sample drawn from a heterogeneous population, which comprises 5,758 of large German companies with more than 500 employees. Since we use cross-sectional data, our results may not apply to a specific industry type. Alternatively, there is no indication that the issues discussed in our research have different relevance with respect to specific industries. A second statistical limitation results from the quasi-formative measurement of the variable Data integration by means of an additive index. As this index is measured as a manifest variable, it ignores an error term that regular formative latent variables usually have. This error term represents the impact of all remaining causes other than those represented by the indicators included (Diamantopoulos, 2006). Using the composite index assumes that the underlying indicators completely capture the construct, which in most cases is inappropriate (Diamantopoulos et al., 2008). However, as Diamantopoulos (2006) points out, this approach is legitimate if all possible indicators of a construct can be conceivably specified. Given the two key perspectives of data integration derived from IS literature (Popovič et al., 2012), this requirement should be largely fulfilled in the case of our composite index.

Future research should address the subcategories of data integration, e.g., hybrid forms as well as the individual properties or new technologies, e.g., cloud-computing. In addition, longitudinal studies should be conducted to analyze the impact on variability, e.g., influenced by the proceeding transformation of the digital economy or special periods such as the COVID-19 pandemic, on the effectiveness of controlling.

# Appendix

**Table A1: Item summary**

| Construct | Label | Indicator |
|---|---|---|
| | | (0 = not agree … 5 = completely agree) |
| Data integration | DI1 | Data are scattered everywhere – on the mainframe, in databases, in spreadsheets, in flat files, in ERP applications. … Data are completely integrated, enabling real-time reporting and analysis. |
| | DI2 | Data in the source are mutually inconsistent. … Data in the source are mutually consistent. |
| | | (0 = not agree … 5 = completely agree) |
| Consistency of internal financial language | CL1 | The figures of the controlling department are connected to the figures of the sales department in an easily comprehensible way. |
| | CL2 | Information from Controlling and Sales provides a consistent picture of the business situation. |
| | | (0 = not agree … 5 = completely agree) |
| Controllership output quality | CQ1 | Information from our controlling department is accurate. |
| | CQ2 | Information from our controlling department is up to date. |
| | CQ3 | Information from our controlling department is correct. |
| | | (0 = not agree … 5 = completely agree) |
| Controllership influence on management-decisions | CI1 | Controlling plays a very important role in decision-making in our business area. |
| | CI2 | Management attaches great importance to the opinions of controlling in decision-making. |
| | CI3 | Controlling has a strong influence on management decisions in our business area. |

**Table A2: Summary statistics on item underlying the moderating variable 'OLAP'**

| Item | Min | Max | Mean | SD |
|---|---|---|---|---|
| (0 = not available … 5 = very strong represented) | | | | |
| To what extent can OLAP be used in your business area? | 0.00 | 5.00 | 2.41 | 1.715 |

*n = 156; SD = Standard Deviation*

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# C Controllers as business partners in times of pandemic: The impact of business partnering on controllership effectiveness in revenue forecasting

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Both authors developed theory/hypotheses.
Mark Alexander Sutton performed the data gathering.
Mark Alexander Sutton analyzed the data.
Both authors wrote the paper.
Both authors participated in review process.

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# Controllers as business partners in times of pandemic: The impact of business partnering on controllership effectiveness in revenue forecasting

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# Abstract

For several years, controller roles have been shifting from maintaining financial records and providing financial oversight, towards a strategically-oriented business partner role. However, this shift becomes questionable in times of economic crisis, as triggered by the COVID-19 pandemic, when managerial decision-making is subject to radical uncertainty ('unknown unknowns'), as literature lacks consensus on whether the impact of an economic crisis either makes the involvement of controllers in managerial decision-making processes less pronounced, or whether they instead become even more involved. Our paper contributes to this debate by specifically analyzing (1) whether an increased level of business partnering has an impact on controllership effectiveness, (2) if so, whether this impact works in an instrumental fashion by providing high-quality output or rather conceptually, by integrating controllers in managerial decision-making processes and (3) whether deteriorating information quality under the influence of the COVID-19 pandemic moderates the first mechanism. We use covariance-based structural equation modelling for a sample of 155 controllers surveyed from large German firms. Our results suggest that even though the impact of business partnering behavior is only associated with conceptual information channels, in a deteriorating information environment, instrumental involvement of controllers has a positive impact on controllership effectiveness as well. A supplementary dyadic analysis using managers' answers supports this notion, but also that controllers may to some extent overestimate the relevance of their business partnering role.

**Keywords**: Controllership, business partnering behavior, instrumental vs. conceptual information-processing, uncertainty, COVID-19 pandemic, crisis

**JEL code**: M40, M41

# 1. Introduction

It is generally accepted that managers need useful business information for decision-making and control, and that the quality of decision-making substantially depends on this (Zeng et al., 2006). Even though managerial action is typically directed at non-financial goals, e.g., sales volume or market share, most firms use financial information for decision-making and control purposes, because it is congruent with the organizational goal of profit maximization, and can be tailored appropriately to different hierarchy levels (Malina & Selto, 2004). Thus, providing meaningful internal financial reports as informational support for the prevailing and specific managerial decision-making demands (instrumental or technical information), as well as giving structural insights into the firm as a whole to align decision-making with strategic goals and the business environment (conceptual information), constitutes one of the most important tasks of controllers (or management accountants) (Beyer & Trice, 1982; Rouwelaar et al., 2021; Simon et al., 1954).

For several years, the occupational role of controllers has gradually been shifting away from being mainly a cost recorder and focusing on collecting as well as presenting financial information and analysis. Today, controllers increasingly emphasize that they assume the role of business partners participating proactively in managerial decision-making (Goretzki & Strauß, 2017; S. Wolf et al., 2015) and that managers rely on controller involvement to deal with operational as well as strategic issues (Lambert & Sponem, 2012). In this vein, controllers' business partnering behaviors specifically cover the provision of highly sophisticated financial and non-financial analyses and reports as well as of forward-looking structural business insights, thus proactively initiating and guiding managerial decision-making (S. Byrne & Pierce, 2007; Davis & McLaughlin, 2009). However, in order to become business partners in the sense of "trusted advisors" and "consultants" (McNally, 2002) and thus assume an active part in the management of the business, controllers have to provide high-quality information from the management's point of view as well. Therefore, controllership effectiveness in relation to the business partner role can be seen as a combination of both output quality and the resulting influence on managerial decision-making.

In times of economic crisis, such as triggered by the COVID-19 pandemic, managerial decision-making becomes increasingly difficult due to radical uncertainty ('unknown unknowns') caused by the growing opaqueness of firms' information environment (Hopwood, 2009). This severely affects controllers' tasks. For example, Becker et al. (2015) show that as a response to the financial crisis of 2008/09, controllers stopped using budgets for performance measurement purposes and instead put more emphasis on forecasting and the resource allocation functions of budgets. However, in an uncertain and volatile organizational environment, budgets are generally used by managers as an 'anchor' for strategic decision-making (Marginson & Ogden, 2005). Yet, the literature lacks consensus on whether the impact of an economic crisis makes the involvement of controllers in managerial decision-making processes either less pronounced as, e.g., financial records lose significance, or whether controllers instead become even more involved, as operational, and strategic decisions become increasingly demanding.

Despite the highlighted research potential (e.g., Van der Stede, 2011), the impact of economic crises on controllers' business partnering activities has not yet been analyzed in-depth. Particularly, Hopwood (2009) stated that "… although there have been a number of more general organizational studies, particularly in times of past crises ... management accounting research gives little or no guidance on the modes of organizational response to economic crises", for instance, with respect to the relevant configuration of expertise within the accounting function. To address this research gap, we aim at acquiring and providing a better understanding of the benefits of business partnering in times of economic crisis and in this context, at exploring its impact on controllership influence on management decisions. Especially we want to shed light on how business partnering is linked to controllership influence on management decisions and whether this link changes if the informational environment is impaired by the impact of the COVID-19 pandemic.

Our study therefore seeks to answer the following research questions:

(1) Does an increased level of business partnering activities have a positive impact on controllership effectiveness, as a combination of controllership information output quality and controllership influence on management decisions,

(2) does this impact work in an instrumental fashion by means of providing high-quality output information, or rather conceptually by directly integrating controllers into managerial decision-making processes, and

(3) does the instrumental impact become more pronounced in an increasingly opaque information environment, as caused by the COVID-19 pandemic?

Our research is related to several seminal studies. Rouwelaar et al. (2021) survey controllers in Dutch healthcare organizations and find that both controllers' technical as well as conceptual skills drive controllership effectiveness, but they do not include information quality or economic crisis in their analysis. The latter issue is addressed in the study of Becker et al. (2015) who address the impact of the financial crisis 2008/09 on management controls in terms of budgeting.

Combining broad survey data with archival data from DACH[1] firms, they find in line with Janke et al. (2014), that in times of economic crisis, the budgeting functions shift from diagnostic routines towards rather interactive use and the strategic alignment of resources. In a similar vein, Janka and Günther (2018) use survey data from 276 large DACH firms to investigate the change of management controls in the context of, e.g., sales with new or modified products. They find that in increasingly complex information environments, management control instruments become looser, thus supporting the notion of an increasing relevance of controllers' business partnering role for controllership effectiveness. On the other hand, Weißenberger et al. (2012) find in a survey of 149 manager-controller dyads, that controllers tend to overrate themselves in their business partnering relationship to managers. Our paper draws on this comprehensive body of research by using survey data to not only analyze the mechanisms underlying the business partnering relationship in more detail, but also to better understand the impact of a deteriorating information environment caused by economic crises such as the COVID-19 pandemic on controllership effectiveness.

Our research therefore contributes to the existing literature threefold. First, the connection between controllers' business partnering behaviors and controllership effectiveness is made explicit. Second, we do not limit our analysis to the conceptual mechanisms relating business partnering behaviors to controllership influence on management decisions, but also include the impact of providing high quality information for fast decision-making and contextualized as well as sophisticated financial analysis, which forms an instrumental part of the business partnering role. Third, we examine the impact of the COVID-19 pandemic with respect to information quality on the latter mechanism.

Our research is distinctive, as it sheds lights on the antecedents for controllers becoming (strategic) business partners in times of economic crisis such as the COVID-19 pandemic. Our empirical investigation based on a questionnaire-based online-survey we conducted from June to October 2020 during the COVID-19 pandemic. We chose revenue forecasting in line with Janka and Günther (2018) as a specific anchoring point within controllers' tasks, because it is not only common in virtually all firms, but also an accounting and control issue of the highest relevance that typically requires a comprehensive and sophisticated understanding of the firm's business and its environment. Although we conduct our investigation in a national context by surveying large German companies, our contributions are also of interest to the international debate on management accounting and control, as well as to organizational research, as the COVID-19 pandemic is a global issue across most industries (Conde et al., 2022).

[1] DACH firms are firms based in German-speaking countries (Germany, Austria, Switzerland).

Our paper is structured as follows. Section 2 provides a review of the literature underlying our study. Section 3 presents the research model and four derived hypotheses. Section 4 describes the empirical design of our study. Section 5 provides information on measuring the variables recorded in our model. Section 6 presents the results of our study, which were derived using covariance-based structural equation modelling (CB-SEM). Section 7 adds an exploratory multi-group analysis supplementing our main analysis in Section 6, by using dyadic firm data surveyed from controllers and closely-related managers. Finally, Section 8 discusses our results and outlines implications for future research.

## 2. Literature review

Our research is nested in two major streams of literature. First, we draw from the broad literature on accounting and control response to crisis situations, with a specific focus on information-processing theory. Second, we rely on the ongoing debate on the shifting occupational role of controllers towards business partnering, and the resulting interaction with management. Both streams are used as a theoretical underpinning for our hypotheses regarding the impact of controller business partnering behaviors on controllership effectiveness.

For firms, major economic crises, such as that caused by the ongoing COVID-19 pandemic, are substantial threats (Ury & Smoke, 1985; Weick, 1988). Achieving organizational goals by choosing and implementing appropriate strategies and action plans becomes increasingly challenging, as the business environment in crisis situations is characterized by opaqueness (Turner, 1976) as well as a high level of uncertainty due to the unpredictable course of events (Pearson & Clair, 1998; Rosenthal & Hart, 1991). Compared to other crises, this has been particularly exacerbated during the ongoing COVID-19 pandemic (Verma & Gustafsson, 2020), because of its rapid as well as unprecedented reach across countries and industries (Conde et al., 2022). In a broad sense, uncertainty is an external factor (Widener, 2007) that, according to organizational information-processing theory, determines the level of information that an organization needs to perform a given task. While in situations with low uncertainty, most of the information required to perform managerial decision-making is already available, based on an organization’s experience, in opaque situations with high uncertainty, additional as well as more sophisticated information has to be collected and processed (Galbraith, 1973).

In this vein, the COVID-19 pandemic is typical for situations that lead to increasing "information intensity" (Hopwood, 2009, p. 799), in which the gap between required and available accounting information for organizational control widens (Chapman, 1998; Galbraith, 1974). For example, in the wake of the ongoing COVID-19 pandemic, which may affect firms in several ways, underlying assumptions for planning and forecasting have changed significantly, as unparalleled long-term effects on economic conditions, health or changing work environments resulted in the need for radically new judgments (Humphreys & Trotman, 2022). As the literature on former crises suggests, this is supposed to make firms adjust their planning and budgeting systems in an attempt to better predict and react to environmental uncertainties by using interactive rather than diagnostic mechanisms (Becker et al., 2015). This, in turn, requires an increased level of organizational performance, e.g., in order, to act rapidly as well as appropriately to mitigate threats or seize opportunities (Jauch & Kraft, 1986; Lin et al., 2006). Even though expanded information, figures, and calculations, such as internal financial reports from management accounting to which managers have access, can improve adaptation to new business conditions and reduce vulnerability to uncertainty (Conde et al., 2022) the main assumption of organizational information-processing theory holds, in that only a limited amount of information can be handled by a firms' given information channels (Galbraith, 1974). As a result, under a high level of uncertainty, information channels tend to overload (Widener, 2007) and organizations then have to comprehensively adjust their decision-making and control processes (Lin et al., 2006; Passetti et al., 2021).

With respect to the underlying mechanisms within these information channels, accounting literature distinguishes between instrumental and conceptual mechanisms. The first type of mechanisms has an emphasis on formal or technical features and relates to expert knowledge, as well as analytical skills that can be applied by using appropriate computer-based tools and enabling controllers to support managers with additional information through analyses and internal reports. The latter type is rather process-based and comprises interaction through initiating, guiding, and aligning managerial decisions with strategic goals and the business environment (Beyer & Trice, 1982; Katz, 1974; Rouwelaar et al., 2021).

Rouwelaar et al. (2021) indicate that both instrumental as well as the conceptual mechanisms have an impact on the effectiveness of controllership, allowing controllers to wield more influence on managerial decision-making, which closely relates this body of literature to the second stream underlying our research, and which deals with the ongoing shift in controllers' roles towards becoming a business partner (for an overview, see T. Wolf et al., 2020). Järvenpää (2007, p. 100) defines the business orientation of controllers as "the willingness and ability of management accounting to provide more added value to the management (decision-making and control)". The underlying reasoning is that controllers, as business partners, are better able to provide enhanced services to managers and thus contribute to organizational goals (Burns & Baldvinsdottir, 2005). Evidence of this role change has been found by various researchers since the 1990s (Ahrens & Chapman, 2000; Granlund & Lukka, 1998; Siegel & Sorensen, 1999). The change has been driven by external factors, e.g., megatrends like globalization or digitalization, but also by the need for controllers to establish their identity as an essential function for a firm's management (S. Wolf et al., 2015; T. Wolf et al., 2020) and thus to maintain "organizational validity" (Pierce & O'Dea, 2003, p. 258). The latter issue is especially important, as several case studies have shown that managers tend to turn towards other sources of information, such as the financial accounting function (Doron et al., 2019; Nilsson & Stockenstrand, 2015), if controllers cannot meet their decision-support requirements (Berlant et al., 1990; Bruns & McKinnon, 1993; Choe, 1998). Evidence on the integration of financial and managerial accounting systems in German-speaking countries since the 1990s supports this notion, indicating managers' need for a consistent financial language for decision-making purposes (Ewert & Wagenhofer, 2007; Weißenberger & Angelkort, 2011).

Nevertheless, the outcome of business partnering is not undisputed, as the traditional role of controllers being rather record-keepers and information providers still exists (De Loo et al., 2011; T. Wolf et al., 2020). Burns and Baldvinsdottir (2005, p. 726) have even denoted the positive impact of business partnering as a "myth". One reason might be the dilemma between independence and involvement resulting from controllers as business partners, given that moral hazard problems, profit manipulations, budget games or other drawbacks in governance might result from decentralized controllers becoming close to the management team (Bhimani & Bromwich, 2009; Lambert & Sponem, 2012; Maas & Matejka, 2009). Other potential reasons are personal characteristics, such as individual controller tendencies towards Machiavellianism (F. Hartmann & Maas, 2010). In consequence, there is evidence of a preparer-user perception gap, with controllers overstating their impact within management, as well as misinterpreting the mechanisms relating their work to controllership effectiveness (Pierce & O'Dea, 2003; Weißenberger et al., 2012).

Combining both streams of literature, we summarize that even though the positive impact of controller business partnering behaviors is not undisputed, one of the major antecedents for its effectiveness would be an amplified level of business knowledge, as well as close interaction with management, which is increasingly fostered in times of crisis and uncertainty.

