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ORIGINAL ARTICLE

Digital Maturity of Forecasting and its Impact in Times of Crisis

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Abstract Especially in times of crisis, reliable predictions about probable future developments are difficult, but critical for successfully managing business operations. At the same time, it remains unclear what constitutes a good forecasting process during crises. The aim of this study is to analyze whether and how digital transformation can enhance forecasting processes and enable firms to better deal with crises. To do so, we refer to the concept of digital maturity, i.e., the extent to which digital transformation is adopted in internal processes, studied at the practice of forecasting. Specifically, we analyze whether digitally more mature forecasting processes positively influence (1) satisfaction with forecasting during crises, (2) the effectiveness of countermeasures, and (3) the economic situation during crises. We conduct a cross-sectional survey among 195 medium-sized and large companies in Germany to shed light on the forecasting process and its digital maturity as well as on the impact of the COVID-19 economic crisis on companies. Based on ordinary least squares (OLS) regression, we find that digitally more mature forecasts increase satisfaction with forecasting and the effectiveness of countermeasures. Overall, this study provides new insights into relevant aspects of forecasting to support successful crisis management, and it highlights the importance of advancing digital transformation in forecasting, especially to successfully deal with crises.

Availability of data Data are available from the corresponding author upon request.

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1 Introduction

> "Prediction is very difficult, especially if it's about the future." (Nils Bohr, Nobel laureate in Physics)

The COVID-19 pandemic is just one of many disruptions that the economy has faced during recent decades (Donthu and Gustafsson 2020), with scholars arguing that the probability and occurrence of crises is rising steadily (Fainshmidt et al. 2017; Vargo and Seville 2011). This business environment is often characterized by volatility, uncertainty, complexity and ambiguity, thus giving rise to the term "VUCA". To tackle these challenges, forecasting, that is, "the prediction of future events and their quantification for planning purposes" (CIMA 2005), has become a core management process (Morlidge and Player 2010). The estimation of possible developments and the generation of various courses of action as a reaction to these developments are essential to an efficient and effective planning process (Armstrong 1983; Hogarth and Makridakis 1981; Hyndman and Athanasopoulos 2018). The abilities to adequately respond to current economic conditions, remain future oriented and act on up-to-date information are fundamental to all business decisions (Morlidge and Player 2010; Zaich et al. 2012). Especially in times of crisis, which are characterized by threats to basic structures, high uncertainty and time pressure (Ezzamel and Bourn 1990), making swift decisions with short lead time is vital to the success of businesses.

Although the general importance of forecasting is widely recognized, in times of crisis, it is unclear what constitutes a good forecasting process and a good forecast (Morlidge and Player 2010). The general aspects determining successful forecasting that have been discussed in the literature are manifold and comprise, among others, the degree of detail, the cycle time, the frequency of updating, the length of the forecasting horizon and the level of accuracy (Morlidge and Player 2010). Beyond these technical features, in practice, there is a need for an understanding of how the forecasting process can be further integrated successfully within organizations (Armstrong 1988; Danese and Kalchschmidt 2011b). Thus, we expect that digital transformation plays a crucial role in forecasting as an instrument for successfully managing crises. In general, new information technologies, more advanced prediction methods and applications, and trends toward big data are disrupting the field of management accounting and have the potential to change the way forecasts are generated and interpreted (Möller et al. 2020; Oesterreich et al. 2019). Whether such changes are adopted and integrated into firms' internal (forecasting) processes is captured by their *digital maturity* (Aslanove and Kulichkina 2020). We refer to this general concept and apply it to the specific context of forecasting. Based on prior literature, we identify three main determinants of the digital maturity of forecasting. In particular, a higher digital maturity of forecasting can translate into more digitalized and automated processes, a higher methodological sophistication, i.e., a larger variety of forecasting techniques available, and changes in the volume of data considered and generated (Faloutsos et al. 2019; Gandomi and Haider 2015; Morlidge and Player 2010). Digitally more mature forecasts can result in cost and time savings and in a lower susceptibility to errors with respect to data entry and consolidation (Bergmann et al. 2020; Dmytrenko et al. 2020), which should be particularly relevant during crises when quick predictions and reactions are needed.[1]

Based on this reasoning, we investigate in this paper how the three determinants of digital maturity of forecasting noted above, i.e., digitalization and automation, methodological sophistication, and data volume, affect successful forecast generation and its application during crises. In the first step, we deduce how the determinants influence satisfaction with forecasting during crises. For the purpose of this paper, we define forecasting satisfaction as satisfaction with the entire forecasting process, including configurations of the inputs, methods, processes, outputs, and systems involved. Specifically, we predict that a higher level of digitalization and automation, a higher level of methodological sophistication, and a lower, more focused level of input and output data volume positively influence satisfaction with forecasting. In the second step, we look at the potential benefits of the three determinants of the digital maturity of forecasting for the effectiveness of the countermeasures taken as part of crisis management. Again, we predict that digitalization and automation, and methodological sophistication are positively associated with the effectiveness of countermeasures during crises, while data volume is negatively associated. Third, we investigate whether digitally more mature forecasting processes are ultimately also positively associated with the economic situation during a crisis, which we use to describe firms' activities in crisis situations. To be able to adequately link forecasting to the overall management and economic situation of the firm, we focus our considerations on internal management forecasts, i.e., condensed forecasts comprising various functional forecasts, e.g., production or sales forecasts, to support management in steering their businesses at the company level.