## 3. Research model and hypothesis development

Our study is driven by the research question of how controllers' business partnering behavior is related to controllership effectiveness, and whether the instrumental mechanism relating both variables is becoming more pronounced under an increasingly opaque information environment, as caused by the COVID-19 pandemic. Based on the literature, we first hypothesize that there is a direct conceptual relationship, i.e., controllers as business partners guide and advise managers by providing insights into how organizational functions or value drivers interact and relate to the firm's strategic goals (S. Byrne & Pierce, 2007; Rouwelaar et al., 2021). This is supported by Janke et al. (2014), who observe a growing conceptual interaction between controllers and managers, e.g., adapting or even setting new goals and priorities, challenging new ideas and permanent learning as well as involving subordinates. We therefore posit:

*H1: An increased level of controllers' business partnering behavior leads to an increased level of controllership influence on management decisions.*

We further assume that controllers' business partnering behavior also drives controllership effectiveness via an instrumental mechanism, by supplying highly sophisticated financial and business analysis, combined with data modelling for managerial decision-making (Fleischman et al., 2016). With our second and third hypotheses, we stipulate that the quality of controlling output increases with a more pronounced business partner role, as reports and analyses are assumed to become more nuanced and tailored to specific managerial information needs. This in turn leads to a growing influence on managerial decision-making (Burns et al., 1999; Goretzki & Strauß, 2017; Rouwelaar et al., 2021; S. Wolf et al., 2015). Whereas controllership information output quality refers directly to the results of the controllers' work, their influence on managerial decision-making extends far beyond this, and rather represents the outcome dimension. In accordance with the assumptions of rational choice theory (Hedström & Swedberg, 1996), we assume that increased controllership information output quality will cause its more extensive use, and thus lead to a stronger influence on management decisions. Furthermore, we assume that controllership effectiveness is the result of both output and outcome, because it is the combination of high output quality and a high level of influence on management decisions that in fact constitutes controllers' support function within management. We therefore hypothesize:

*H2: An increased level of controllers' business partnering behavior leads to an increased level of controllership information output quality.*

and

*H3: An increased level of controllership information output quality leads to an increased level of controllership influence on management decisions.*

With respect to an organizations' increasingly opaque information environment caused by the COVID-19 pandemic, we further assume that it especially has an impact on the relationship between controllers acting as business partners and the resulting quality of information provided for managerial decision-making. This notion is supported by both Mouritsen (1996) who finds a significant relation between environmental uncertainty and the controllers' work, particularly in consulting activities, and by F. G. Hartmann and Maas (2011), who find in a similar vein that uncertainty is related to a stronger business partner role. Nonetheless, we do not anticipate the direction of the resulting moderating effect. On the one hand, the uncertainty resulting from a volatile and unpredictable business setting caused by the COVID-19 pandemic may hamper controllers in providing high-quality information as suggested by Becker et al. (2015). Alternatively, controllers acting as business partners are, to a greater extent, able to extract high-quality information if the information environment is impaired, as they understand much better which business insights managers need for decision-making under increasing uncertainty. We therefore finally hypothesize:

*H4: The relation between the level of controllers' business partnering behavior, and the level of controllership information output quality, is moderated by the level of COVID-19 influence impairing information quality.*

The full research model is presented in Figure 1.

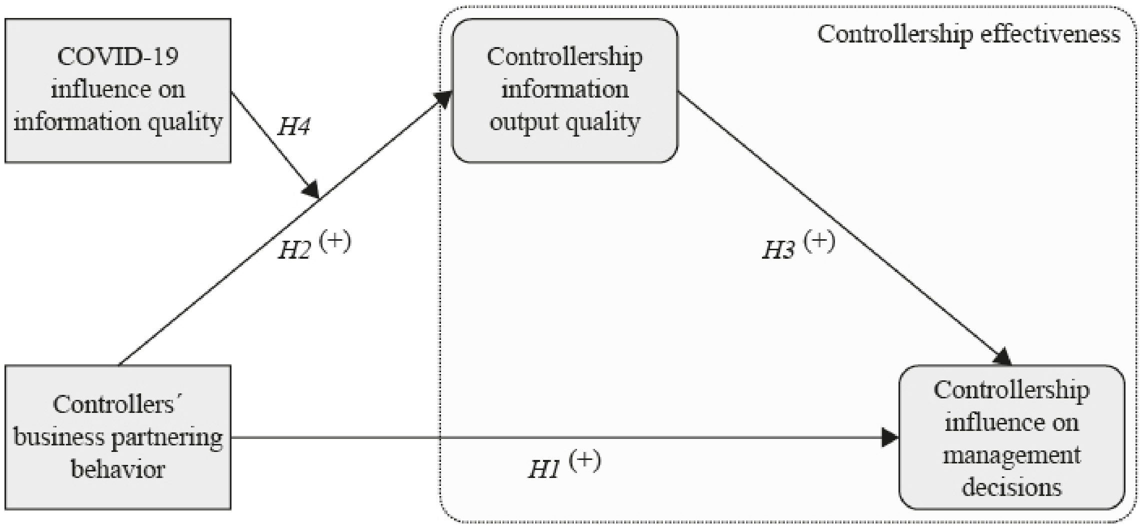



**Fig. 1** Full research model

# 4. Data and measurement

## 4.1. Sample selection and survey design

For our investigation, we chose revenue forecasting as a specific anchoring point for identifying the impact of controllers' business partnering behavior on controllership influence with respect to management decisions. We selected this anchor not only because revenue forecasting is a common controller task in almost all firms, but also because in most firms, it is of the highest relevance, and forecasting quality especially in times of high uncertainty requires a sophisticated understanding of a firm's business environment. We therefore assume that controllers use all available information to provide revenue forecasts that are as accurate and meaningful as possible, and that this type of information is an appropriate indicator of the overall quality of their work and their influence on managerial decision-making.

The underlying data for our study were collected in the period from June to October 2020 by means of a questionnaire-based online survey. Our starting point was the database Markus with contact data of all German companies. We concentrated on large companies, as small firms usually do not have a specialized controlling department (e.g., Hiebl et. al. 2013). As a criterion for firm size, we selected only firms with at least 500 employees, thus excluding small- and medium-sized enterprises (SME; IfM Bonn, 2020). We also excluded finance and real estate firms, due to their diverging business models compared to firms from industrial, service or trading industries. Our database was finally adjusted by eliminating duplicate entries, so that 5,758 companies remained in our population. Of these, for reasons of time and resources, 20% were randomly selected and contacted by telephone or, in the case of several missed calls, by e-mail. To capture the various aspects of controllers' tasks in providing revenue forecasts, we addressed the controlling manager ('Leiter Controlling'), a functional controller responsible for sales controlling or a similar function in each company. To ensure ex ante completeness and understandability, we followed the recommendations of Dillman (2007), and pre-tested our online-questionnaire with three executives from business practice, three consultants and five academic researchers.

In total, we received 159 completed questionnaires, of which three had to be excluded due to unfulfilled requirements concerning the number of employees. The remaining sample of 156 questionnaires corresponds to return rates of 13.3% of the participant population. Table 1 presents the companies' industry affiliation of our sample.

**Table 1: Surveyed firms by industry**

| Variable | Frequency | Percentage |
|---|---|---|
| Automotive | 21 | 13,5% |
| Construction | 9 | 5,8% |
| Chemicals/Pharma/Health care | 18 | 11,5% |
| Industrial Goods | 7 | 4,5% |
| Energy/Utility | 18 | 11,5% |
| Wholesale/Retail | 14 | 9,0% |
| Consumer goods | 15 | 9,6% |
| Engineering | 20 | 12,8% |
| Software/Technology | 5 | 3,2% |
| Telecommunication | 2 | 1,3% |
| Transport/Logistics | 7 | 4,5% |
| Others | 20 | 12,8% |
| n | 156 | |

Summary statistics of company size are shown in Table 2.

**Table 2: Summary statistics on company size measures of surveyed firms**

| Variable | n | Mean | SD | Median |
|---|---|---|---|---|
| Number of employees | 156 | 22,474 | 65,646 | 4,477 |
| Sales (Million EUR) | 155 | 6,089 | 13,618 | 1,129 |
| Assets (Million EUR) | 148 | 11,103 | 33,899 | 754 |

As our survey is part of a larger research project, we surveyed several items which are not related to the research questions of our study. A summary of items used for our research model is given in the appendix.

## 4.2. Variable measurement

Our research model based on two exogenous variables *Controllers' business partnering behavior* and *COVID-19 influence on information quality* as well as two endogenous variables *Controllership information output quality* and *Controlling influence on management decisions*. The measurement model of the four variables used in our study contains self-developed instruments by means of questions derived from the relevant literature, as well as scales already validated in prior research, following the recommendations of Bisbe et al. (2007). All scales are provided in Table A1 (see appendix).

To measure the level of our first exogenous variable *Controllers' business partnering behavior*, we relate to the literature on controllers' roles which addresses to a large extent controllers' own perception (e.g., Burns & Baldvinsdottir, 2005; Endenich et al., 2017) describing their functions or tasks (Rieg, 2018). In this respect, Rouwelaar et al. (2021) propose a conditional range from the ability to computerize data modelling and analysis to making decisions in line with strategic goals. Still, for our study we decided to use a role model provided by Gleich and Lauber (2013), differentiating between four distinctive types of roles (analyst/scorekeeper, supervisor/guardian, business partner, change agent) which are quite common in controller occupational practice (e.g., Weber & Schäffer, 2020). We asked survey participants to allocate their working time to each of these roles, resulting in a total time spent of 100%, as controllers often cover more than one of these role types (Burns & Baldvinsdottir, 2005; S. Byrne & Pierce, 2007). To ensure a common understanding of the controllers' roles, each role was briefly described within the questionnaire. Following established research practice (e.g., Angelkort et al., 2009), we use the percentage of time spent in the role of business partner as an appropriate indicator for the level of *Controllers' business partnering behavior* (see Table A1 in the appendix). With all other scales, we applied six-point rating scales ranging from '… not agree' to '…completely agree' as anchor labels. With respect to the even number of points, we did not provide an 'in between'-category as such a category may be misinterpreted by survey respondents as 'no opinion' or 'no answer', which in turn impairs data quality.

Our second exogenous variable *COVID-19 influence on information quality* measures the impairing influence of the pandemic on information available to controllers. The economic impact of the COVD-19 pandemic differs widely from previous crises such as the financial crisis in 2008 (Passetti et al., 2021), so that established scales from previous research regarding its impact on management accounting could not be used. As our variable relates to a specific object, i.e., the impact on information quality, single-item measurement is appropriate (Rossiter, 2002). Moreover, as the variable is established as a moderator, a single-item measurement is considered suitable as well (Fuchs & Diamantopoulos, 2009). Specifically, we asked survey participants to what extent controlling information had been negatively affected by the COVID-19 pandemic. The item is reported in Table A1 (see appendix). As further reported in Table A2, 40% of the participants stated that the quality of controlling information was not at all negatively affected by the COVID-19 pandemic, whereas 60% stated a deterioration of the controlling information quality at least to a slight extent.

In general, single-item measures raise concerns regarding their reliability and validity, bearing the risk to not sufficiently capturing the construct being measured. However, in a few cases we decided to employ single-item measures in order to shorten the questionnaires in order to reduce the risk of break-offs (e.g., Fuchs & Diamantopoulos, 2009). That was especially important for our survey during of the COVID-19 pandemic, hampering the acquisition of participants.

For the two endogenous latent variables *Controllership information output quality* and *Controlling influence on management decisions*, we adopt a reflective measurement approach using established scales from the literature (see Table A1 in the appendix, e.g., Weißenberger & Angelkort, 2011). In both cases, the underlying manifest indicators are interchangeable and assumed to be dependent on the respective latent construct. *Controllership information output quality* measures the quality of information provided by controllers regarding correctness, accuracy, and timeliness. It consists of three reflective indicators, which were adopted as a modified version of a measurement model developed by Bauer (2002), which originally consisted of eight indicators on a seven-point rating scale, measuring the output quality of the controlling department. Of these, we selected the items that explicitly related to the quality of information. *Controllership influence on management decisions* reflects how controllers assess their impact in the context of managerial decision-making and thus feature the outcome of their activities. This represents a modified version of a measurement model developed by Spillecke (2006) and consists of three reflective indicators originally measured on a five-point rating scale. The third item was originally from Bauer (2002).

To avoid subjective bias, we surveyed the items for our variable *Controllership influence on management decisions* in our questionnaire well before measuring the level of *Controllers'* *business partnering behavior*.

## 4.3. Reliability and validity of measurement

To establish reliability and validity of both our latent variables we use common measures recommended in the literature (Bagozzi & Yi, 1988; Schäffer, 2007). Cronbach's alpha (CA) measures the internal reliability of a construct and should exceed the critical value of .70 (Nunnally & Bernstein, 1995). As the high CA of .941 for the construct *Controllership influence on management decisions* is an indicator of item redundancy, we removed item 2 from the construct (Streiner, 2003). Factor reliability (FR) is based on the standardized factor loadings of individual items on a given construct and exceeds the critical value of .60. Convergent validity is measured by the average variance extracted (AVE) and describes the average variance shared between a construct and the associated indicators (Fornell & Larcker, 1981), exceeding a critical value of .50 in both cases. Table 3 summarizes the descriptive statistics for all variables, as well as the respective reliability and validity measures.

**Table 3: Summary statistics, reliability and validity measures**

| Item | Indicator | Min | Max | Mean | SD | SMC | CA | FR | AVE |
|---|---|---|---|---|---|---|---|---|---|
| Controllers' business partnering behavior | CBP | 0.00 | 55.00 | 22.52 | 10.653 | | | | |
| COVID-19 influence on information quality | COV | 0.00 | 5.00 | 1.29 | 1.468 | | | | |
| Controllership information output qualtiy | CQ1 | 2.00 | 5.00 | 4.05 | .776 | .670 | .808 | .962 | .685 |
| | CQ2 | 1.00 | 5.00 | 3.84 | .957 | .539 | | | |
| | CQ3 | 1.00 | 5.00 | 3.61 | .879 | .590 | | | |
| Controllership influence on management-decisions | CI1 | 1.00 | 5.00 | 3.73 | 1.147 | .784 | .894 | .964 | .855 |
| | CI3 | 1.00 | 5.00 | 3.45 | 1.163 | .832 | | | |

*n = 155; SD = Standard Deviation; SMC = Squared Multiple Correlation; CA = Cronbach's Alpha; FR = Factor Reliability; AVE = Average Variance Explained*

To test for non-response bias, we compared early (the first 20%) and late (the last 20%) respondents (Armstrong & Overton, 1977). We use Chi-square difference test in order to determine whether there are significant differences between the two groups regarding several firm characteristics (return, industry, group level, digitalization strategy, number of employees, firm size). As shown in Table 4, we cannot find presence of non-response bias, as the related p-value for each firm characteristic tested is ≥ .05.

**Table 4: Chi-square test**

| Firm characteristic | $X^2$ | *p*-value |
|---|---|---|
| Return | 8.658 | .124 |
| Industry | 8.914 | .445 |
| Group level | 1.778 | .620 |
| Digitalization strategy | .057 | .812 |
| Employees | 78.000 | .384 |
| Size | 73.000 | .412 |

*$X^2$ = chi-square; p-value = probability value*

To test for discriminant validity, i.e., the extent to which indicators associated with one latent variable vary independently of those associated with another latent variable, we use the Fornell-Larcker (1981) criterion, according to which the AVE of each factor must be higher than any squared correlation of that factor with another factor (Table 5).

**Table 5: Discriminant validity according to the Fornell-Larcker criterion**

| Variable | AVE | Squared correlation with variable | |
|---|---|---|---|
| | | Controllership information output quality | Controlling influence on management decisions |
| Controllership information output quality | .685 | - | .265 |
| Controllership influence on management decisions | .855 | .265 | - |

Finally, we conducted Harman's (1967) single-factor test to examine indications of common method bias. As shown in Table 6, the test revealed no evidence of a common factor underlying the tested items, as the eigenvalues of all variables indicating that no single factor emerged, and the first factor accounts for less than 50% of the variance among variables (Fuller et al., 2016).

**Table 6: Harman's single-factor test**

| Factor | Initial eigenvalues | | | Extraction sums of squared loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of variance | Cumulative % | Total | % of variance | Cumulative % |
| 1 | 3.194 | 45.626 | 45.626 | 3.194 | 45.626 | 45.626 |
| 2 | 1.283 | 18.322 | 63.949 | 1.238 | 18.322 | 63.949 |
| 3 | .930 | 13.289 | 77.237 | | | |
| 4 | .634 | 9.054 | 86.292 | | | |
| 5 | .443 | 6.332 | 92.624 | | | |
| 6 | .332 | 4.742 | 97.366 | | | |
| 7 | .184 | 2.634 | 100.000 | | | |

*n = 155; Extraction Method: Principal Component Analysis*

# 5. Data analysis technique

## 5.1. Method of analysis

For our hypothesis testing, we employ a covariance-based structural equation modelling (CB-SEM) using maximum likelihood (ML) estimation, applying the SPSS software package AMOS

28. It is the most common method for causal analysis (Weiber & Mühlhaus, 2014) and provides advantages over other techniques such as multiple regression or variance-based path analysis, from a methodological point of view, as it allows including both manifest (observed) and latent (unobserved) variables in order to apply a holistic approach to model building that also considers indirect effects. This in turn enables a confirmatory (rather than an exploratory) approach to data analysis, and also provides several metrics that allow to evaluate the overall model fit (B. Byrne, 2016; Smith & Langfield-Smith, 2004).

A critical assumption of CB-SEM is multivariate normality of the underlying data (B. Byrne, 2016). Nonetheless, several simulation studies, such as Lei and Lomax (2005) or Boomsma and Hoogland (2001), have shown that CB-SEM is quite robust to violation of the normality assumption, producing only slightly biased parameter estimates. However, because standard errors can be underestimated, leading to statistically significantly biased results of the regression weights, we use bootstrapping with 2,000 samples as an accepted technique for countering the problem of non-normally distributed data (B. Byrne, 2016; Cheung & Lau, 2008; Shrout & Bolger, 2002). Bootstrapping is also a common method for testing moderation and mediation (Preacher & Hayes, 2004; Shrout & Bolger, 2002), as it improves the accuracy of confidence intervals (MacKinnon et al., 2004). The literature recommends a minimum sample size of five times as large as the number of estimated parameters $n \geq 5*t$ (Bagozzi & Yi, 1988; Loehlin, 1987), other paper also suggests $n - t \geq 50$ (Bagozzi, 1981) or $n > 100$ (Kline, 2016), which are met by our analysis. To counter non-normally distributed data, we also calculate Mahalanobis $d^2$ as a generalized distance measure to identify and, if present, eliminate possible outliers (B. Byrne, 2016). In this process, we excluded one more questionnaire from our data set, because its Mahalanobis $d^2$ value indicates a high distance compared to others, resulting in a final sample of $n = 155$.

We perform a conditional process analysis to test for moderated mediation (Hayes & Preacher, 2013). This means we first test for mediation before testing for moderation, and only finally test for moderated mediation (Hayes, 2018). By applying CB-SEM, coefficients of the mediation models as well as the moderated mediation models can be estimated simultaneously, as well as iteratively (Preacher et al., 2007). As effect size measure for models that test mediation and moderation simultaneously have not yet been developed (Fairchild & MacKinnon, 2008), we compare the $R^2$ values of the mediation and moderated mediation models to evaluate the amount of variance explained. The difference between the $R^2$ values provides the part of the $R^2$ attributed to interaction between the independent variable and the moderator (Maslowsky et al., 2014).

As pointed out in Section 4.2, a large part of our sample stated that the quality of controlling information is not negatively affected by the COVID-19 pandemic. We therefore have, as a robustness check, repeated our analysis excluding the datasets of corresponding participants. The results do not reveal any significant differences to our findings. A summary of the results is given in Table A3 (see appendix).

## 5.2. Mediation and moderated mediation

We start with testing our hypotheses *H1* to *H3*, by performing a mediation analysis and using the product-of-coefficients method as a common way to analyze indirect effects (MacKinnon et al., 2002; MacKinnon et al., 2004). We employ a simple mediation model that comprises only one mediator, as it is the most common type of mediation (Preacher et al., 2007). Our structural model is presented in Figure 2, including our variable *COVID-19 influence on information quality* as a control variable to avoid endogeneity issues (Hill et al., 2021).

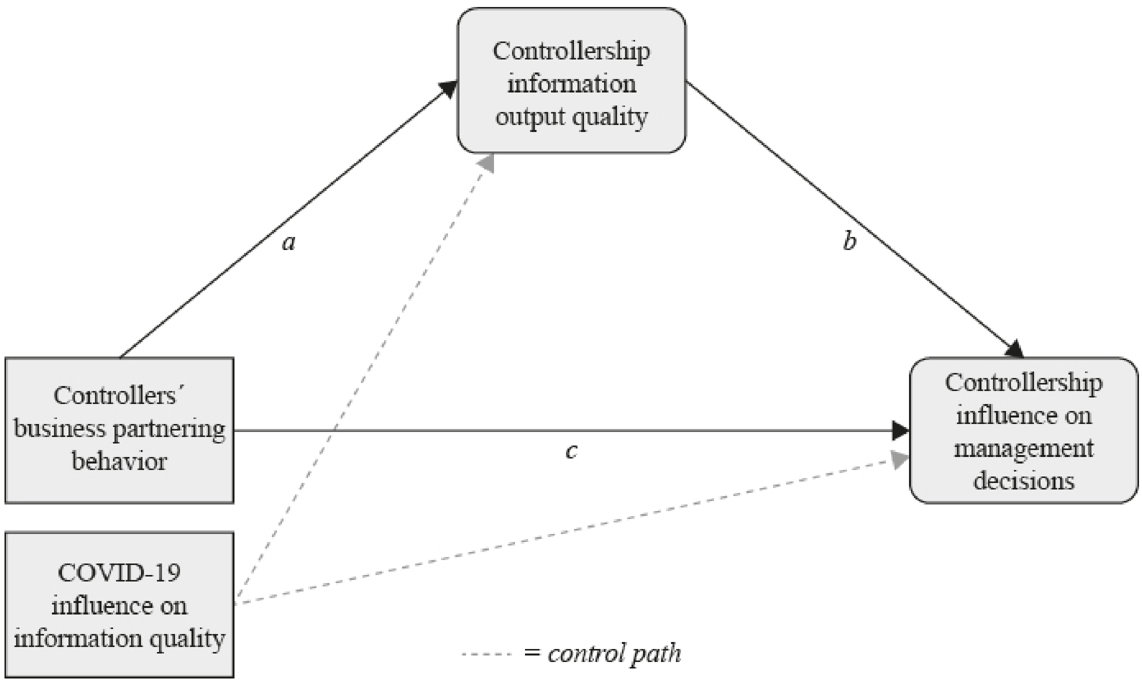



**Fig. 2** Mediation analysis

We test the direct effect of *Controllers' business partnering behavior* on *Controllership influence on management decisions* (path *c*), as well as the indirect effect of *Controllers' business partnering behavior* on *Controllership influence on management decisions* via *Controllership information output quality* (path *a**b*). We calculate how much of the effect size relates to the mediation effect by dividing the $R^2$ value of *Controllership information output quality* by the $R^2$ value of *Controllership influence on management decisions*, i.e., the total amount of explained variance of our dependent variable (MacKinnon, 2008).

After testing the mediation effects, we test our final hypothesis *H4* for moderated mediation, i.e., conditional indirect effect, according to the established procedures suggested by Hayes and Rockwood (2020). Different forms of moderated mediation exist, depending on the type and number of moderators as well as the affected paths (Edwards & Lambert, 2007; Preacher et al., 2007). Our measurement model based on Preacher et al. (2007). To capture the hypothesized moderating impact of the deteriorating information environment during the pandemic, we follow established procedures (Morgan-Lopez & MacKinnon, 2006; Preacher et al., 2007) and introduce an interaction term (*Business partnering X COVID-19*) by multiplying the mean-centered values of *Controllers' business partnering behavior* with *COVID-19 influence on information quality* (Hayes, 2018). If the path *a3* (see Figure 3) representing the impact of the interaction term on *Controllership information output quality*, is significant, a moderation is established (Aiken et al., 2003). More specifically, the conditional effect (so-called simple slope) of the exogenous variable *Controllers' business partnering behavior* on *Controllership information output quality* is statistically significant for various conditional values of the moderator *COVID-19 influence on information quality* (*a1+a3*COVID-19 influence on information quality*), typically tested on a low (–1 *SD*), moderate (mean), as well as high (+1 *SD*) level of *COVID-19 influence on information quality* (Hayes & Rockwood, 2020; Preacher et al., 2007). The structural model for the moderated mediation analysis is depicted in Figure 3, also including control paths.

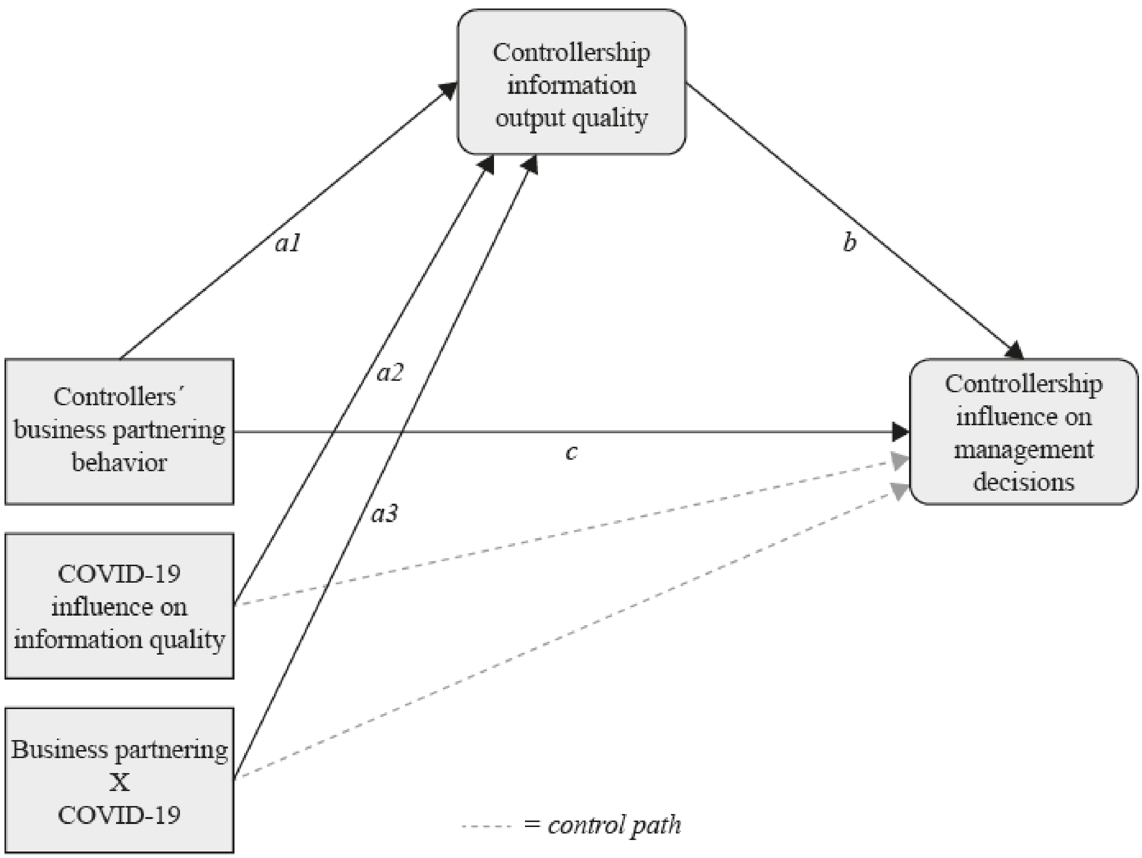



**Fig. 3** Moderated mediation analysis

To test for the moderated mediation effect, i.e., if the overall indirect effect is also affected by *COVID-19 influence on information quality*, we examine the effect of *COVID-19 influence on information quality* with respect to the indirect effect of *Controllers' business partnering behavior* on *Controllership influence on management decisions* via *Controllership information output quality* (*a3*b*), the so-called index of moderated mediation (Hayes, 2015; Morgan-Lopez & MacKinnon, 2006). If the index is significant, moderated mediation, i.e., the conditional indirect effect, can be examined for different conditional values of *COVID-19 influence on information quality* [(*a1+a3*COVID-19 influence on information quality*)*b*], analogous to the test of moderation (Edwards & Lambert, 2007; Preacher et al., 2007).

# 6. Results

## 6.1. Mediation analysis

The results of our mediation analysis testing the direct as well as indirect relationship between *Controllers' business partnering behavior* and *Controllership influence on management decisions* (*H1*, *H2* and *H3*) are presented in Table 7.

**Table 7: Results of mediation and moderated mediation confirmatory factor analysis**

| | | Coeff | Bootstrapped CI (95%) | | $p$ | $X^2/df$ | RMSEA | GFI | CFI | TLI | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mediation model** | | | Lower | Upper | | | | | | | |
| | | | | | .122 | 1.53 | .059 | .972 | .987 | .972 | |
| Quality | | | | | | | | | | | .14 |
| Influence | | | | | | | | | | | .38 |
| Behavior on Quality (*a*) | | .15 | -.032 | .335 | .110 | | | | | | |
| Quality on Influence (*b*) | | .48 | .288 | .634 | .001*** | | | | | | |
| Behavior on Influence | direct effect (*c*) | .34 | .188 | .517 | .001*** | | | | | | |
| | indirect effect | .07 | -.012 | .188 | .094 | | | | | | |
| **Moderated mediation model** | | | | | | | | | | | |
| | | | | | .145 | 1.41 | .052 | .971 | .987 | .973 | |
| Quality | | | | | | | | | | | .19 |
| Influence | | | | | | | | | | | .38 |
| Behavior on Quality (*a1*) | | .17 | -.005 | .358 | .058 | | | | | | |
| COVID-19 on Quality (*a2*) | | -.23 | -.413 | -.060 | .012* | | | | | | |
| Behavior x COVID-19 on Quality (*a3*) | | .24 | .062 | .413 | .009** | | | | | | |
| Quality on Influence (*b*) | | .48 | .287 | .643 | .001*** | | | | | | |
| Behavior on Influence (*c*) | | .34 | .182 | .514 | .001*** | | | | | | |
| Simple Slope[a] | low (-1 SD) | -.005 | -.022 | .008 | .425 | | | | | | |
| | mean | .021 | .008 | .035 | .003** | | | | | | |
| | high (+1 SD) | .026 | .010 | .043 | .003** | | | | | | |
| Index of moderated mediation[a] | | .008 | .003 | .017 | .005** | | | | | | |
| Conditional indirect effect[a] | low (-1 SD) | -.004 | -.018 | .007 | .399 | | | | | | |
| | mean | .016 | .005 | .033 | .003** | | | | | | |
| | high (+1 SD) | .020 | .006 | .040 | .002** | | | | | | |

*$n$ = 155; standardized estimates; *** $p \leq .001$; ** $p \leq .01$; * $p \leq .05$; $p$ = probability value; CI = confidence intervals; $X^2/df$ = chi-square / degrees of freedom; RMSEA = root mean square error of approximation; GFI = goodness of fit index; CFI = comparative fit index; TLI = Tucker-Lewis index; [a]unstandardized estimates*

In terms of overall model fit, we estimate the denoted goodness-of-fit indices for each confirmatory factor analysis (CFA). The ratio of chi-squared ($X^2$) and degrees of freedom ($df$) refers to the null hypothesis that the specification of factor loadings, factor variances, covariances, and error variances are valid (Bollen, 1989). The closer the fit of the hypothesized model to a perfect fit, the higher the probability value ($p$-value) associated with $X^2/df$. The $X^2$-test is commonly accepted, but has various limitations. Two important limitations are its dependence on sample size and model complexity. With larger sample sizes, the $X^2$-test tends to reject hypothesized models falsely (type-1-error), while with smaller sample sizes it tends to accept a model, even if it is wrong (type-2-error). Furthermore, the $X^2$-test is subject to model size, i.e., the more variables are included, the higher the risk of a type-1-error. To counter the limitations of the $X^2$-test, additional goodness-of-fit indices have been developed. However, alternative fit indices often based on the $X^2$-test (Backhaus et al., 2015). The root mean square error of approximation (RMSEA) index considers the error of approximation in the population and compares it to optimally chosen parameter values (Browne & Cudeck, 1992), i.e, accounts for whether the hypothesized model provides a close approximation of the empirical reality, instead of an exact fit. Comparison indices compare the fit of a hypothesized model with fit of a baseline model, which is particularly appropriate for nested models. Their measures are commonly range between 0 (no fit) and 1 (perfect fit) (Hu & Bentler, 1995). Three fit indicies from this category are widely used in practice. The absolute goodness-of-fit index (GFI) compares the hypothesized model with no model at all by measuring the explained amount of variance and covariance in the data (Hu & Bentler, 1995). In contrast, the comparative fit index (CFI) as well as the Tucker-Lewis index (TLI) are additional incremental fit measures that compare the hypothesized model to a so-called null model, which allows all variables in the model to have variation but no correlation (Byrne, 2016). As shown in Table 7, all goodness-of-fit indices are above or respectively below their critical thresholds reported in Table 8. Therefore, we conclude that our model fits the empirical data well.

**Table 8: Critical values of goodness-of-fit indices**

| Index | Critical Value | References |
|---|---|---|
| $X^2/df$ | $\leq 2$ | Byrne (1989) |
| $p$-value | $\geq .05$ | Bagozzi and Yi (1988) |
| RMSEA | $\leq .06$ | Hu and Bentler (1999) |
| GFI | $\geq .90$ | Homburg and Baumgartner (1995) |
| CFI | $\geq .97$ | Schermelleh-Engel et al. (2003) |
| TLI | $\geq .97$ | Schermelleh-Engel et al. (2003) |

*$X^2/df$ = chi-square / degrees of freedom; p-value = probability value; RMSEA = root mean square error of approximation; GFI = goodness of fit index; CFI = comparative fit index; TLI = Tucker-Lewis index*

As Table 7 shows, the results of our mediation model reveal a highly significant direct effect, with a path coefficient of .34 indicating the impact of *Controllers' business partnering behavior* on *Controllership influence on management decisions*. Thus, empirical data are in line with our first hypothesis *H1*. In contrast, our second hypothesis *H2*, assuming a positive impact on *Controllership information output quality* as well, is not supported, as the resulting path coefficient (.15) is not significant. Even though our third hypothesis *H3* is once again corroborated by our results, given that the path coefficient (.48) is highly significant, the assumed overall indirect effect on *Controllership influence on management decisions* is not confirmed by our data. Even so, *Controllers' business partnering behavior* together with *Controllership information output quality* explain 38% of the variance of the variable *Controllership influence on management decisions*. Our results therefore suggest that controllers attribute the impact of their role as business partners rather to the conceptual dimension of their interaction with managers, than to an increased instrumental ability to produce high-quality reports.