We test our hypotheses with data collected via a survey among German companies between July and September 2020, shortly after the start of the COVID-19 pandemic. Using ordinary least squares (OLS) regression, we provide evidence that the determinants of digital maturity play a significant role in forecasting during crises. Regarding our first set of hypotheses, we find that higher digitalization and automation and a lower data volume result in higher satisfaction with forecasting during crises. We trace this finding back to the fact that digitalization as well as focused, precise (input and output) data help to analyze a company's situation in a timely manner. Second, regarding the effectiveness of countermeasures, all three determinants have a significant effect. While digitalization and automation, and

[1] Irrespective of digitally more or less mature forecasting, past data used to forecast might only be of limited use during crises, as, per definition, crisis situations are unique and cannot be (fully) predicted by past developments (Ezzamel and Bourn 1990; Janke et al. 2014). Nevertheless, digitally more mature forecasts can be advantageous as they are less prone to errors due to automated data entry and consolidation possibilities, and might help to process data more quickly and flexibly.

methodological sophistication are positively associated with effective countermeasures, the data volume again reveals a negative association, pointing to the benefits of focused data sets. Finally, we find slight support for the notion that the digital maturity of forecasting also influences the economic situation during crises. Here, only digitalization and automation exert a significant positive effect, which might be traced back to the limited period of the crisis captured by our survey.

Within our additional analyses, we first investigate the influence of the digital maturity of forecasting on cost- and liquidity-saving measures. Second, we elaborate the differences observed in forecasting practices within our sample, comparing the forecasting process during the crisis with the process used prior to the crisis. We use the additional insights to provide possible explanations for our main results.

Our study contributes to research and practice in several ways. First, we elucidate how digital transformation changes forecasting, especially during crises. Although it is expected that digital transformation influences or will influence nearly every process and every business transaction, little is known about its specific effects on forecasting (Möller et al. 2020; Oesterreich et al. 2019). Hence, we investigate the advantages of digitally more mature forecasting as a tool for crisis management. Therefore, we are the first to apply the general concept of digital maturity as proposed by Aslanove and Kulichkina (2020) to the forecasting process and establish three main determinants of the digital maturity of forecasting. Additionally, by empirically testing aspects that contribute to satisfaction with forecasting within organizations, we investigate the factors that constitute good forecasting. Hence, we respond to the need for research that identifies the determinants of effective forecasting (Danese and Kalchschmidt 2011a, b; Morlidge and Player 2010), but we focus on times of crisis. Second, as our results also reveal positive effects on the effectiveness of countermeasures and slight effects on the economic situation, we show that the value of a higher maturity of forecasting goes beyond satisfaction and has further economic benefits for companies. In this regard, our findings empirically underline the value of digitally mature forecasting (Doering and Suresh 2016) and are especially valuable because crisis conditions mark a unique possibility to test the value of forecasting during times where reliable information for steering a business is most needed (Pavlatos and Kostakis 2018). Third, within our additional analyses, we provide insights into whether more or fewer cost- and liquidity-saving measures are perceived as advantageous during crises and how these measures are associated with the digital maturity of forecasting. Furthermore, we analyze how forecasting changes during times of crisis. Hence, we illuminate various aspects of forecasting and how firms use these levers to react to increased volatility and uncertainty in business environments.

The remainder of this paper is structured as follows. Section 2 provides the theoretical background and related literature. Section 3 develops the hypotheses. Section 4 describes the design and methodology of our research, whereas Section 5 presents the empirical results. Section 6 concludes the paper by discussing the results and directions for further research.

2 Background and Related Literature

2.1 Crisis Management

In general, crises can have different origins, including technical, societal, organizational, or environmental reasons (Mitroff 2004; Mitroff et al. 1988). To characterize crises by their origin, Mitroff et al. (1988) distinguish between internal vs. external and technically/economically induced (i.e., nonhuman) vs. human induced. Becker et al. (2016) take certain crisis characteristics into account and differentiate between global and idiosyncratic crises. According to both, the COVID-19 crisis can be categorized as external, nonhuman induced and global. Although it started as a pandemic with primary sanitation issues, political reactions, including lockdowns, trade barriers or production and consumption restrictions, it resulted in severe economic and financial impacts that led to a global economic crisis (Donthu and Gustafsson 2020; Verma and Gustafsson 2020). Consequently, from the firms' perspective, the ramifications of COVID-19 are characterized by general crisis conditions, such as a high degree of uncertainty and volatility, unexpected and surprising elements, ambiguous and ill-structured decision-making, threats to firm survival, and the need for rapid reactions (Ezzamel and Bourn 1990; Fainshmidt et al. 2017; Janke et al. 2014). In this context, crisis management has become an important part of the general planning process (Preble 1997). When effectively combined with the general planning process, it can help to anticipate possible changes in economic conditions, to adapt to them accordingly, and to thus take upcoming chances and fight possible risks (Makridakis 1996).