## 6.2. Moderated mediation analysis

Even though the indirect effect in our mediation model is not significant, there might still be a moderating effect of *COVID-19 influence on information quality*, i.e., if the impact of *Controllers' business partnering behavior* on *Controllership information output quality* is either weaker or stronger in an impaired information environment in the context of the pandemic (*H4*). The results of our moderated mediation model reported in Table 7 support this hypothesis and point to a reinforcing impact, because path *a3* (.24), reflecting the effect of the interaction term on *Controllership information output quality*, has a positive sign and is significant at a moderate as well as high (+1 *SD*) level of *COVID-19 influence on information quality*. All goodness-of-fit indices are above or respectively below their critical thresholds reported in Table 8.

As the index of moderated mediation is significant, the $R^2$ value of *Controllership information output quality* increases from .14 to .19. This indicates that 5 percentage points of the variance of *Controllership information output quality* is explained by the interaction between *Controllers' business partnering behavior* and *COVID-19 influence on information quality*, which corresponds to a 35.7% increase in the total explained variance.

From a theoretical perspective, the empirical results suggest that the model structure we hypothesize in Figure 3 is fully supported in the case of an impaired information environment. The model maps the empirical data and thus confirms our understanding of controllers' business partnering in the context of COVID-19 pandemic, i.e., our data suggest a positive direct effect of *Controllers' business partnering behavior* on *Controllership influence on management decisions* as well as a mediating effect via *Controllership information output quality*, but only if information quality is impaired.

For management accounting practice, the results imply various insights. One the one hand, an increased controllers' business partnering behavior leads to an increased controllership influence on management decisions in a conceptual manner, despite of whether the firms' information environment is impaired. This might result from increased communication skills, strengthening the interaction of controllers and managers. Nevertheless, from an instrumental point of view, the results indicate that controllers' business partnering behavior per se might not affect the output quality of information provided by controllers. Only if the information environment is moderate to highly impaired, controllers' business partnering behavior contributes to an increased information output quality, which in turn strengthens the controllership influence from an instrumental perspective, by providing more qualitative information as basis for management decisions. The findings support our notion that with a more pronounced business partnering behavior, controllers are more able to assess the validity of information and to evaluate it in a more global firms' context, if the information environment is impaired by uncertainty or volatility such as triggered by the COVID-19 pandemic.

## 6.3. Data and method of analysis

Because our analysis might be subject to key informant bias, i.e., biased by controllers' subjective views, we extend our conditional process analysis by conducting a multi-group analysis following the recommendations of B. Byrne (2016). This is possible because in our survey, we had as a complementary part, not only addressed controllers but also their closest general manager, i.e., a member of upper management such as the CEO, managing director or division manager, to fill out a functionally customized questionnaire. Out of the received 155 controller questionnaires, 67 related managers also took part in the survey, so that we received in total 67 dyadic datasets, which correspond to a dyadic return rate of 43%. For our supplementary analysis, each dyad forms a unit of observation. In each dyad, the variable *Controllers' business partnering behavior* is measured by using controllers' ratings, as we assume that managers are not able to provide valid judgments on the time controllers spend on different role behaviors. All other variables in each dyad are measured by using the ratings from the respective managers. Compared to our research setting in which only controllers are surveyed, this enables us to draw valid conclusions with respect to managers' perceptions as well (see Figure 4).

For our supplementary analysis we compare the results of our analysis for two groups, i.e., controllers (baseline model, Section 6.1 and 6.2) and managers by conducting a multi-group causal analysis, thus testing both groups for the equality of the estimated path coefficients (Steenkamp & Baumgartner, 1998), i.e., we test if differences in path coefficients can be observed between the group of controllers and the group of managers (see Figure 4).

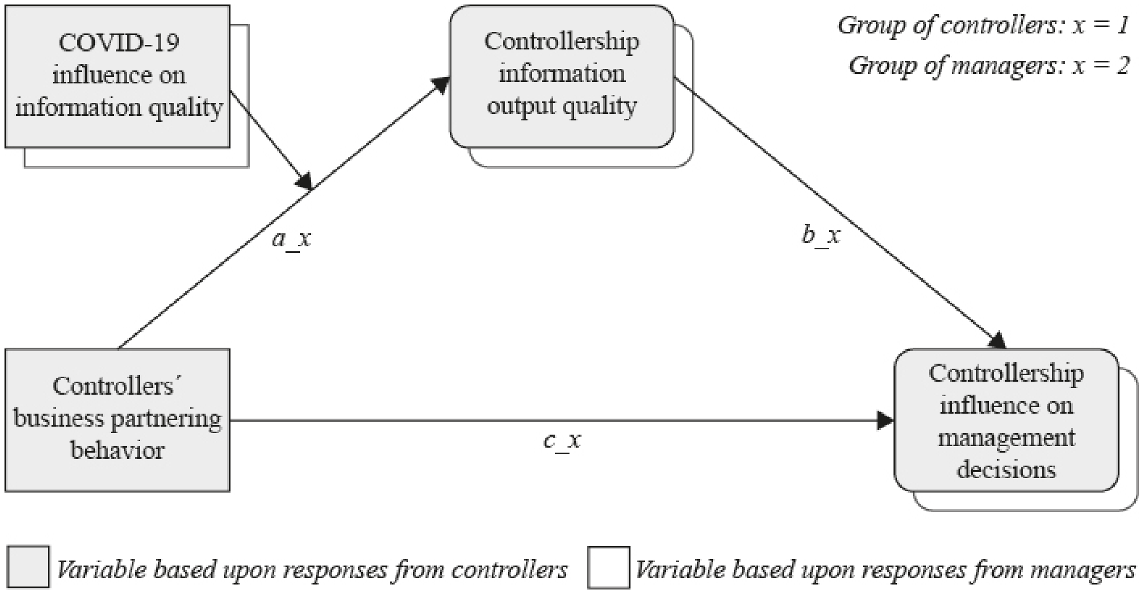



**Fig. 4** Multi-group analysis

Technically, this involves testing a series of nested models (Bagozzi & Yi, 1988; Steinmetz et al., 2009). Following the recommendations of B. Byrne (2016), each nested model (one for each group) consists of a set of sub-models, of which the parameters are estimated simultaneously. During the test series, certain sets of parameters are constrained to the extent that they are equal in all sub-models across the groups. As the parameter sets become equal over the test series, each model is subject to more stringent constraints than its predecessor. Evaluating the change in model fit, as well as individual model parameters, can then be performed by an $X^2$-difference test for each step in the nested models (Reinecke, 2014). A deterioration of the model fit leads to a higher value for $X^2$. However, the model gains one degree of freedom with each constraint, so that the increase in $X^2$ has to be compared to the degrees of freedom gained. If the deterioration of the model fit is significant, it follows that the last set of constrained parameters in the model are not equal between the groups. In the next two sections, we test for mediation before moderated mediation, similar to our previous main analysis (Hayes, 2018).

## 6.4. Multi-group mediation analysis

The goodness of fit of our multi-group mediation model achieves a moderate, but acceptable fit with respect to global criteria, as shown in Table 9.

**Table 9: Results of mediation and moderated mediation confirmatory multi-group factor analysis**

| | | | | Coeff | Bootstrapped CI (95%) | | $p$ | $X^2/df$ | RMSEA | GFI | CFI | TLI | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mediation model** | | | | | Lower | Upper | | | | | | | |
| | | | | | | | .05 | 1.57 | .066 | .939 | .965 | .927 | |
| Quality | | *Controller* | | | | | | | | | | | .07 |
| | | *Manager* | | | | | | | | | | | .04 |
| Influence | | *Controller* | | | | | | | | | | | .44 |
| | | *Manager* | | | | | | | | | | | .24 |
| Behavior on Influence | direct effect[a] | *Controller* | | .036 | .016 | .059 | .001*** | | | | | | |
| | | *Manager* | | .006 | -.020 | .028 | .583 | | | | | | |
| | indirect effect | *Controller* | | .001 | -.013 | .022 | .849 | | | | | | |
| | | *Manager* | | .003 | -.007 | .022 | .481 | | | | | | |
| **Moderated mediation model** | | | | | | | | | | | | | |
| | | | | | | | .117 | 1.34 | .051 | .941 | .975 | .947 | |
| Quality | | *Controller* | | | | | | | | | | | .21 |
| | | *Manager* | | | | | | | | | | | .18 |
| Influence | | *Controller* | | | | | | | | | | | .46 |
| | | *Manager* | | | | | | | | | | | .32 |
| Index of moderated mediation | | *Controller* | | .012 | .002 | .028 | .014* | | | | | | |
| | | *Manager* | | .010 | .002 | .027 | .014* | | | | | | |
| Conditional indirect effect | | *Controller* | low (-1 SD) | -.019 | -.060 | -.002 | .028* | | | | | | |
| | | | mean | .010 | -.001 | .034 | .074 | | | | | | |
| | | | high (+1 SD) | .016 | .001 | .045 | .039* | | | | | | |
| | | *Manager* | low (-1 SD) | -.015 | -.047 | .001 | .072 | | | | | | |
| | | | mean | .011 | .000 | .036 | .057 | | | | | | |
| | | | high (+1 SD) | .016 | .002 | .049 | .021* | | | | | | |

*$n$ = 67; unstandardized estimates; *** $p \leq .001$; ** $p \leq .01$; * $p \leq .05$; $p$ = probability value; CI = confidence intervals; $X^2/df$ = chi-square / degrees of freedom; RMSEA = root mean square error of approximation; GFI = goodness of fit index; CFI = comparative fit index; TLI = Tucker-Lewis index; [a]full metric invariance*

It should be noted that our analysis does not focus on the absolute values of our observed variables, but on the covariances which reflect the causal relationships. If differences can be observed regarding the direct or indirect effects, this indicates different causal relationships between the group of controllers and the group of managers. Our structural model corresponds to that of our baseline model in Section 6.1, illustrated in Figure 2. We test for significant differences concerning the direct (*c_1* and *c_2*) and indirect paths (*a_1 * b_1* and *a_2 * b_2*) between the variables *Controllers' business partnering behavior* and *Controllership influence on management decisions* as depicted in Figure 4 across the groups in a test series of four models. The results for each model of the test series are shown in Table 10.

**Table 10: Test series of (moderated) mediation multi-group confirmatory factor analysis**

| | | Mediation model | | Moderated mediation model | |
|---|---|---|---|---|---|
| **Model** | **Compared Model** | $X^2$ (*df*) | $\Delta X^2$ ($\Delta$ *df*) | $X^2$ (*df*) | $\Delta X^2$ ($\Delta$ *df*) |
| A: Configural invariance | - | 31.382 (20) | - | 34.753 (26) | - |
| B: Full metric invariance | A | 32.970 (23) | 1.588 (3) | 36.450 (29) | 1.697 (3) |
| C: Invariance of indirect effect | B | 34.679 (25) | 1.709 (2) | 36.702 (32) | .252 (3) |
| D: Invariance of direct effect | B | 38.094 (24) | 5.124 (1) | | |

*$X^2$ = chi-square; df = degrees of freedom; p-value = probability value*

Model A tests for configurational invariance by estimating an unconstrained model for both groups. In this model, all parameters (e.g., factor loadings) are freely estimated for both groups. That is, the model is constrained only to the extent that it is identical in structure and design between groups. As shown in Table 10, the fit measures ($X^2/df = 1.57$) of the unconstrained model indicate that the same model structure applies to both groups, i.e., the identical variables, items, and paths are measured for both groups.

Model B tests for full metric invariance, i.e., whether the manifest indicators measure the same construct in both groups. In this model, all factor loadings of the measurement constructs are constrained to be the same in both groups. This means, that for both groups the indicators underlying a construct are appropriate to measure the common latent variable in a similar way. Although these restrictions result in an increase of $X^2$ of 1.588, the decrease in model fit is not significant, as 3 *df* are gained. Therefore, full metric invariance can be assumed, which allows us to test for structural invariance in terms of the structural relationships of both groups.

Model C tests for invariance of the indirect effects. Therefore, in addition to the constraints from Model B, the indirect effect between the variables *Controllers' business partnering behavior* and *Controllership influence on management decisions* is set equal in both groups. In other words, we constrain the effect *a_1* to be equal to *a_2* as well as the effect *b_1* equal to *b_2*. As Table 10 shows, the equalization of the indirect effects leads to a deterioration of the model fit, as $X^2$ increases by 1.709 compared to Model B. However, the deterioration in model fit is far below the threshold of 5.99 (for 2 *df* gained). Therefore, different indirect effects between the two groups cannot be established. In other words, different perceptions on the influence of *Controllers' business partnering behavior* on *Controllership influence on management decisions* cannot be observed between controllers and managers.

In Model D, we finally test for invariance of the direct effects between the variables *Controllers' business partnering behavior* and *Controllership influence on management decisions*, i.e., we test whether significant differences for the perceptions of controllers and managers can be observed for the direct influence of *Controllers' business partnering behavior* on *Controllership influence on management decisions*. Thus, in addition to the constraints from Model B, we fixed the effect *c_1* identical to *c_2*. As shown in Table 10, the equalization of the direct effects leads to a significant deterioration of the model fit, as $X^2$ increases by 5.124 compared to Model B, given that the threshold of 3.84 (for 1 *df* gained) is exceeded. Therefore, it can be assumed that group affiliation has a moderating effect on the direct relationship between the variables *Controllers' business partnering behavior* and *Controllership influence on management decisions*, i.e., the perception of managers differs significantly from the controllers' perception.

For more precise insight into the differences between the two groups, we consider the unstandardized results of Model B with full metric invariance. As shown in Table 9, the direct effect for the group of controllers is significant, whereas it reveals no significance for the group of managers. Obviously, there is no relation between the controllers' perceived level of business partnering behavior and managers' perceived controllership influence on management decision. In other words, in contrast to our baseline model, managers' assessment of controllers' impact does not vary with controllers' assessment of their business partnering role. This result is in line with Pierce and O'Dea (2003) or Weißenberger et al. (2012), as it also indicates a user-preparer perception gap.

## 6.5. Multi-group moderated mediation analysis

In a second step of our supplementary analysis, we also test whether there is a moderating effect in the group of managers, if information quality under the COVID-19 pandemic is impaired, as the corresponding moderated mediation analysis in Table 9 suggests with a significant index of moderated mediation for the group of managers. We therefore test for significant differences concerning the conditional indirect effects (*a1_1 + a3_1 * b_1* and *a1_2 + a3_2 * b_2*), i.e., moderated mediation across the groups in a test series of three models. Our structural model is illustrated in Figure 3, similar to our baseline model in Section 6.2. Our results in Table 10 show that we can establish configurational invariance, full metric invariance as well as invariance of the indirect effect.

The results of our moderated mediation analysis within the group of managers are thus in line with our previous findings for the group of controllers, i.e., there is evidence of a moderating influence of an impaired information environment under the COVID-19 pandemic, establishing a mediated relationship between *Controllers' business partnering behavior* and *Controllership influence on management decisions* via *Controllership information output quality*, which cannot be observed otherwise.

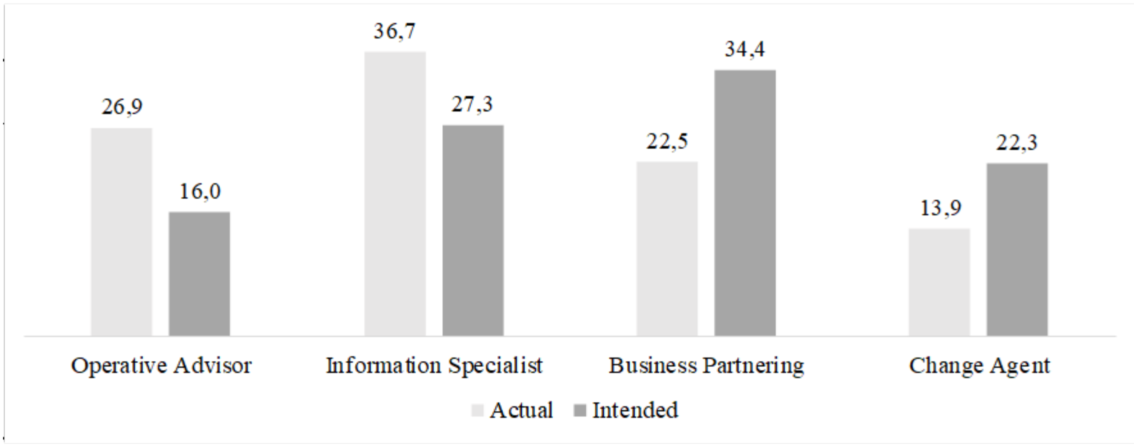
## 7. Discussion

Our study was motivated by the changing role of controllers as business partners and thus on their effectiveness with respect to managerial decision-making. Our particular interest was also in the impact caused by the COVID-19 pandemic on controllership effectiveness, using revenue forecasting as an anchoring point for our analysis. The main results of our research are based on a survey of 155 controllers from large German companies with at least 500 employees.

First, our results suggest that controllers acting as business partners does not in general have an impact on the quality of the information output provided by them. Only in interaction with an opaque information environment which creates an uncertain and volatile decision-making context, can we observe that business partnering enables controllers to address managerial information needs in a superior manner. The results therefore support the notion that in times of economic crisis, controllers perceive that information quality and – as a result – the influence on managerial decision-making increases if their role as strategic business partners is more pronounced. This suggests that controllers acting as business partners acquire skills enabling them to more effective exploit the information environment in a crisis situation, thus providing more accurate, reliable and timely information for managerial decision-making. As a consequence, adopting the role of a business partner in good times can also be interpreted as building slack and resilience for controllership effectiveness in bad times. Only an established relation as business partner allows for the relevant analytical and technical skills to provide the necessary sophistication to support decision-making under uncertainty. In a similar vein, business partnering can be assumed to reduce uncertainty among controllers with respect to the information needed by management for decision-making.

Our findings also indicate that controllers perceive their influence on management decision-making as high, if they demonstrate high levels of business partnering behavior, which explains the continuing occupational trend for controllers to position themselves in this role (Mahlendorf & Weißenberger, 2021). This is also reflected in our survey, as controllers intend to spend more time on business partnering behavior than on any other role (see Table 11).

**Table 11: Time spend on different controllers' roles (in %)**




*n = 155*

Our supplementary analysis using a smaller sample of 67 dyads provides evidence in two directions. First, we find a difference with respect to the direct conceptual mechanism relating controllers' business partnering to their influence on management decision-making. While the results support a highly significant influence from the controller perspective, this influence is not corroborated for the manager perspective. Such a perception gap between controllers and managers might consequently indicate that controllers overestimate their conceptual influence on management decisions which, in turn, might result from an involvement-independence dilemma. That is, whereas controllers probably feel that they are "strong controller[s]" in the sense of Sathe (1983, p. 34), managers perceive their behavior less as involved but rather as independent, being more of a guardian or a supervisor. This notion is supported by the results of our multi-group moderated mediation analysis, as under a deteriorating information environment, the main impact on managerial decision-making as perceived by managers, did not relate to business partnering per se, but only to controller abilities to provide high quality information output. In this respect, our study also indicates that research on controllership effectiveness might be subject to misinterpretation due to a key informant bias, if only controllers are surveyed. Future research should therefore explore this user-preparer perception gap more intensively.

Obviously, there are some limitations to the generalizability of our results. First, our results concentrate on decision-support in revenue forecasting and only addresses the influence of the COVID-19 pandemic in one area of controller tasks. Moreover, our analysis is based on data drawn from large companies with at least 500 employees, which means that our results must be interpreted carefully with respect to SMEs. Since we use cross-sectional data, our results may not apply to a specific industry type. Nonetheless, there is no indication that the issues discussed in our research have different relevance with respect to specific industries. In addition, our results solely refer to the controllers' business partnering behavior, and thus ignores behaviors which are only relevant with respect to other roles. Furthermore, our study concentrates on the robustness of the controllers' business partnering behavior, but not whether firms increase or reduce their management control activities under an uncertain information environment (e.g., Janka & Günther, 2018).

As is common in survey-based research, our results could be biased by subjectivity and/or a single-respondent bias with respect to our main analysis which is why we complement it with a multi-group analysis. Moreover, our study might be affected by unit response bias, as our sample does not cover the entire target population as well as it is likely that for the participants of our study, digitization is in general of more interest. Furthermore, our supplementary analysis is subject to a moderate violation of the normal distribution for the group of managers. This may lead to slightly biased results. Although the use of bootstrapping in our analyses counters this issue, the results of our supplementary analysis must therefore be interpreted with caution, also given a rather small sample size of 67 dyads.

As our survey took place during the COVID-19 pandemic, this has the unique advantage that the impact could be surveyed at an early stage of the crisis, but also requires repeating the survey at a later stage to test for possible time effects, such as, problems of uncertainty or intergroup relations among the decision-making process being improved (Fink et al., 1971).

Finally, the total effect between the variables *Controllers' business partnering behavior* and *Controllership influence on management decisions*, which is mediated by the variable *Controllership information output quality* and moderated by *COVID-19 influence on information quality*, is highly significant and indicates a strong effect (.43), explaining 38% of the total variance of *Controllership influence on management decisions*. However, this leaves open the question of which additional causes could explain this variable, an important issue for further research, which should yield additional insights into the impact of other types of controller roles and behaviors.

# Appendix

**Table A1: Item summary**

| Construct | Label | Indicator |
| --- | --- | --- |
| | | (0 … 100) |
| Controllers' business partnering behavior | CBP | Please allocate your actual time spent on the controller role as Business partner / Advisor of management (i.e. active support of management in decision-making process) in % |
| | | (0 = not agree … 5 = completely agree) |
| COVID-19 influence on information quality | COV | The quality of controlling information is negatively affected by the COVID crisis. |
| | | (0 = not agree … 5 = completely agree) |
| Controllership information output qualtiy | CQ1 | Information from our controlling department is accurate. |
| | CQ2 | Information from our controlling department is up to date. |
| | CQ3 | Information from our controlling department is correct. |
| | | (0 = not agree … 5 = completely agree) |
| Controllership influence on management-decisions | CI1 | Controlling plays a very important role in decision-making in our business area. |
| | CI2 | Management attaches great importance to the opinions of controlling in decision-making. |
| | CI3 | Controlling has a strong influence on management decisions in our business area. |

**Table A2: Frequencies of the variable 'COVID-19 influence on information quality'**

| Valid | Frequency | Percent | Percent (cumulative) |
| --- | --- | --- | --- |
| 0 = not agree | 62 | 40.0 | 40.0 |
| 1 | 46 | 29.7 | 69.7 |
| 2 | 11 | 7.1 | 76.8 |
| 3 | 16 | 10.3 | 87.1 |
| 4 | 16 | 10.3 | 97.4 |
| 5 = completely agree | 4 | 2.6 | 100.0 |
| Total | 155 | 100.0 | |

*n = 155*

**Table A3: Results of mediation and moderated mediation confirmatory factor analysis for conditional COVID-19 sample**

| | | Coeff | Bootstrapped CI (95%) | | $p$ | $X^2/df$ | RMSEA | GFI | CFI | TLI | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Mediation model** | | | Lower | Upper | | | | | | | |
| | | | | | .194 | 1.36 | .062 | .961 | .985 | .968 | |
| Quality | | | | | | | | | | | .09 |
| Influence | | | | | | | | | | | .44 |
| Behavior on Quality (*a*) | | .21 | -.095 | .464 | .173 | | | | | | |
| Quality on Influence (*b*) | | .43 | .191 | .638 | .002** | | | | | | |
| Behavior on Influence | direct effect (*c*) | .45 | .238 | .646 | .001*** | | | | | | |
| | indirect effect | .09 | -.025 | .252 | .125 | | | | | | |
| **Moderated mediation model** | | | | | | | | | | | |
| | | | | | .285 | 1.18 | .045 | .961 | .991 | .981 | |
| Quality | | | | | | | | | | | .26 |
| Influence | | | | | | | | | | | .45 |
| Behavior on Quality (*a1*) | | .03 | -.254 | .273 | .872 | | | | | | |
| COVID-19 on Quality (*a2*) | | .01 | -.232 | .235 | .919 | | | | | | |
| Behavior x COVID-19 on Quality (*a3*) | | .50 | .233 | .752 | .001*** | | | | | | |
| Quality on Influence (*b*) | | .48 | .221 | .711 | .001*** | | | | | | |
| Behavior on Influence (*c*) | | .48 | .274 | .664 | .001*** | | | | | | |
| Simple Slope[a] | low (-1 SD) | -.028 | -.057 | -.003 | .027* | | | | | | |
| | mean | .022 | .007 | .035 | .005** | | | | | | |
| | high (+1 SD) | .031 | .014 | .050 | .001*** | | | | | | |
| Index of moderated mediation[a] | | .016 | .006 | .033 | .001*** | | | | | | |
| Conditional indirect effe | low (-1 SD) | -.023 | -.056 | -.004 | .015* | | | | | | |
| | mean | .018 | .005 | .040 | .003** | | | | | | |
| | high (+1 SD) | .025 | .008 | .053 | .001*** | | | | | | |

*n = 93; standardized estimates; *** p ≤ .001; ** p ≤ .01; * p ≤ .05; p = probability value; CI = confidence intervals; X²/df = chi-square / degrees of freedom; RMSEA = root mean square error of approximation; GFI = goodness of fit index; CFI = comparative fit index; TLI = Tucker-Lewis index;* [a]*unstandardized estimates*

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# D From data to insights: How advanced analytical capabilities strengthens the controllers' role in managerial decision-making

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Both authors developed theory/hypotheses.
Mark Alexander Sutton performed the data gathering.
Mark Alexander Sutton analyzed the data.
Both authors wrote the paper.

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# From data to insights: How advanced analytical capabilities strengthens the controllers' role in managerial decision-making

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# Abstract

For several decades, digital innovations have disrupted firms' strategies, processes, as well as internal structures, as they vastly influence information processing capacities through improved data collection, storage, processing, and use. Particularly, modern technologies of data analysis enable a fundamental information change that can be gained from a firm's data environment. These so-called advanced analytics are used for managerial decision-making to achieve competitive advantages through information leadership. Thus, advanced analytical capabilities are closely linked to the controllers' decision support function, which becomes more amplified due to the availability of new data and analytics and consequently, the need for more intensive management support in interpreting information. A greater emphasis on these more conceptual activities of controllers is in line with the ongoing transformation of the controllers' role, which has moved from financial record keeping to a more strategic-oriented business partnering over the past years. As research on the advantages of advanced analytics on management accounting is still limited, our paper contributes to this field by empirically analyzing (1) whether the level of advanced analytical capabilities has a direct, i.e., instrumental influence on controllership effectiveness in managerial decision-making, and (2) whether the controllers' business partnering behavior mediates the influence of advanced analytical capabilities on controllership effectiveness from a conceptual perspective of information use. We supplement our findings by means of an explorative analysis to address a potential user-preparer perception gap. Our analysis is based on covariance-based structural equation modelling using a sample of 156 management accountants surveyed from large German companies. Our findings reveal a significant direct effect of advanced analytical capabilities on controllership influence on management decisions as well as a significant indirect mediating effect of a controllers' business partnering behavior on the controllership influence on management decisions. Therefore, our results indicate that advanced analytical capabilities not only have a beneficial impact on controllership effectiveness in managerial decision-making from an instrumental perspective, but also increases organizational validity by strengthen the role of controllers as business partners.

**Keywords**: Controllership, business partnering behavior, instrumental vs. conceptual information-processing, advanced analytics, business intelligence, data integration

**JEL code**: M15, M40, M41

# 1. Introduction

It is widely accepted that the quality of decisions depends to a great extent on the underlying information which are available to managers for decision-making and control purposes (Zeng et al., 2006). For several decades, digital innovations are changing strategies, processes, and internal business relations (Bharadwaj et al., 2013), as they increase information processing capacities through enhanced data collection, storage, processing, and use (Knudsen, 2020). In recent times, advanced technologies of data analytics are again disrupted the information processing in organizations, having "the potential to make a lasting difference to the ways that accounting ... is carried out" (Bergmann et al., 2020, p. 26). Today, organizations collect and provide information by a broad set of accounting information systems (AIS) technologies. Thus, in addition to internal financial data derived from a firm's accounting system, modern business intelligence (BI) systems – introduced by the Gartner Group in the mid-1990s (Caserio & Trucco, 2018) – provides technologies to collect data from several data sources, which cover not only transactional accounting data from enterprise resource planning (ERP) systems, but also operational, non-financial data from corporate and business units (Marx et al., 2012), as well as analytical tools that in addition to fundamental descriptive analytics, enable advanced analytical capabilities with predictive, prescriptive, or even autonomous qualities, including functionalities of data mining, statistical data modeling, simulation, and optimization (Davenport & Harris, 2007; Kowalczyk & Buxmann, 2014; Watson, 2010).

Underlying data quality is one of the most crucial factors contributing to analytical capabilities (Davenport & Harris, 2007) which have already been discussed in previous accounting research in terms of their influence on decision making based on various criteria such as relevance, sufficiency, reliability, or feasibility (e.g., Snavely, 1967). With increasingly complex data infrastructures within BI data warehouses (i.e., storage for structured data) or data lakes (i.e., large pools of unstructured data) (Romero et al., 2012), data integration becomes more and more important (Chapman & Kihn, 2009), enabling controllers to rely on a "single source of truth", i.e., a consistent data base across a firms' business units to grasp all factors relevant to a specific decision situation, in order to achieve both operational and strategic goals in a more effective manner (Cho et al., 2019). Further, advanced analytics, i.e., the combination of data mining and highly-sophisticated mathematical-statistical techniques, enable in-depth analyses of (big) data sets (Chen et al., 2012) that wield a great influence on decision-making (Sharma et al., 2014) as they can gain competitive advantage (LaValle et al., 2011).

In order to obtain business insights as basis for managerial decision making, the use of BI systems is one of the most important tasks of highly specialized management accountants, in German companies often referred to as controllers (Ewert & Wagenhofer, 2007). In line with the dynamic development of AIS technology, the controllers' role has been moving over the past few years from a mere cost collector, collecting and providing financial information, reports, and analyses, to a business partner, participating proactively in operational and strategic managerial decision-making (Goretzki & Strauß, 2017; Wolf et al., 2015). Sophisticated data and analysis techniques within BI systems thus strengthens the role of controllers as "trusted advisors" or "consultants" (McNally, 2002).

However, other studies emphasize that the adoption of digital technologies for data collection and processing do not necessarily leads to information advantages, which might be caused by a lack of organizational factors. For example, Quinton et al. (2018) highlight, that especially large firms lack integration of such technologies into business processes due to insufficient management skills. Even more, Szukits (2022) suggests that the "reliance on analytical information does not replace intuition, but both are completing and shaping each other". These findings are also supported by earlier studies in AIS research, indicating that organizational and behavioral implications are of highest relevance in the context of BI success (Lodh & Gaffikin, 2003).

In light of this ambiguous situation, it is the objective of our paper to get a better understanding about the impact of advanced analytical capabilities on controllership effectiveness in managerial decision-making in more detail. Two potential mechanisms may link both constructs. On the one hand, there may be an instrumental relation, as AIS research have been already suggested in earlier studies (DeLone & McLean, 1992; Melville et al., 2004), indicating that BI systems especially improve data processing as well as reporting of information (Nespeca & Chiucchi, 2018). On the other hand, the underlying mechanism connecting advanced analytical capabilities and controllership effectiveness may also be found in an organizational context (Beyer & Trice, 1982; DeLone & McLean, 2003), as advanced analytical capabilities allows for a conceptual information use by facilitating the controllers' business partnering behavior, fostering a proactive involvement in managerial decision-making by allowing forward-looking structural business insights (S. Byrne & Pierce, 2007; Davis & McLaughlin, 2009). Thus, providing meaningful reports and analyses as informational support for managerial decision-making demands (instrumental information), as well as giving structural insights into the whole firm, to align decision-making with strategic goals and the business environment (conceptual information), constitute key objectives of the controllers' decision-support function (Beyer & Trice, 1982; Rouwelaar et al., 2021; Simon et al., 1954).

Research on advantages of BI systems in management accounting is still limited (Nespeca & Chiucchi, 2018). The aim of our study is to provide a better understanding about the benefits of advanced analytical capabilities for controllership effectiveness in managerial decision-making. In particular, we want to shed light on how advanced analytical capabilities are linked to controllership influence on management decisions. Our work extends the existing body of research by addressing the following research questions:

(1) Does an increased level of advanced analytical capabilities have a positive impact on controllership effectiveness in managerial decision-making,

(2) and if so, does the underlying causal inference relate both variables in an instrumental fashion and/or rather in a conceptual way?

The contribution that our research provides is threefold. First, we draw a specific connection between advanced analytical capabilities as a key feature of modern BI systems and controllership effectiveness in managerial decision-making. Second, in addition to the instrumental and/or technological features of advanced analytical capabilities, we also address their impact on controllers' business partnering behavior within a conceptual perspective. Third, our study is distinctive as it provides insights on the mechanisms underlying the effectiveness of controllership in managerial decision-making, thus contributing to the discussion on the antecedents for controllers becoming (strategic) business partners.

We chose revenue forecasting as a specific anchor point for our research because it is common in virtually all firms as well as a management accounting and control subject of highest relevance for most organizations. As our empirical investigation solely focuses on large German companies, our study is limited to a national context. However, our contributions are also of interest for the international discussion on IS success in the context of management accounting and control.

Our paper is structured as follows. Section 2 reviews the existing literature underlying our study. Section 3 presents the research model and describes four derived hypotheses. Section 4 describes the empirical design of our study, including information on the measurement of the variables used in our model. Section 5 presents the results of our study using covariance-based structural equation modeling (CB-SEM). Section 6 adds an exploratory multi-group analysis based on our previous baseline model. Finally, we discuss our results and draw implications for future research in Section 7.

## 2. Literature review

Our research draws on three major streams of literature. We built on (1) AIS literature on the use of BI systems, (2) information systems (IS) literature relating to the technological key features driving BI success, as well as (3) management accounting and control literature discussing the underlying theory of controllership effectiveness, focusing on the ongoing debate on the shifting role of controllers towards business partnering and the resulting interaction with management.

All three streams form the theoretical foundation for our hypotheses addressing the impact of advanced analytical capabilities on controllership effectiveness in managerial decision-making.