Various definitions of crisis management exist, one of which defines it as "an ongoing systematic and comprehensive effort that organisations put in place in an attempt to identify and prevent potential risks and problems and to manage those that occur to minimise damages and maximise opportunities, considering learning, planning and training activities as well as the interests of organisations' stakeholders" (Wang and Ritchie 2012, p. 1058). This definition appeals to several important aspects of crisis management and reflects the three phases that are often discussed with respect to crisis management (John-Eke and Eke 2020; Wang and Ritchie 2012). First, in the pre-crisis phase, the anticipating element of crisis management is stressed (Preble 1997). Better situational awareness and general preparedness can consequently be used to act proactively in arising crisis situations (Prochazkova et al. 2015). This is especially important in light of the unpredictability of crises (John-Eke and Eke 2020). Second, in the in-crisis phase, appropriate actions related to the crisis situation must be taken as a response to adverse circumstances (Prochazkova et al. 2015; Vargo and Seville 2011; Wang and Ritchie 2012). Due to the dynamicity and volatility that normally come with crisis situations, decisions made regarding crisis reactions are often time critical and have to be made on the basis of incomplete information (Prochazkova et al. 2015). Last, the after-crisis phase is characterized by evaluation and learning activities to better prepare for upcoming crises (Wang and Ritchie 2012). Thus, the objective of crisis management is to ensure the survival of organizations and to provide conditions that allow for a fast recovery and redevelopment by ensuring the smooth running of the basic functions of firms at all times (Prochazkova et al. 2015). In our investigation, we focus on the extent to which the digital maturity of forecasting contributes to overcoming and managing crises in general, which is important for businesses to be successful.

2.2 Forecasting as an Important Tool in Corporate Planning and Management

In general, forecasting, i.e., the generation of forecasts[2], is concerned with detecting patterns and relationships from past data and, based on the information available and reasonable assumptions made, projecting these trends into the future (Makridakis 1996). Considering the idea of uncertainty from Knight (1921), who defines uncertainty as a lack of information when deciding what future courses of action to take, forecasts can directly help to reduce uncertainty by providing management with the necessary information about probable future developments. Forecasting further forms an important input to corporate planning and strategy formulation (Hogarth and Makridakis 1981; Makridakis 1981), and if linked adequately, it helps not only to anticipate future developments but also to respond to them accordingly (Morlidge and Player 2010). By doing so, forecasting supports companies in implementing the measures needed not only in everyday business, but also, especially, in times of crisis, when fast and precise reaction is needed (Slaughter 1990).

Within business and economics, a series of different forms of forecasting exist. In macroeconomics, long series of historical economic data are typically used to forecast variables such as inflation, GDP or unemployment (Stekler 2007). In contrast, managements' earnings forecasts represent voluntary disclosed financial information usually issued within interim financial reporting (e.g., Hirst et al. 2008; Knauer and Wömpener 2011). Third, and most relevant to the remainder of this paper, are forecasts used within a firm for purposes of corporate planning and management. Within an organization, forecasts serve as decision support in various functional areas, including operations, marketing, sales, finance, risk management and strategy (Armstrong 1983; Diebold 2006). Prior research shows that demand forecasts as well as sales and operations forecasts are used as the basis for most planning and control activities in organizations (Petropoulos et al. 2022). Different strands of literature exist for the respective functional forecasts, e.g., the production forecasting literature, which is concerned with improving the forecasting process not only inside a company (Danese and Kalchschmidt 2011a, b) but also along the supply chain using collaborative forecasting (Eksoz et al. 2014; Henttu-Aho 2018). To the best of our knowledge, however, there is only a limited amount of literature that explicitly focuses on the use and effects of forecasting on a holistic corporate level and in times of crisis. On the one hand, this situation implies that we broadly rely on specific area forecasting studies and transfer these findings to our research model. On the other hand, this situation shows that our paper can make a meaningful contribution to the literature in that it explicitly considers forecasting within a general planning setting and examines its effects on the overall situation of firms in times of crisis.

[2] We use the terms "forecasting", "forecasting process" and "forecast generation" interchangeably and describe the process of generating a forecast, i.e., the use of input data, which, by means of particular forecasting methods, generates a forecast, i.e., the output of the forecasting process.

We therefore specifically focus on high-level internally aggregated forecasts that are prepared by management accounting departments and serve as decision support for corporate planning decisions. Within this context, most firms use sales figures as forecast figures and break down their forecasts to lower levels for more specific planning purposes (Lawrence et al. 2000).

2.3 Digital Maturity of Forecasting and Its Effect On Crisis Management

When analyzing how forecasting contributes to crisis management, we are especially interested in whether and how the digital maturity of forecasting improves firms' situations during crises. Digital maturity can be defined as the extent to which firms systematically adapt to ongoing digital change and integrate digitalization into their processes, ultimately translating into improvements in firm operations (Aslanove and Kulichkina 2020). Currently, firms generally build increasingly on new business intelligence and more digitally mature processes when generating and interpreting their forecasts (Bhimani and Willcocks 2014). Doing so might offer enhanced opportunities to adjust to crises, as digital technologies change the speed and flexibility of information processing. To investigate whether more digitalized forecasting helps to address a crisis, we consider three determinants that relate to the digital maturity of forecasting.