AIS research links accounting and IS research through relating technologies, e.g., for capturing, storing, and processing business data in financial accounting or other data sources (e.g., Romney & Steinbart, 2018). In the early 1970s, the first AIS technology was introduced with computerized Management Information Systems (MIS) for storing, organizing, and processing information from different sources in order to improve business (Azvine et al., 2006; Roetzel & Fehrenbacher, 2019), also known as decision support systems (DSS). In a short time, new technologies and features, e.g., dashboards or graphical user interfaces (GUI) were added, which enabled a customized visualization of key figures (Watson & Frolick, 1993) in order to support managers in their decision-making (Power, 2007). In the 1990s, additional tools, e.g., customer relationship management (CRM) systems, were introduced to allow for a comprehensive coverage of a firms' value chain, complementing modern enterprise resource planning (ERP) systems (Caserio & Trucco, 2018). Storing data derived from such transactional systems in large databases as a basis for analysis, planning, decision-making, or control purposes requires advanced MIS architectures, which have been referred to as business intelligence (BI) or strategic enterprise management systems (SEMS) (Brignall & Ballantine, 2004; Frolick & Ariyachandra, 2006). BI systems combine operational applications, e.g., ERP or CRM, and provide tools of data collection and storage, as well as numerous different platforms, suites, and solution tiers for data usage (Zeng et al., 2006). Thus, BI systems contribute in a twofold way by allowing for integration of large amounts of data from disparate heterogeneous sources (Elbashir et al., 2008) as well as providing analytical tools for analysis of business data (Trkman et al., 2010). In short, business intelligence comprises computerized methods for transforming data into information, which is in the end transferred into knowledge (Lönnqvist & Pirttimäki, 2006). Therefore, it is closely linked to organizational decision-making (Williams & Williams, 2007), allowing for a better communication and collaboration across an organization (Turban et al., 2010).

The second stream of literature underlying our research deals with the question of whether AIS technology can be implemented successfully, addressing data integration as well as analytical capabilities as antecedents for IS success. A separate consideration of both impact factors, data, and analytics, to evaluate the success of BI systems has become more and more established in IS research (e.g., Chae et al., 2014; Popovič et al., 2012). Based on the concepts of Shannon and Weaver (1963) as well as Mason (1978), DeLone and McLean (1992) identified six success factors, i.e., system quality, information quality, usage, user satisfaction, individual influence, and organizational influence, which are still an integral part of IS success research. The original model has been conceptually modified or extended by various researchers (e.g., DeLone & McLean, 2003; Lowry et al., 2007), but the initial factors are still validated as well predictors for IS success in several studies (e.g., McKinney et al., 2002; Petter et al., 2013; Rai et al., 2002). Nevertheless, the understanding of IS success and its measurement varies widely (Glass, 2005; Linberg, 1999), so that IS success models must be adapted specifically to the type of system being evaluated (Petter et al., 2008). As BI systems are typically implemented across the entire enterprise, their success is more difficult to measure and tends to be long-term in nature (Seddon et al., 2010). Given this similarity to ERP systems, research on the success of BI systems is often based on studies of enterprise IS, although ERP systems are more application-oriented while BI systems are data-oriented and concentrate on tools required for data integration and analysis (Frolick & Ariyachandra, 2006). With the growing scope of data sourcing and analysis, data integration as "consolidation of dispersed silos of data" (Frolick & Ariyachandra, 2006, p. 47) has become increasingly important for IS success as a cross-system key issue (Lenzerini, 2002). Data integration is all about standardizing data in terms of definitions and structures by using a coherent conceptual scheme in one or more data sources (Heimbigner & McLeod, 1985; Litwin et al., 1990), as well as data harmonizing, which means, e.g., providing measurement standards, data cleansing or master data management (Halevy, 2001; Popovič et al., 2009). In IS literature, data integration is considered to be one of the key factors contributing to the long-term benefits of all IS systems (Seddon et al., 2010). Therefore, it is not surprising that Elbashir et al. (2008) find data integration is a relevant topic in the relationship between business intelligence and organizational performance. The second key feature that BI systems provide are tools and technologies for online analytical processing (OLAP), data mining, analysis, as well as reporting, enabling information analysis of collected data (Chen et al., 2012). As Davenport et al. (2010, p. 23) points out: "You can't be analytical without data, and you can't be really good at analytics without really good data".

Whereas IS research addresses the question of technological benefits of advanced analytics per se, the issue whether advanced analytics make controllers more effective in decision-support has not yet been researched in depth. Furthermore, it cannot be assumed that previous tested relations are still valid in light of the ongoing transformation towards a digital economy (Wadan et al., 2019), which affects the business environment of both controllers as well as managers and causes significant organizational changes for most firms (Klus & Müller, 2021). Organizations focus not only on how much and how fast information can be processed, but rather on the value of information provided (Glazer, 1993). By collecting, structuring, and transforming data into information, BI systems create their value at the beginning of a business process, prior to organizational factors which are crucial for a successful use of information provided, such as in managerial decision-making (Popovič et al., 2009). Thus, a relevant link between the use of a firms' BI system and its performance on an organizational level within managerial decision-making is the controllers' decision-support function (Rikhardsson & Yigitbasioglu, 2018), as the availability of new data and analytics changes the need for managers to have more intensive support from controllers in interpreting information (Scapens & Jazayeri, 2003). In accordance with the International Association of Controllers (ICV), controllership as a function "encompasses the entire process, from setting the target, to planning, to management in the area of finance and performance management", with taking "the responsibility for the results transparency." Thus, digital transformation changes the work and function of controllers, which has a substantial influence on the use of information. As already noted, integrated data as well as analytical capabilities are important in order to provide relevant information to support managerial decision-making (Appelbaum et al., 2017), or – in the words of Russell L. Ackoff – management's need is not more relevant information, but less irrelevant information (Ackoff, 1989, p. 3). In this light, our third literature stream on management accounting and control research supports a behavioral information theory approach by following the idea of conceptual information use, i.e., to provide an overall understanding and enlightenment of the business at hand (Burchell et al., 1980; Menon & Varadarajan, 1992). Whereas the instrumental use of information refers to the direct use of information for decision-making at hand, i.e., supporting managers with additional information through analyses and internal reports, the conceptual use of information relates to influencing a decision-makers' thinking without putting information to a specific use (Pelz, 1978). In the accounting literature, the conceptual information use is closely related to the controllers' business partnering behavior, comprises interaction through initiating, guiding, and aligning managerial decisions with strategic goals and the business environment (Beyer & Trice, 1982; Katz, 1974; Rouwelaar et al., 2021). Järvenpää (2007, p. 100) describes the business alignment of controllers as "the willingness and ability of management accounting to provide more added value to the management (decision-making and control)", as controllers acting as business partners are more able to provide advanced services to managers and thus supporting organizational goals (Burns & Baldvinsdottir, 2005). Since the 1990s, researchers have started to find evidence of a role shift toward business partnering (Ahrens & Chapman, 2000; Granlund & Lukka, 1998; Siegel & Sorensen, 1999), which is driven by external factors such as digitalization, as well as the need for controllers to maintain "organizational validity" (Pierce & O'Dea, 2003, p. 258), as several case studies have shown that managers change their sources of information, e.g., financial accounting function (Doron et al., 2019; Nilsson & Stockenstrand, 2015), if controllers do not meet their requirements in decision-support (Berlant et al., 1990; Bruns & McKinnon, 1993; Choe, 1998). Rouwelaar et al. (2021) suggest that the conceptual use of business partners have an impact on the effectiveness of controllership, allowing controllers to wield more influence on managerial decision-making.

Our research draws on all these strands of literature, combining the technological advancement in AIS technology as an antecedent for IS success and the use of BI systems by controllers to provide meaningful business information as well as to gain and understand insights for management accounting and control purposes. Whereas the technological benefit of advanced analytics is to provide instrumental information for decision-making, it facilitates in an organizational context the conceptual use of business information by supporting the controllers' business partnering behavior to allow an integral view on the firm's business.

# 3. Research model and hypothesis development

Our study is driven by the research question of how advanced analytical capabilities are related to controllership effectiveness, i.e., their influence on management decisions, and to what extent this effect is rather based on the technical features of advanced analytical capabilities affecting controllership influence on management decisions in an instrumental fashion or whether both constructs are – at least to some extent – linked in a conceptual way as advanced analytical capabilities strengthens the controllers' business partnering behavior.

Starting from the literature, we first concentrate on the technical inferences within a firms' BI system, thus examining the antecedent impact of data integration on advanced analytical capabilities. Although quality constructs are fundamentally multidimensional, previous research on IS success evaluate data quality on a holistic level (Rai et al., 2002), from either an intrinsic or contextual perspective (Nelson et al., 2005). The intrinsic perspective assesses the properties of data without reference to their context (e.g., user or task), measured by the degree of consistency between data values and the real world (Lee et al., 2002; Seddon, 1997). Thus, consistency is a common quality dimension from the intrinsic perspective (Fisher & Kingma, 2001). More expansively, the contextual perspective relates to the assessment of data quality in a particular context or a specific analysis (Wang & Strong, 1996). This allows, for example, to value data quality provided by a BI system in the context of a specific decision task. The need for consistency arises when data are derived from different sources (Daft & Lengel, 1986). In this respect, data integration serves to reduces inconsistency between data, allowing for higher availability and reduction of delays (Huber, 1982). By harmonizing multiple data sources, data integration consequently improves the collection, comparison, and aggregation of data (Gattiker & Goodhue, 2004), allowing for less error-prone and more efficient analyses (Doan et al., 2012). Moreover, from a management accounting perspective, it enables to discover new relations or to test new assumptions (Davenport, 1998). The disadvantages of data integration are higher costs as well as compromises that must be made depending on the specific application (e.g, Orlikowski, 1991). However, we agree with Gattiker and Goodhue (2004) that long-term benefits resulting from data integration exceed the potential costs, as data integration provides a more qualitative data base for reports and analyses. Thus, we assume that there is a positive direct relationship between data integration and advanced analytical capabilities. We therefore hypothesize:

*H1: An increased level of data integration leads to an increased level of advanced analytical capabilities.*

Data integration itself does not result in a tangible output, but is rather an enabler for, e.g., better analytical capabilities, which in turn could foster, e.g., controllership influence on management decisions. Advanced analytics improve the quality of information derived from data, which is available for controllers to perform their tasks, e.g., to support managers with useful information in the scope of their decision-support function. While descriptive and diagnostic analytics are long-established, more advanced predictive and prescriptive analytics also become prevalent in today's business practice (Davenport, 2013; Davenport et al., 2019). For example, Cao and Duan (2017) show that the use of data analytics has a positive impact on decision effectiveness. However, as already noted, the benefits of advanced analytical capabilities per se may not guarantee their use in decision-making processes. Organizational factors must also be considered (Lismont et al., 2017) to ensure their value for decision-making (Popovič et al., 2012). This is supported by Janssen et al. (2017), who found that not only the quality, but also the processing and transmission of data have an influence on the quality of decision making. Analytics create a direct value if they provide meaningful information that can be used for different purposes (Grover et al., 2018). Thus, we assume that advanced analytical capabilities drive controllership effectiveness in an instrumental fashion, by providing high-quality reports and analyses to the management. We therefore hypothesize:

*H2: An increased level of advanced analytical capabilities leads to an increased controllership influence on management decisions.*

Providing reports and analysis to managers is in line with the traditional role of controllers as information providers. But information provided can be hampered by misinterpretation, such as lack of knowledge or time constraints of the management (Arnaboldi, 2018). Thus, interpreting information requires more sense of the business than technical knowledge (Kowalczyk & Buxmann, 2014). Recent studies have called for experience in analysis, (Bhimani & Willcocks, 2014; Oesterreich et al., 2019), emphasizing not the technical knowledge but "the 'nose for the numbers' - tacit knowledge which supports the ability to spot patterns and anomalies and ask the right questions" (Payne, 2014, p. 494). With respect to the processing and interpretation of analytical information, Kowalczyk and Buxmann (2014, p. 276) postulate that "Within the set of organizational information processing mechanisms, the analytic integrator role is particularly noteworthy, as it is utilized throughout the different decision types to bridge understanding gaps between decision makers and analytics experts". This implies that the contribution of controllers in their role as business partners comes into play between advanced analytical capabilities and the ability to set information provided in a specific decision-making context, so that controllers contribute to a better understanding of information (Quinn, 2014) and thus become more involved in operational and strategic decision-making processes (S. Byrne & Pierce, 2007; Zoni & Merchant, 2007).

Thus, we suggest that advanced analytical capabilities drive controllership effectiveness also via a conceptual mechanism, i.e., an increased controller's business partnering behavior as controllers are more able to supply highly sophisticated financial and business analysis, combined with data modelling for managerial decision-making (Fleischman et al., 2016). With our third and fourth hypotheses, we assume that the controllers' business partner role is more pronounced with advanced analytical capabilities, as individual reports and analyses are assumed to become more nuanced and tailored to specific managerial information needs, so that controllers are more able to guide and advise managers by providing additional insights into how organizational functions or value drivers interact and relate to the firm's strategic goals (S. Byrne & Pierce, 2007; Rouwelaar et al., 2021) This is also supported by Janke et al. (2014) who observe a growing conceptual interaction between controllers and managers, which in turn leads to a growing influence on managerial decision-making (Burns et al., 1999; Goretzki & Strauß, 2017; Rouwelaar et al., 2021; Wolf et al., 2015). In line with the assumptions of rational choice theory (Hedström & Swedberg, 1996), a higher information quality will cause a more extensive use, leading to a stronger influence on management decisions. We therefore hypothesize:

*H3: An increased level of advanced analytical capabilities leads to an increased level of controllers' business partnering behavior.*

and

*H4: An increased level of controllers' business partnering behavior leads to an increased level of controllership influence on management decisions.*

The full research model is presented in Figure 1.

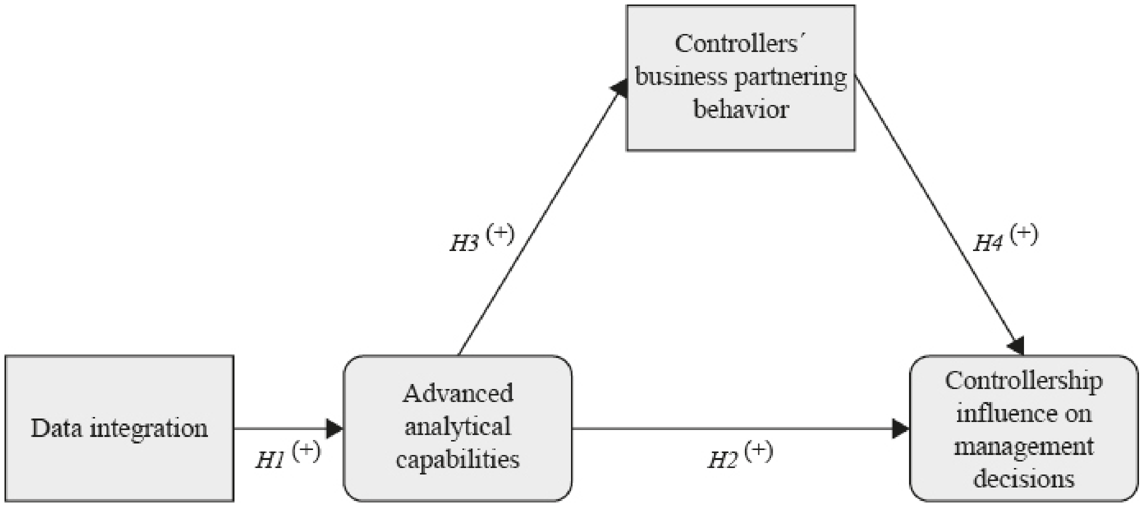


**Fig. 1** Full research model.

# 4. Research design

## 4.1. Sample selection and survey design

For identifying the impact of advanced analytical capabilities on controllership effectiveness with respect to their influence on management decisions we chose revenue forecasting as a specific anchoring point for our investigation. This anchor was selected not only because revenue forecasting is a common controller task, but also of the highest relevance in virtually all firms. Therefore, we suppose that controllers use all information available to provide revenue forecasts that are as relevant and qualitative as possible, and that this information reflects an appropriate indicator of their overall influence on managerial decision-making.

We collected the underlying data for our study in the period from June to October 2020 performing a questionnaire-based online survey. We used the database Markus to locate contact data of all German companies. We selected only large companies with at least 500 employees, thus excluding small- and medium-sized enterprises (SME; IfM Bonn, 2020), as smaller firms usually do not have a specialized controlling department, e.g., supported by Hiebl et al. (2013). Furthermore, we excluded finance and real estate firms, because of their specific business models compared to firms from industrial, service or trading industries. Finally, we adjusted our database by eliminating duplicate entries, so that 5,758 firms left in our population. For reasons of time and resources, we randomly selected thereof 20% and contacted them by telephone or, in the case of several missed calls, by e-mail. To capture different aspects of controllers' tasks in providing revenue forecasts, we addressed the controlling manager ('Leiter Controlling'), a functional controller responsible for sales controlling or a similar function of each company. To revise ex ante completeness and understandability, we followed the recommendations of Dillman (2007), and pre-tested our questionnaire with three executives from business practice, three consultants as well as five academic researchers.

In total, we received 159 completed questionnaires, of which three had to be excluded due to unfulfilled requirements concerning the number of employees. The final sample of 156 questionnaires corresponds to return rates of 13.3% of the participant population. The companies' industry affiliation of our sample is presented in Table 1.

**Table 1: Surveyed firms by industry**

| Variable | Frequency | Percentage |
|---|---|---|
| Automotive | 21 | 13,5% |
| Construction | 9 | 5,8% |
| Chemicals/Pharma/Health care | 18 | 11,5% |
| Industrial Goods | 7 | 4,5% |
| Energy/Utility | 18 | 11,5% |
| Wholesale/Retail | 14 | 9,0% |
| Consumer goods | 15 | 9,6% |
| Engineering | 20 | 12,8% |
| Software/Technology | 5 | 3,2% |
| Telecommunication | 2 | 1,3% |
| Transport/Logistics | 7 | 4,5% |
| Others | 20 | 12,8% |
| n | 156 | |

Summary statistics of company size are shown in Table 2.

**Table 2: Summary statistics on company size measures of surveyed firms**

| Variable | n | Mean | SD | Median |
|---|---|---|---|---|
| Number of employees | 156 | 22,474 | 65,646 | 4,477 |
| Sales (Million EUR) | 155 | 6,089 | 13,618 | 1,129 |
| Assets (Million EUR) | 148 | 11,103 | 33,899 | 754 |

Our survey is part of a wider research project, so that additional items were surveyed which are not refer to the research questions of our study. A summary of items used for our research model is given in Table A1 (see appendix).

## 4.2. Variable measurement

Our research model is composed of one exogenous variable *Data integration* as well as three endogenous variables *Advanced analytical capabilities*, *Controllers' business partnering behavior* and *Controllership influence on management decisions*. The measurement model of the four variables used in our study features self-developed instruments by means of questions derived from the relevant literature, as well as scales that have already been validated in previous research, following the recommendations of Bisbe et al. (2007). Table A1 provides an overview of all items used (see appendix).

Our exogenous variable *Data integration* measures the extent to which data within a firms' infrastructure are integrated and relates to IS literature, in which various BI maturity models have been identified (Chuah & Wong, 2011). The differences between the models are attributed to individual dimensions. However, most models have in common that a data management perspective is considered separately from analytical capabilities (e.g., Cates et al., 2005; Glancy & Yadav, 2011). Accordingly, there is consensus in the current literature that data and analytics represent two separate parameters when assessing BI systems. This corroborates with empirical studies which stipulating that data integration, as a key success factor for IS, constitutes a fundamental quality of BI systems (Seddon et al., 2010). Data integration enables a standardized access to autonomous as well as heterogeneous data sources, which in consequence reveals two major challenges – the number of sources as well as the heterogeneity of data. The more data sources are added, the more complex data integration becomes. This in turn fosters the second issue of heterogeneity, as data sources are usually customized for different user needs or applications, resulting in different data systems and types of data. While some sources are fully structured, e.g., relational databases, others are unstructured or semi-structured, e.g., XML or text (Doan et al., 2012).

For the conceptualization of our exogenous variable *Data integration*, we rely on the measurement of Popovič et al. (2012), who measure data integration as a distinctive dimension of BI system maturity by means of two indicators related to the number of sources, i.e., the centrality of data sources, and the consistency of data (see Table A1 in the appendix). We chose these two items as they cover the key challenges of data integration, which is in line with the extant literature. Thus, our exogenous variable represents the extent to which data used by controllers for revenue forecasting are integrated and consistent within a firms' organization. We assume that its underlying character is continuous, as partial integration can be observed in practice.

The operationalization of latent variables can be based on formative or reflective measurement. The prevailing factor is whether the indicators influence (formative) or are influenced by (reflective) the latent variable (Bollen, 1989). Reflective measurement is the most common approach in CB-SEM research, which is fundamentally consistent with the underlying test theory which implies that the observed variables (i.e., the indicators) are reliable manifestations of the latent variable. Changes in the latent variable consequently lead to changes in all related indicators (Bollen & Lennox, 1991; Diamantopoulos, 2008; Diamantopoulos & Winklhofer, 2001). The formative measurement approach, in contrast, requires that a latent variable is described by its indicators. In this case, changes among the indicators lead to changes in the latent variable. Therefore, a formative variable is also referred to as a composite variable (MacKenzie et al., 2005), or index. As our used indicators influence data integration, we choose a formative measurement approach for our variable *Data integration* by building an additive index. In formative measurement, high correlation between indicators is not expected, but can be observed (Bollen & Lennox, 1991). The fact that greater centralization of data from a theoretical perspective leads to greater data integration, even if consistency remains constant, also promotes our approach of formative measurement. Diamantopoulos and Winklhofer (2001) confirm that formative measurement is also a reliable approach in CB-SEM.

For our first endogenous latent variable *Advanced analytical capabilities* we adopt a reflective measurement, since the underlying indicators are intended to be interchangeable and depend on the latent variables. For the conceptualization, we consider analytical types that are enabled by BI systems and especially focus on indicators that enable forward-looking analyses, i.e., predictive, and prescriptive analyses. In line with the Gartner (2012)'s analytic value escalator, descriptive and diagnostic data analysis are more basic analysis capabilities, explaining what and why something is happened. Based on that, advanced analyses can be understood as those capabilities with a predictive or prescriptive orientation, which include methods of, e.g., statistical analyses, simulations, optimizations, and data mining (Davenport & Harris, 2007; Watson, 2010). Our measurement model consists of four reflective indicators. Two items were adopted from the BI system maturity model of Popovič et al. (2012). The last two items are self-developed scales reflecting predictive statistical forecast models as well as prescriptive simulations, including recommendations for actions. All items are shown in Table A1 (see appendix).

The measurement for our second endogenous variable *Controllers' business partnering behavior* relates to the literature on controllers' roles which refers to a great extent to the controllers' own perception (e.g., Burns & Baldvinsdottir, 2005; Endenich et al., 2017), describing their functions or tasks (Rieg, 2018). In this context, Rouwelaar et al. (2021) suggest a conditional range from capabilities of data modeling and analysis to abilities of strategic decision-making. However, for our study we rely on a role model by Gleich and Lauber (2013) which distinguishes four roles (analyst/scorekeeper, supervisor/guardian, business partner, change agent) derived from relevant management accounting practice (e.g., Weber & Schäffer, 2020). During the survey, we asked participants to allocate their working time between the different roles, as controllers often cover more than one (Burns & Baldvinsdottir, 2005; S. Byrne & Pierce, 2007). The resulting percentage of working time spent on the role of a business partner serves us as a useful indicator for the level of *Controllers' business partnering behavior* (see Table A1 in the appendix). For all other scales, we applied six-point rating scales labeled from '… not agree' to '…completely agree'. Thus, we prevented an 'in-between'-category, as it could be misinterpreted by survey participants as "no opinion" or "no answer", which in turn affects the empirical data quality.

Our third endogenous latent variable *Controllership influence on management decisions* is constructed by means of a reflective measurement approach using established scales from the literature (see Table A1 in the appendix, e.g., Weißenberger & Angelkort, 2011). Similar to our first endogenous variable, the underlying manifest indicators are interchangeable and assumed to depends on the latent construct. The variable measures how controllers assess their influence in the context of management decisions, i.e., the value of their activities on managerial decision-making. It reflects a modified version of a measurement model developed by Spillecke (2006) and consists of three reflective indicators originally measured on a five-point rating scale. The third item was originally developed by Bauer (2002). All items are provided in the appendix in Table A1.

We countered subjective bias as we surveyed the items for our variable *Controllership influence on management decisions* in our questionnaire before measuring the variable *Controllers' business partnering behavior*.

## 4.3. Reliability and validity of measurement

We use common measures suggested in the literature to establish reliability and validity of our latent variables (Bagozzi & Yi, 1988; Schäffer, 2007). To test for internal reliability of a construct we use Cronbach's alpha (CA) which exceeds the critical value of .70 (Nunnally & Bernstein, 1995). Factor reliability (FR) relies on the standardized factor loadings of individual items on a given construct, which is well above its critical value of .60. Average variance extracted (AVE) describes the average variance shared between a construct and the associated indicators to test for convergent validity (Fornell & Larcker, 1981). Again, the critical value of .50 is exceeded in both cases. Table 3 summarizes the descriptive statistics for all variables, as well as the respective reliability and validity measures.

**Table 3: Summary statistics, reliability and validity measures**

| Item | Indicator | Min | Max | Mean | SD | SMC | CA | FR | AVE |
|---|---|---|---|---|---|---|---|---|---|
| Data integration | DI | 0.00 | 10.00 | 5.49 | 1.955 | | | | |
| Advanced analytical capabilities | AC1 | 0.00 | 5.00 | 2.02 | 1.361 | .607 | .769 | .966 | .563 |
| | AC2 | 0.00 | 5.00 | 1.05 | 1.259 | .432 | | | |
| | AC3 | 0.00 | 5.00 | 1.57 | 1.325 | .410 | | | |
| | AC4 | 0.00 | 5.00 | 2.08 | 1.412 | .410 | | | |
| Controllers´ business partnering behavior | CBP | 0.00 | 55.00 | 22.70 | 10.844 | | | | |
| Controllership influence on management decisions | CI1 | 1.00 | 5.00 | 3.73 | 1.144 | .739 | .939 | .976 | .853 |
| | CI2 | 1.00 | 5.00 | 3.61 | 1.184 | .906 | | | |
| | CI3 | 1.00 | 5.00 | 3.44 | 1.165 | .878 | | | |

*n = 156; SD = Standard Deviation; SMC = Squared Multiple Correlation; CA = Cronbach's Alpha; FR = Factor Reliability; AVE = Average Variance Explained*

We use the Fornell-Larcker (1981) criterion to test for discriminant validity, i.e., the extent to which indicators associated with one latent variable differ independently from those related to another latent variable. The criterion is fulfilled if the AVE of each factor is higher than any squared correlation of that factor with another factor (see Table 4).

**Table 4: Discriminant validity according to the Fornell-Larcker criterion**

| Variable | AVE | Squared correlation with variable | |
|---|---|---|---|
| | | Advanced analytical capabilities | Controlling influence on management decisions |
| Advanced analytical capabilities | .563 | - | .201 |
| Controllership influence on management decisions | .853 | .201 | - |

To examine indications of common method bias, we finally conducted Harman's (1967) single-factor test. The test disclosed no evidence of a common factor underlying the tested items, as the eigenvalues of all variables indicating that no single factor emerged, and the first factor accounts for less than 50% of the variance among variables (Fuller et al., 2016), as shown in Table 5.

**Table 5: Harman's single-factor test**

| Factor | Initial eigenvalues | | | Extraction sums of squared loadings | | |
|---|---|---|---|---|---|---|
| | Total | % of variance | Cumulative % | Total | % of variance | Cumulative % |
| 1 | 3.924 | 43.598 | 43.598 | 3.924 | 43.598 | 43.598 |
| 2 | 1.674 | 18.603 | 62.201 | 1.674 | 18.603 | 62.201 |
| 3 | .873 | 9.701 | 71.902 | | | |
| 4 | .718 | 7.979 | 79.881 | | | |
| 5 | .614 | 6.819 | 86.700 | | | |
| 6 | .516 | 5.735 | 92.436 | | | |
| 7 | .369 | 4.104 | 96.540 | | | |
| 8 | .209 | 2.320 | 98.860 | | | |
| 9 | .103 | 1.140 | 100.000 | | | |

*n = 156; Extraction Method: Principal Component Analysis*

## 4.4. Method of analysis

We apply a covariance-based structural equation modelling (CB-SEM) with maximum likelihood (ML) estimation for testing our hypothesis, using the SPSS software package AMOS 28. The methodological advantage compared to other techniques such as multiple regression or variance-based path analysis is the inclusion of both manifest (observed) and latent (unobserved) variables. This allows for a holistic approach in model building, accounting indirect effects as well. Subsequently, it enables a confirmatory (rather than exploratory) approach to data analysis and gives more extensive metrics to evaluate overall model fit (B. Byrne, 2016; Smith & Langfield-Smith, 2004), thus constituting to the most common method for causal analysis (Weiber & Mühlhaus, 2014).

We perform a mediation analysis for testing our hypotheses *H1 – H4* using the product-of-coefficients method as a common way to analyze indirect effects (MacKinnon et al., 2002; MacKinnon et al., 2004). We employ a simple mediation model, i.e., with one mediator, as it is the most common type of mediation (Preacher et al., 2007). Figure 2 presents our structural model.

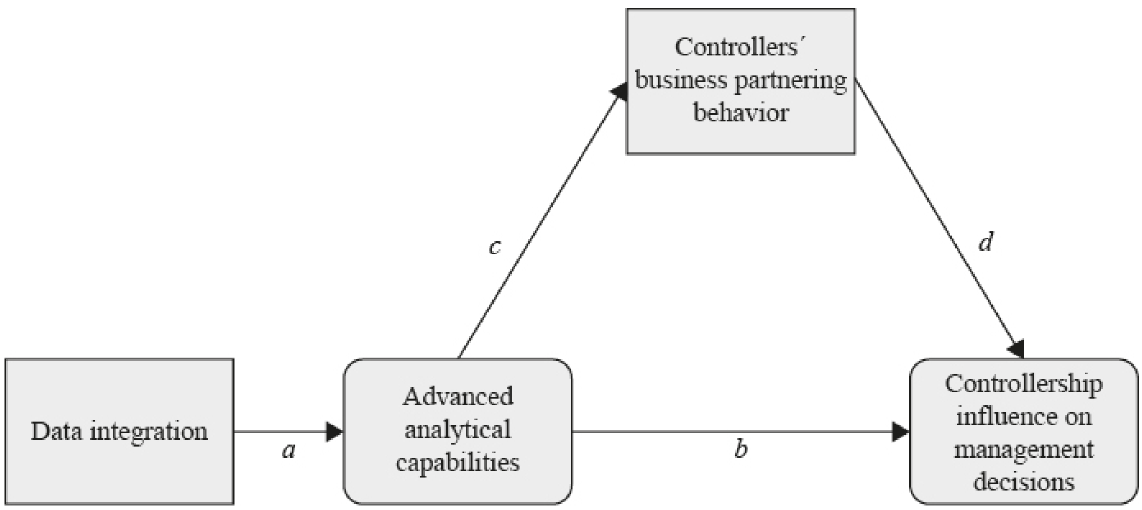


**Fig. 2** Structural mediation model

We test the direct effect (path *b*) of *Advanced analytical capabilities* on *Controllership influence on management decisions* and indirect effect via *Controllers' business partnering behavior* (path *c*d*) as well. The effect size that relates to the mediation effect we calculate by dividing the $R^2$ value of *Controllers' business partnering behavior* by the $R^2$ value of *Controllership influence on management decisions*, i.e., the total amount of explained variance of our dependent variable (MacKinnon, 2008).

# 5. Results

The results of our baseline analysis are presented in Table 6.

**Table 6: Results of confirmatory factor analyses**

| | | Coeff | Bootstrapped CI (95%) | | $p$ | $X^2/df$ | RMSEA | GFI | CFI | TLI | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Baseline analysis** | | | Lower | Upper | | | | | | | |
| | | | | | .060 | 1.473 | .055 | .949 | .982 | .975 | |
| Analytics | | | | | | | | | | | .24 |
| Behavior | | | | | | | | | | | .09 |
| Influence | | | | | | | | | | | .27 |
| Data integration on Analytics (*a*) | | .49 | .302 | .635 | .005** | | | | | | |
| Analytics on Behavior (*c*) | | .30 | .113 | .472 | .004** | | | | | | |
| Behavior on Influence (*d*) | | .28 | .102 | .425 | .006** | | | | | | |
| Analytics on Influence | direct effect (*b*) | .36 | .213 | .520 | .003** | | | | | | |
| | indirect effect | .08 | .027 | .183 | .002** | | | | | | |
| | total effect | .45 | .309 | .599 | .004** | | | | | | |
| **Multi-group analysis** | | | | | | | | | | | |
| | | | | | .053 | 1.343 | .051 | .906 | .961 | .944 | |

*n = 156; standardized estimates; *** p ≤ .001; ** p ≤ .01; * p ≤ .05; p = probability value; CI = confidence intervals; X²/df = chi-square / degrees of freedom; RMSEA = root mean square error of approximation; GFI = goodness of fit index; CFI = comparative fit index; TLI = Tucker-Lewis index*

For testing the overall model fit, we estimate several goodness-of-fit indices for each confirmatory factor analysis (CFA). The ratio of chi-squared ($X^2$) and degrees of freedom (*df*) relates to the null hypothesis that the specification of factor loadings, factor variances, covariances, and error variances are valid (Bollen, 1989). The closer the hypothesized model fits to a perfect model, the higher the probability value (*p*-value) associated with $X^2/df$. However, the $X^2$-test has various limitations. Two major limitations are dependence on sample size as well as model complexity. With large samples, the $X^2$-test tends to reject robust models (type-1-error), while with small samples it tends to accept poor models (type-2-error). Furthermore, the $X^2$-test is subject to model complexity, i.e., the more variables are included, the higher the potential risk of a type-1-error. Because of the limitations of the $X^2$-test, additional goodness-of-fit indices have been developed. However, the $X^2$-test is the basis for most alternative fit indices (Backhaus et al., 2015). The root mean square error of approximation (RMSEA) considers the error of approximation in the population and compares it to optimally chosen parameter values (Browne & Cudeck, 1992), i.e, accounts for whether the hypothesized model provides a close approximation of the empirical reality, instead of an exact fit. Comparison indices compare the fit of a hypothesized model with the fit of a baseline model, which is particularly appropriate for nested models. Their measures are commonly range between 0 (no fit) and 1 (perfect fit) (Hu & Bentler, 1995). Three comparison goodness-of-fit indizies are widely applied in practice. The absolute goodness-of-fit index (GFI) compares the hypothesized model with no model at all by measuring the explained amount of variance and covariance in the data (Hu & Bentler, 1995). In contrast, the comparative fit index (CFI) as well as the Tucker-Lewis index (TLI) are additional incremental fit measures that compare the hypothesized model to a so-called null model, which allows all variables in the model to have variation but no correlation (Byrne, 2016). As reported in Table 6, all goodness-of-fit indices are above or respectively below their critical thresholds given in Table 7, indicating that our model fits the empirical data very well.