The first determinant we consider is *digitalization and automation*. Digitalization and automation are major trends that influence nearly every business transaction (Gulin et al. 2019; Haaker 2020). They set the framework for how tasks and processes are carried out and determine opportunities and requirements (Neuburger and Fiedler 2020; Oesterreich et al. 2019). Although they are strongly related, they can manifest in different ways within management accounting (Mancini et al. 2017; Erichsen 2019). Specifically, digitalization within a management accounting context can be defined as "the use of digital technologies and of data in order to [...], improve business, replace/transform business processes [...] whereby digital information is at the core." (Clerck 2017; Reis et al. 2020). With respect to forecasting, value can be derived by new possibilities to generate future-oriented information more conveniently and with higher assurance in decision-making (Schneider et al. 2015). Furthermore, the digitalization of forecasting enables more data-driven decisions, as computational power is increasing steadily (Faloutsos et al. 2019). Similarly, automation, that is, "a device or system that accomplishes [...] a function that was previously, or conceivably could be, carried out [...] by a human operator" (Parasuraman et al. 2000, p. 287), changes the forecast generation process (Lorain 2010; Möller et al. 2020). Armstrong (1988) pointed out that there are many aspects in forecasting that have the potential to be automatized. Internal and external data warehouses can be permanently accessed to reliably generate forecasts with the most current data input available, especially regarding data retrieval (Castellina 2013). Hence, the digitalization of structures and data and the automation of processes, especially with respect to data updating and retrieval, contemporaneously influence and shape the forecasting process. That is, the digitalization and automation of forecasting represent an important determinant of the digital maturity of forecasting and will probably be advantageous during crises.

Second, we expect *methodological sophistication* to exert positive effects on crisis management since it is generally essential for the appropriate forecasting methods for the purpose of a forecast to be applied (Morlidge and Player 2010). In this regard, methodological sophistication describes the variety of forecasting techniques, such as regression and time series analysis, clustering and classification analysis, that a company potentially has for use in forecast generation. These techniques help to uncover patterns in historical data and establish cause-effect relationships to make inferences from past events to facilitate future developments (Abraham and Ledolter 1983; Armstrong 1983; Zaich et al. 2012). Having more sophisticated quantitative methods available makes it possible to better extract patterns from the past and thus allows more meaningful predictions to be generated for the future (Armstrong 1988; Faloutsos et al. 2019). On the one hand, being able to apply a series of different forecasting techniques increases the likelihood of using the technique that best fits the data and the decision situation at hand. On the other hand, this idea is amplified by the fact that findings from the literature suggest that a combination of different forecasting methods provides the opportunity to integrate more information and reduces judgment bias regarding forecasting (Armstrong 2001; Danese and Kalchschmidt 2011b). However, there are also approaches assuming that the use of these methods is not exclusively beneficial. For example, Blackburn et al. (2015) reported that inertia is often a problem when implementing more sophisticated forecasting methods, as model parameters have to be fitted to the new methods to be integrated meaningfully into the forecasting process. Additionally, several authors stress that more sophisticated methods add complexity to the forecasting process (Blackburn et al. 2015; Doering and Suresh 2016). Additionally, for forecasts to be applied correctly, the capabilities of employees using forecast information are crucial (Elliott and Timmermann 2008). Nevertheless, we believe that the possibility of using more sophisticated forecasting methods, alone or in combination, improves forecasting during crises.

Third, we refer to the input/output *data volume*, which contains the indicators of forecasting and, thus, the number of input variables used in the forecasting process as well as the key performance indicators (KPIs) of forecasting, i.e., the number of outputs generated in the forecasting process. Research suggests that the information base that forms the input of forecasts and the outputs plays an important role (Georgoff and Murdick 1986). Generally, the trend toward digital progress and big data enhances the pool of readily available data usable for forecasting purposes (Gandomi and Haider 2015; Hofmann 2015). However, opinions on whether more or less data (out of this pool) are best for good forecasting diverge. On the one hand, regarding forecast input, research suggests that forecasts should be generated on the basis of "all information available" (Hyndman and Athanasopoulos 2018; Nordhaus 1987). Consistent with this, several studies have investigated the relationship between the quantity of indicators used as input for forecasts and forecasting quality and find a positive relationship (Danese and Kalchschmidt 2011a, b; Faloutsos et al. 2019; Georgoff and Murdick 1986). Furthermore, regarding forecast output, more KPIs could give a better orientation and provide a broader picture of what companies should aim for when deciding on the courses of action to take. On the other hand, Fan et al. (2014) describe big data as an "explosion of available info", pointing out not only new possibilities but also new challenges regarding forecasting as selecting the most relevant input and output data becomes even more crucial (Bhimani and Willcocks 2014; Stratigakis and Kallen 2017). Regarding the inputs for forecasts, Brockhoff (1984) claimed that the better the inputs are understood and selected, the better the quality of the forecasts generated. Hence, although big data provides vast amounts of data, the selection of limited but suitable input data becomes a core challenge. Concerning the outputted KPIs, theory as well as practice stressed the fact that it is crucial to forecast only those KPIs that are critical to business success (Capon and Hulbert 1985; Vieweg Verlag Wiesbaden 2016; Claus and Rüthers 2017; Becker and Schäffer 2017). If instead too many KPIs are generated, they can lead to confusion and cannot be used in a meaningful manner, especially for (quick) decision support. Accordingly, especially during the 2008 financial crisis, companies aimed to simplify their forecasting data and focused on fewer but critical input and output variables (Weber and Zubler 2010). Especially in times of crisis, we expect that it is expedient not to use and generate all data possible but to rely on less but suitable data to generate useful and interpretable forecasts.

To deduce whether the three presented determinants of the digital maturity of forecasting enhance the crisis management of firms, we analyze how they affect (1) satisfaction with forecasting during crises, (2) the effectiveness of countermeasures, and (3) the economic situation of companies during crises.

3 Hypothesis Development

3.1 Effects of the Digital Maturity of Forecasting on Satisfaction with Forecasting during Crises

To investigate the contribution to a firm's crisis management, first, we focus on how the digital maturity of forecasting affects satisfaction with the forecasting process during crises. In general, digitally more mature forecasting can save resources and thus increase the convenience for the employees who are responsible for and/or use forecasts (Brynjolfsson and Hitt 1995, 2000; Davenport and Short 1990). These aspects should be particularly relevant during crises when, on the one hand, an analysis of the situation and, building on that, the decision of how to proceed and react must be made as timely as possible (Ezzamel and Bourn 1990; Fainshmidt et al. 2017; Janke et al. 2014). On the other hand, the increased complexity of the situation renders effective forecasting even more critical (Armstrong 1983).

The context described directly relates to the *digitalization and automation* of forecasting. When the forecasting process is digitalized and automated, fewer (human and time) resources are necessary to generate forecasts, which should increase satisfaction with forecasting, especially among forecast preparers (Bergmann et al. 2020). Specifically, digitalization and automation in forecasting free up a significant amount of time that, for instance, would be needed for manual data entry, data update, or data analysis. This time could instead be used to challenge assumptions in a collaborative manner when aggregating forecasts, to better reflect on the forecasted results or to devote time to other tasks (Dmytrenko et al. 2020). Although we focus on forecast preparers, literature also suggests that more digitalized and automated forecasting also increases the satisfaction of forecast users, as it allows decision-makers to receive forecasts more quickly (Bhimani and Willcocks 2014). Hence, as both faster generation and faster decision-making are crucial during crises since developments in crises are fast and volatile (Prochazkova et al. 2015; Vargo and Seville 2011; Wang and Ritchie 2012), digitalized and automated forecasts should disburden forecast preparers and users and thus make them feel more satisfied. Accordingly, we predict a positive association between digitalization and automation and satisfaction with forecasting during crises.

Similarly, *methodological sophistication* is expected to enhance employees' satisfaction with forecasting. Especially during crises, it is important to use the technique that best fits the data, which is more likely when employees are able to apply a series of different forecasting techniques. Then, important drivers of crisis development can be more easily and quickly discovered, which in turn helps to generate predictions that are more meaningful and, based on these predictions, decide how to react (Armstrong 1988; Faloutsos et al. 2019). Hence, we expect that employees who generate forecasts that more precisely predict future developments and decision-makers who determine the measures to counter and overcome crises are more satisfied with forecasting when methodological sophistication is higher, which again reflects a positive association.

Lastly, we refer to the *data volume* and its effect on satisfaction with forecasting. Especially during crises, we expect that fewer and thus more pinpointed data are beneficial, focusing only on the most important forecast inputs and KPIs. The reason is that focusing on only a few critical input and output variables can save time and increase efficiency in generating forecasts and decision-making to steer businesses accordingly. This is confirmed by firm practice where responsible forecast preparers and users state that a more focused approach on only the most relevant control-related KPIs relieves management accountants, ensures planning quality and effectively enhances the steering of the business based on the forecasts generated (Vieweg Verlag Wiesbaden 2016; Claus and Rüthers 2017; Becker and Schäffer 2017). It is further found that the planning quality is not significantly better with more detailed forecasting based on a higher number of inputs and outputs (Vieweg Verlag Wiesbaden 2016; Claus and Rüthers 2017) and that a high number of variables to consider might even distort the information retrieval and processing (Armstrong 1983). A lower but better fitting data volume therefore increases the convenience of forecasting and, consequently, satisfaction with forecasting as more time can be dedicated to analyzing the underlying causes and effects of the predicted variables (Brynjolfsson and Hitt 1995, 2000; Davenport and Short 1990; Vieweg Verlag Wiesbaden 2016). Hence, we expect the data volume to be negatively associated with satisfaction with forecasting during crises.

In summary, we predict that the three determinants of the digital maturity of forecasting affect satisfaction with forecasting during crises as follows:

- **H1a:** Digitalization and automation in forecasting are positively associated with satisfaction with forecasting during crises.
- **H1b:** Methodological sophistication in forecasting is positively associated with satisfaction with forecasting during crises.
- **H1c:** The data volume in forecasting is negatively associated with satisfaction with forecasting during crises.