**Table 7: Critical values of goodness-of-fit indices**

| Index | Critical Value | References |
|---|---|---|
| $X^2/df$ | $\leq 2$ | Byrne (1989) |
| *p*-value | $\geq .05$ | Bagozzi and Yi (1988) |
| RMSEA | $\leq .06$ | Hu and Bentler (1999) |
| GFI | $\geq .90$ | Homburg and Baumgartner (1995) |
| CFI | $\geq .97$ | Schermelleh-Engel et al. (2003) |
| TLI | $\geq .97$ | Schermelleh-Engel et al. (2003) |

*$X^2/df$ = chi-square / degrees of freedom; p-value = probability value; RMSEA = root mean square error of approximation; GFI = goodness of fit index; CFI = comparative fit index; TLI = Tucker-Lewis index*

As Table 6 shows, the results of our mediation model reveal a significant effect of *Data integration* on *Advanced analytical capabilities*, with a path coefficient of .49. This effect explains 24% of the variance of the variable *Advanced analytical capabilities*. Thus, empirical data are in line with our first hypothesis *H1*. With respect to our second hypothesis *H2*, the assumed direct effect of *Advanced analytical capabilities* on *Controllership influence on management decisions* is also supported, as the resulting path coefficient (.36) is significant. With our third and fourth hypotheses, we assume a positive indirect effect of *Advanced analytical capabilities* on *Controllership influence on management decisions*, mediated by *Controllers' business partnering behavior*. As both hypotheses are corroborated by our results, given that the path coefficients for *H2* (.30) and *H3* (.28) are significant, the assumed overall indirect effect is confirmed by our data. Within this association, the effect of *Advanced analytical capabilities* on *Controllers' business partnering behavior* explains 9% of the variance of the variable *Controllers' business partnering behavior*. In total, *Advanced analytical capabilities* together with *Controllers' business partnering behavior* explain 27% of the variance of the variable *Controllership influence on management decisions*. From a theoretical perspective, the empirical results suggest that the model structure we hypothesized is fully supported. In short, our results suggest that controllers attribute the impact of advanced analytical capabilities to both an instrumental ability to produce high-quality reports and analyses as well as the conceptual dimension of their business partnering behavior, i.e., an improved interaction with managers.

# 6. Supplementary analysis

## 6.1. Data and method of analysis

In addition to our conditional process analysis, we conduct a multi-group analysis following the recommendations of B. Byrne (2016). This is useful as our analysis might be subject to key informant bias, i.e., biased by controllers' subjective views. As a complementary part of our survey, we not only addressed controllers but also their closest general manager, i.e., a member of upper management such as the CEO, managing director or division manager, to fill out a specific questionnaire. Out of the received 156 controller questionnaires, 67 related managers also participated, giving us a total of 67 dyadic datasets, which represent to a dyadic response rate of 43%. Each dyad forms a unit of observations for our supplementary analysis, in which the variables *Data integration*, *Advanced analytical capabilities* and *Controllers' business partnering behavior* are measured by using controllers' ratings. For these variables, we questioned only controllers as we assume that managers are not suitable respondents to rate the integration of data as well as analytical capabilities underlying the controller's work or to make valid judgments on the specific time controllers spend on different roles. In turn, the variable *Controllership influence on management decisions* is also measured by the ratings from the respective managers. In contrast to our research setting in which only controllers are surveyed, we can therefore draw valid conclusions with respect to managers' perceptions as well.

For our supplementary analysis, we compare the results of both groups, i.e., for controllers (similar to our baseline model, Section 4.4) and managers by conducting a multi-group causal analysis. Thus, we test both groups for the equality of the estimated path coefficients (Steenkamp & Baumgartner, 1998), i.e., we test if differences in path coefficients can be observed between the group of controllers and the group of managers (see Figure 3).

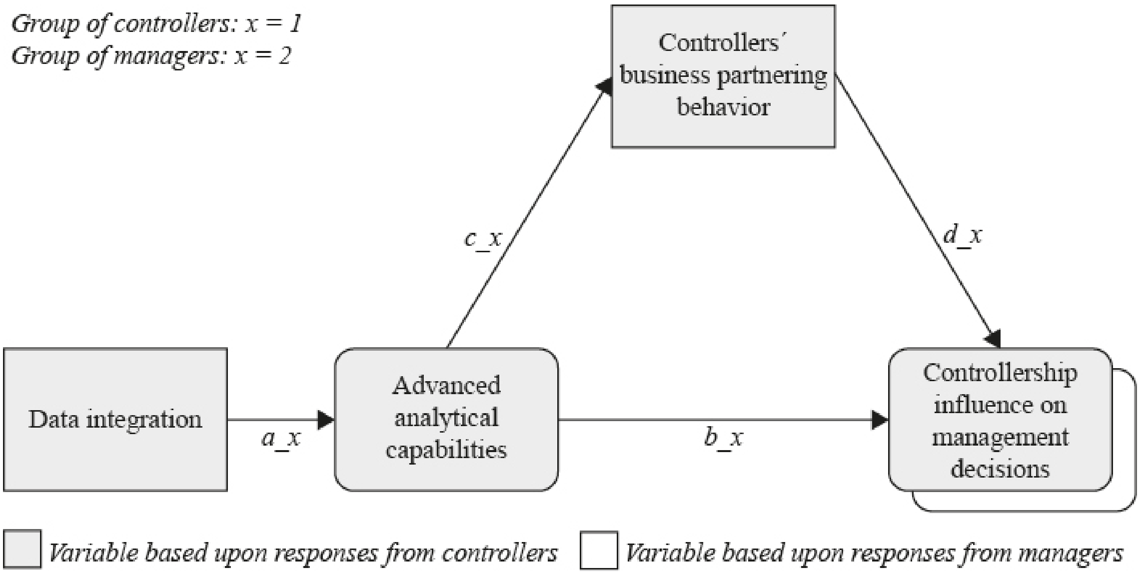


**Fig. 3** Multi-group analysis

The technical process involves testing a series of nested models (Bagozzi & Yi, 1988; Steinmetz et al., 2009). According to the recommendations of B. Byrne (2016), each nested model (one for each group) consists of a set of sub-models, for which the parameters are estimated simultaneously. A series of tests is used to constrain certain sets of parameters to be the same in all sub-models of all groups. As the individual sets of parameters are converged over time, each model is more stringently constrained than its preceding model. A $X^2$-difference test is used to evaluate the change in model fit as well as individual model parameters for each step in the nested models (Reinecke, 2014). If the model fit deteriorates, it results in a higher value for $X^2$. However, since the model gains one degree of freedom with each constraint, the increase in $X^2$ must be compared to the degrees of freedom gained. If the deterioration of the model fit is significant, it shows that the last set of constrained parameters in the model are not equal between the groups.

## 6.2. Multi-group analysis

The goodness of fit of our multi-group mediation model achieves a moderate, but acceptable fit with respect to global criteria, as *p*-value, RMSEA and GFI exceed their critical values, reported in Table 6. The analysis does not focus on the absolute values of our observed variables, but on the covariances reflecting the causal relationships. If differences in the direct or indirect effects can be observed, it indicates different causal relationships between both groups, i.e., controllers and managers. The structural model is similar to that of our baseline model, shown in Figure 2. We test for significant differences concerning the direct (*b_1* and *b_2*) and indirect paths (*c_1 * d_1* and *c_2 * d_2*) between the variables *Advanced analytical capabilities* and *Controllership influence on management decisions* across the groups in a test series of four models, as illustrated in Figure 3. The results for each model of the test series are shown in Table 8.

**Table 8: Test series of multi-group confirmatory factor analysis**

| Model | Compared Model | $X^2$ ($df$) | $\Delta X^2$ ($\Delta df$) | RMSEA | CFI |
|---|---|---|---|---|---|
| A: Configural invariance | - | 67.126 (50) | - | .051 | .961 |
| B: Full metric invariance | A | 71.578 (55) | 4.452 (5) | .048 | .962 |
| C: Invariance of direct effect | B | 73.228 (56) | 1.650 (1) | .048 | .961 |
| D: Invariance of indirect effect | B | 74.383 (57) | 2.805 (2) | .048 | .960 |

*X² = chi-square; df = degrees of freedom; p-value = probability value*

To test for configurational invariance, Model A estimates an unconstrained model for both groups. In this case, all parameters (e.g., factor loadings) are freely estimated for both groups, so that the model is restricted only to the extent that it is identical in structure and design between the groups, i.e., if the same variables, items, and relations applied for both groups. As shown in Table 6, the fit measures ($X^2/df$ = 1.343) of the unconstrained model indicate that the same model structure applies to both groups.

To test for full metric invariance, i.e., whether the manifest indicators measure the same construct in both groups, all factor loadings of the measurement constructs in both groups are constrained to be equal in Model B. This means, that for both groups all indicators underlying a construct are appropriate to measure the latent variable in a similar way. Even if these limitations lead to an increase of $X^2$ of 4.452, the decrease in model fit is not significant, as 5 *df* are gained. We can therefore assume full metric invariance, which allows us to test for structural invariance, i.e., whether the structural relationships of the two groups are also identical.

Model C tests for invariance of the direct effects by setting the direct effect between the variables *Advanced analytical capabilities* and *Controllership influence on management decisions* equal in both groups, in addition to the constraints from Model B. That means, we constrain the effect *b_1* to be equal to *b_2*. As shown in Table 8, the equalization of the direct effects leads to a deterioration of the model fit, as $X^2$ increases by 1.650 compared to Model B. However, the deterioration in model fit is far below the threshold of 3.84 (for 1 *df* gained), so that different direct effects between the two groups cannot be observed. That means, that significantly different perceptions on the influence of *Advanced analytical capabilities* on *Controllership influence on management decisions* cannot be observed for controllers and managers.

Finally, Model D test for invariance of the indirect effects between the variables *Advanced analytical capabilities* and *Controllership influence on management decisions*, i.e., we test whether significant differences for the perceptions of controllers and managers can be revealed for the indirect influence of *Advanced analytical capabilities* and *Controllership influence on management decisions*. Therefore, we fix the effect *c_1* identical to *c_2* and the effect *d_1* equal to *d_2*, in addition to the constraints from Model B. As reported in Table 8, the equalization of the indirect effects leads to a deterioration of the model fit, as $X^2$ increases by 2.805 compared to Model B. Given that 2 *df* are gained, the threshold of 5.99 is not exceeded, thus, different indirect effects between the two groups cannot be established.

In sum, the results reveal no moderating effect of group affiliation on the direct as well as indirect relations between our variables *Advanced analytical capabilities* and *Controllership influence on management decisions*. This implies that according to the findings of our baseline analysis, the perception of an instrumental as well as a conceptual impact of advanced analytical capabilities on controllership influence on management decisions holds for both the controllers' perspective and the managers' perspective, so that no indication of a user-preparer perception gap exist, as found, e.g., by Pierce and O'Dea (2003) or Weißenberger et al. (2012).

## 7. Discussion

Our study was motivated by the ongoing digitalization of accounting information technologies as well as the changing role of controllers towards business partnering, both linked to effective support in operational as well as strategic managerial decision-making and control. In this context, our interest focused on advanced analytical capabilities, which are strongly driven by the increasing amount of data available as well as the growing complexity and dynamics of the business environment. Our research contributes to the question of whether advanced analytical capabilities have a positive impact on controllership effectiveness in managerial decision-making and whether the underlying relation between both variables is direct, i.e., technology-driven, or indirect, i.e., via conceptual use by controllers acting in their role as business partners. Based on 156 controller responses from large German companies with at least 500 employees, the results of our research reveal a positive significant association of advanced analytical capabilities with the influence of controllership in managerial decision making, which causes directly, i.e., instrumental, as well as conceptually, i.e., a mediated effect instigated by the controllers' business partnering behavior resulting from advanced analytical capabilities. Thereby, our results provide new insights into the discussion of whether advanced analytical capabilities are related to controllership effectiveness, which at first glance is not necessarily the case, e.g., due to the prevailing opinion that high-value IS make certain controllers’ functions become obsolete.

We show that a solely technology-based approach to the controllers’ tasks ignores the relevance of the conceptual contribution in their role as business partners as a driver of controllership effectiveness in managerial decision-making. Even if the information use through reports and analyses is advantageous from an IS-theoretical perspective, it does not fulfil the managers’ need of a holistic view on a firm’s business to guide and advise mangers, which is made possible through supportive controllers' business partnering behavior. Therefore, our results show that advanced analytical capabilities not only contribute in an instrumental fashion by the quality of reports and analyses provided by controllers, but also conceptually through an increased business partnering behavior resulting in a higher controllership influence on management decisions.

Obviously, there are some limitations to the generalizability of our results. Our results focus on decision support in revenue forecasting, which thus concerns solely one area of controllers' tasks. Furthermore, our analysis draws on data from large companies with at least 500 employees, so that the results must be interpreted carefully with respect to SMEs. As common in survey-based research, our results could be biased by subjectivity and/or single-respondent bias given that we have limited to representatives of the controlling function. It should also be considered that our survey took place during the COVID-19 pandemic. Thus, our results could be biased by the specific time period, with the consequence that in order to test for robustness of our results, our survey must be repeated at a later stage to discover possible time effects, such as problems of uncertainty or intergroup relations within the decision-making process that should be improved (Fink et al., 1971). However, endogeneity issues in general, i.e., unobserved firm characteristics that might affect our results, can only be ruled out by repeating a study using different designs and analyses (Hill et al., 2021).

Although the total effect between the variables *Advanced analytical capabilities* and *Controllership influence on management decisions*, which is mediated by the variable *Controllers’ business partnering behavior*, is well significant and the path coefficient between *Advanced analytical capabilities* and *Controllers’ business partnering behavior* indicates a strong (.30) significant effect, *Advanced analytical capabilities* explains only 9% of the variance in *Controllers’ business partnering behavior*. This opens the question which additional causes could explain the variable and should be an additional subject of further research.

In terms of the statistical point of view, our results are limited in terms of representativeness because of our non-randomized sample selection. However, our sample was drawn from a heterogeneous population composed of 5,758 large German companies with more than 500 employees. Given cross-sectional data, our findings may not hold for a specific industry. On the other hand, there is no evidence that the issues discussed in our study have distinct relevance with respect to specific industries. A further statistical limitation arises from the quasi-formative measurement of the variable data integration by means of an additive index. As the index is measured as a manifest variable, it neglects an error term that common formative latent variables in general have. An error term represents the impact of all remaining causes other than those represented by the indicators included (Diamantopoulos, 2006). Thus, using a composite index assumes that the underlying indicators completely grasp the construct, which is most usually inappropriate (Diamantopoulos, 2008). However, as Diamantopoulos (2006) emphasize, indexing is contingently if all possible indicators of a construct can be specified. This requirement is expected to be fulfilled in case of our composite index, as the used two key perspectives of data integration are derived from established IS literature (Popovič et al., 2012).

Since digital transformation has a tremendous impact on structures and processes within an organization – e.g., communication shifts to digital media – additional organizational factors could be subject of further research. In addition, longitudinal studies should be conducted to analyze the impact on variability, which is also influenced by the ongoing transformation of the digital economy.

# Appendix

**Table A1: Item summary**

| Construct | Label | Indicator |
|---|---|---|
| | | (0 … 100) |
| Controllers' business partnering behavior | CBP | Please allocate your actual time spent on the controller role as Business partner / Advisor of management (i.e. active support of management in decision-making process) in % |
| | | (0 = not agree … 5 = completely agree) |
| Data integration | DI1 | Data are scattered everywhere – on the mainframe, in databases, in spreadsheets, in flat files, in ERP applications. … Data are completely integrated, enabling real-time reporting and analysis. |
| | DI2 | Data in the source are mutually inconsistent. … Data in the source are mutually consistent. |
| | | (0 = not agree … 5 = completely agree) |
| Advanced analytical capabilities | AC1 | Analytical applications, including trend and scenario analysis |
| | AC2 | Data Mining |
| | AC3 | Statistical forecast models |
| | AC4 | Simulations, including recommendations for actions |
| | | (0 = not agree … 5 = completely agree) |
| Controllership influence on management-decisions | CI1 | Controlling plays a very important role in decision-making in our business area. |
| | CI2 | Management attaches great importance to the opinions of controlling in decision-making. |
| | CI3 | Controlling has a strong influence on management decisions in our business area. |

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# E Affidavit

Ich erkläre hiermit, dass ich die vorgelegten und nachfolgend aufgelisteten Aufsätze selbstständig und nur mit den Hilfen angefertigt habe, die im jeweiligen Aufsatz angegeben oder zusätzlich in der nachfolgenden Liste aufgeführt sind. Bei den von mir durchgeführten und in den Aufsätzen erwähnten Untersuchungen habe ich die Grundsätze guter wissenschaftlicher Praxis, wie sie in der Satzung der Heinrich-Heine-Universität Düsseldorf zur Sicherung guter wissenschaftlicher Praxis niedergelegt sind, eingehalten.

Düsseldorf, 21. April 2023

*Mark Alexander Sutton*

***Papers of this dissertation:***

Paper 1: It's more than just numbers: The impact of data integration on controllership effectiveness

Paper 2: Controllers as business partners in times of pandemic: The impact of business partnering on controllership effectiveness in revenue forecasting

Paper 3: From data to insights: How advanced analytical capabilities strengthens the controllers' role in managerial decision-making