3.2 Effects of the Digital Maturity of Forecasting on the Effectiveness of Countermeasures during Crises

Since crises are characterized by high uncertainty, elements of surprise and threats to the basic structures of companies, the pressure to react properly and in time is high (Ezzamel and Bourn 1990). Otherwise, crisis conditions most often strongly weaken companies' cost and liquidity situations, rendering adequate countermeasures highly important (Eichholz et al. 2021; Janke et al. 2014; Milic 2011; Wright 2020). To be precise and effective, the measures must take the core competencies as well as the specific situation of the company and its environment into account (Briciu and Sas 2009). To deduce countermeasures, decision-makers build on forecasting since forecasts help to reduce uncertainty and provide orientation for decisions (Abraham and Ledolter 1983; Makridakis 1981). Hence, it is crucial that forecasts are generated adequately and present the necessary data to decision-makers in a timely manner (Zaich et al. 2012). Only then can the implemented measures help to effectively improve firms' situations. To generate a better decision base that is quickly available, it is conceivable that the digital maturity of forecasting influences the effectiveness of countermeasures during crises, which is the focus of our second set of hypotheses.

Regarding the first determinant of digital maturity, which is *digitalization and automation* in forecasting, we expect a positive effect on the effectiveness of countermeasures. According to Warren et al. (2015), digital processes help to provide relevant information in a timely manner and to gain insights that are crucial for managers' decision-making, which is considered to be a key aspect of effective forecasting (Morlidge and Player 2010). Therefore, digitalized and automated forecasts should help to quickly present the necessary data to decision-makers to deduce which countermeasure should be taken to address a crisis in the best way possible (Zaich et al. 2012). Hence, as digitalization and automation in forecasting are likely to enhance the decision base in terms of the timing of the provision and presentation of data, they should be highly advantageous to effectively react to crises.

Comparably, we also expect the second determinant, *methodological sophistication*, to improve the decision base for effective countermeasures. Research suggests that more sophisticated analyses increase the quality of forecasts and thus enable more transparency and better comprehensibility, therefore improving decisions (Arnaboldi et al. 2017; Warren et al. 2015). Thus, methodological sophistication forms a central prerequisite for determining countermeasures that effectively mitigate crisis threats and improve firms' situations. Again, this should be specifically relevant in times of crisis, supporting the quick design and implementation of appropriate countermeasures. Therefore, we also expect a positive association between methodological sophistication and the effectiveness of countermeasures during crises.

Third, we predict that *data volume*, as the last aspect of digital maturity, is negatively associated with the effectiveness of countermeasures during crises. On the one hand, the necessity of fast reactions in crises underlines the fact that forecasts have to be generated quickly (Prochazkova et al. 2015; Zaich et al. 2012), which should be easier to realize if fewer input variables have to be considered for the generation of forecasts. On the other hand, the outputted KPIs should also be deliberately reduced. As firms are generally impaired in their cost and liquidity situation during crises, they have limited financial and human resources (Janke et al. 2014; Milic 2011; Wright 2020). Evidence from practice further stresses that too much data might lead to a loss of focus in the analysis (Vieweg Verlag Wiesbaden 2016) due to cognitive limitations in information processing (Hogarth and Makridakis 1981) and that it is crucial to concentrate on only the most relevant drivers of firm performance, especially in volatile and uncertain times (Claus and Rüthers 2017). Against this backdrop, we expect that decision-making on countermeasures is facilitated when only the most relevant KPIs are generated within forecasts and are afterward presented and analyzed. Overall, we therefore expect a negative association between the (input and output) data volume and the effectiveness of countermeasures.

Therefore, we predict that the three determinants of the digital maturity of forecasting affect the effectiveness of countermeasures during crises as follows:

- **H2a:** Digitalization and automation in forecasting are positively associated with the effectiveness of countermeasures during crises.
- **H2b:** Methodological sophistication in forecasting is positively associated with the effectiveness of countermeasures during crises.
- **H2c:** The data volume in forecasting is negatively associated with the effectiveness of countermeasures during crises.

3.3 Effects of the Digital Maturity of Forecasting on the Economic Situation during Crises

Finally, we examine whether digitally more mature forecasts are also directly beneficial for companies' economic situation during crises. In line with our general expectation, Teach (1993) reported a strong link between the ability of management to forecast outcomes and their firms' performance. Similarly, Danese and Kalchschmidt (2011a) explain that improvements in forecasting processes can positively affect the economic situation. As a comparable improvement, we expect that digitally more mature forecasts exert positive effects and should also translate into a better economic situation. In line with precise corporate planning being useful in situations that are complex and uncertain (Hogarth and Makridakis 1981) and have the potential to change rapidly (Zaich et al. 2012), this should be particularly relevant during crises (Hyndman and Athanasopoulos 2018). As digital maturity of forecasting describes the systematic adaption to ongoing digital change and the integration of digitalization into processes, both of which cannot be changed in the short run, the digital maturity as of before the crisis should benefit the economic situation during the crisis. In the following, we deduce the association between the three determinants of digital maturity and the economic situation during crises in more detail.

First, we refer to *digitalization and automation*. Research shows that more structured forecasting processes can help to improve the economic situation (Danese and Kalchschmidt 2011a). As one approach to conduct forecasts in a more structured and standardized way is to automize them (Neuburger and Fiedler 2020; Oesterreich et al. 2019), we expect a positive association between digitalization and automation and the economic situation during crises. As digitalization and automation are major changes with respect to management accounting and forecasting (Gulin et al. 2019; Erichsen 2019) and often require considerable time to materialize (Brynjolfsson et al. 2019), the degree of digitalization and automation before the crises should translate into the economic situation during crises. If implemented successfully before the crises, digitalized and automated forecasts are advantageous as they are less prone to judgment bias or the consideration of irrelevant information (Makridakis et al. 1998). Hence, digitalized and automated forecasts should enhance the decision base for business decisions, which should translate into an improved economic situation, representing a positive association.

This argumentation regarding providing a better decision base and thus enhancing the economic situation is also transferrable to the second determinant of digital maturity, which is *methodological sophistication*. Methodological sophistication corresponds to the precept that it is of critical importance to apply “the right approach for the right problem” (Danese and Kalchschmidt 2011a, p. 205). This is more likely if the methodological sophistication in forecasting is higher. Furthermore, as outlined above, by more easily detecting relevant drivers in the past to predict the future, developments and reactions can be better determined, which will probably have a positive influence on the economic situation (Abraham and Ledolter 1983; Armstrong 1983; Zaich et al. 2012). Hence, especially in times of crisis, where developments can change rapidly, methodological sophistication is expected to exert the positive effects on the economic situation of firms described above.

Third, the economic situation should benefit from what is contextually the right *data volume* in forecasting. Prior research reveals that changes in prices, margins and costs are firms’ most frequent measures in adjusting operational steering during crises (Fabiani et al. 2015). Furthermore, the results of Wright (2020) show that good liquidity management is fundamentally important during crises and that not having enough liquidity is the most prominent reason for firm insolvency (Briciu and Sas 2009). Hence, to improve firms’ economic situation, forecasts should focus their input and output data on these aspects so that managers can promptly react and decide how to behave in these areas regarding the economic situation. Based on this focused view, we expect a negative association between the data volume in forecasting and the economic situation during crises.

Overall, we expect that the three determinants of the digital maturity of forecasting affect the economic situation during crises as follows:

- **H3a:** Digitalization and automation in forecasting are positively associated with the economic situation during crises.
- **H3b:** Methodological sophistication in forecasting is positively associated with the economic situation during crises.
- **H3c:** The data volume in forecasting is negatively associated with the economic situation during crises.

4 Research Method

4.1 Sample Description

To test our hypotheses, we conducted a survey over a six-week period from July to September 2020, shortly after the start of the COVID-19 pandemic. Sampling was carried out using the Dafne database by Bureau van Dijk. Of the total sample of solvent German companies with an annual revenue of at least €50 million as of the last available balance sheet date, 3000 companies were randomly selected. The questionnaire was sent out to management accounting departments by postal mail, allowing the respondents to return the survey by postal mail, e-mail, fax, or online via a link provided using the Unipark platform. In total, 195 questionnaires were returned (6.50%), out of which 180 questionnaires were valid for purposes of analysis (6.00%), offering promising data quality with only minor losses due to poor questionnaire responses.

The respondents mainly included directors (44.44%) and employees (27.22%) in management accounting. An average work experience of 10.5 years with the current company indicates adequate knowledge and ensures a good answer quality specifically with respect to questions including management accounting terminology and topics. Regarding the company characteristics, the sample mainly contained companies with annual revenue between €50 million and €250 million, between €500 million and €1000 million, and between €250 million and €500 million, representing 54.44%, 13.33% and 12.78% of all surveyed companies, respectively. In terms of industry distribution, the sample consisted of firms operating in a wide range of industries, with machinery and plant engineering (16.67%), retail/commerce (12.78%) and chemicals/pharmaceuticals/health care (12.22%) being the most strongly represented industries. Table 1 gives a detailed overview of the sample.

We tested for a potential nonresponse bias by using the widely applied early-late respondents' test, which assumes the structural similarity of the populations of late respondents and nonrespondents (Armstrong and Overton 1977). For that, we divided the sample into the earliest and latest one-third of respondents according to the return date of the questionnaire per the return medium. Conducting a two-sided t test, the late respondents showed a marginally lower level of implementation regarding sophisticated forecasting methods ($p = 0.05$) as well as a marginally higher extent of cost saving measures implemented ($p = 0.05$), while all other variables showed no significant differences regarding the compared means ($p > 0.10$), indicating no significant nonresponse bias.

Table 1 Characteristics of the sample data

Description	Frequency	Percent of Sample
Industry breakdown		
Automotive	17	9.44
Construction/Real Estate	18	10.00
Chemicals/Pharmaceuticals/Health Care	22	12.22
Utilities/Servicing/Disposal	13	7.22
Financial Services	3	1.67
Retail/Commerce	23	12.78
IT/Telecommunications	5	2.78
Consumer Goods	7	3.89
Transport/Logistics	5	2.78
Machinery and Plant Engineering	30	16.67
Product Manufacturers	20	11.11
Other	17	9.44
Total annual revenue (in million euros)		
Less than 50[a]	16	8.89
Between 50 and 250	98	54.44
Between 250 and 500	23	12.78
Between 500 and 1000	24	13.33
Between 1000 and 2500	13	7.22
More than 2500	6	3.33
Ownership structure		
Listed	48	26.67
Private	123	68.33
State-owned	6	3.33
Nonprofit	3	1.67
Strategy		
Cost Leadership/Efficiency	49	27.22
Differentiation/Quality	131	72.78
Respondents' function		
Management Accountant	49	27.22
Director of Management Accounting	80	44.44
CFO	23	12.78
Managing Director/CEO	16	8.89
Other	12	6.67

Note: The percentages may not add up to 100% due to rounding ($n = 180$).
[a]Due to the time lag between when the survey was conducted and the sampling criterion of a minimum annual revenue of €50 million as of the last balance sheet date, there are a certain number of companies with an annual revenue of less than €50 million.

4.2 Variable Measurement and Description

4.2.1 Independent Variables

For the purpose of this study, we developed a standardized questionnaire. Based on thorough literature research, our questionnaire drew on the findings of previous studies in the fields of forecasting, crisis management, and digitalization and automation (Bergmann et al. 2020; Collins et al. 1997; Danese and Kalchschmidt 2011a, b; Doering and Suresh 2016). To the extent possible, we used existing, validated scales and refined them if necessary. The research questions at hand and the rapid advances in digitalization and automation, however, required most items to be self-developed. First, we present the structure of the questionnaire and the measurement of the examined variables before the validity and reliability of the constructs used are discussed.

We divided the questionnaire into two main parts. The first part of the questionnaire examined the companies' situations in the second half of 2019 (pre-crisis), whereas the second part of the questionnaire queried the situation in the first half of 2020 (in-crisis). Within the two parts, the firms were asked about their current economic situation and their forecasting processes, including certain aspects of the digital transformation of this process. Additionally, one section about firms' reaction to the crisis was included within the in-crisis part. The questionnaire mainly consisted of items to be rated on a seven-point Likert scale, where "1" indicates no agreement at all and "7" indicates agreement to a very high degree.

Digitalization and Automation (*DIGI*) The latent variable *DIGI* reflects the computational aspects of digitalization and digital automation as well as their maturity. We asked the respondents to assess the status of forecasting in their organizations before the crisis regarding (1) the degree of digitalization, (2) the degree of automation and (3) the degree of maturity on a scale from "1" (very bad) to "7" (very good). Whereas the degree of digitalization and automation marks important trends in management accounting (Gulin et al. 2019), the degree of maturity accounts for a potential time lag between the implementation and pay-off of new technologies (Brynjolfsson et al. 2019). The final latent variable thus comprises three items, and the derivation can be seen in Table 2.

Methodological Sophistication (*METHSOPH*) Sophistication in the forecasting process is to a great extent driven by adequate methods and technologies in the field of predictive analytics that are used to generate forecasts (Faloutsos et al. 2019). Based on previous studies and related findings, we identified the statistical methods most relevant for the generation of forecasts within a company (Chen et al. 2012; Fan et al. 2014). The respondents were asked to state the extent to which they deployed online analytical processing (OLAP), regression analysis, outlier analysis, time series analysis, cluster analysis, text mining, classification methods, artificial neural networks and association analysis within their forecasting process before the crisis. The answers were recorded on a scale ranging from "1" (not at all) to "7" (to a very high degree). As seen in the measurement model section following the

Table 2 Results of factor analysis

Construct/Indicators	Standardized Factor Loading (CFA)	Composite Reliability	Average Variance Extracted
DIGI		0.906	0.763
Degree of digitalization	0.859		
Degree of automation	0.898		
Degree of maturity	0.863		
METHSOPH		0.835	0.459
Regression analysis	0.675		
Outlier analysis	0.631		
Time series analysis	0.686		
Cluster analysis	0.741		
Text mining	0.576		
DATA_FC		0.896	0.811
Indicators	0.901		
KPIs	0.901		
COUNTEREFF		0.887	0.663
Coping with the consequences of the crisis	0.855		
New opportunities	0.772		
Sufficient measures taken to combat the crisis	0.866		
Taking measures faster than competitors	0.758		
INCRISIS		0.887	0.724
Liquidity situation in the crisis	0.906		
Income situation in the crisis	0.876		
Debt situation in the crisis	0.765		
COSTSAVING		0.913	0.636
Reduction in wages and salaries	0.718		
Reduction in inventory costs	0.791		
Reduction in R&D spending	0.811		
Reduction in G&A expenses	0.873		
Reduction in marketing & sales spending	0.840		
Postponement of projects planned	0.743		
LIQSAVING		0.878	0.508
Faster collection of receivables	0.591		
Reduction in inventories	0.707		
Postponed payment of liabilities	0.817		
Borrowing of new funds	0.738		
Renegotiation of existing loans	0.766		
Use of governmental subsidies	0.717		
Delayed/reduced payment of wages and salaries	0.631		

Note: *CFA* confirmatory factor analysis variable description, not all items met the validity criteria to be included in the final latent variable. The final derivation of the latent variable, comprising five items representing the various statistical methods used for forecasting, is presented in Table 2.

Data Volume (*DATA_FC*) The number of indicators used as input variables for forecasts and the KPIs generated as output of forecasts are important levers for the information to be included as well as the information generated with respect to forecasting (Stekler 2007). Thus, the respondents were asked to state how many indicators they used to generate their forecasts and how many KPIs were recorded as output variables before the crisis. To be able to group the respondents in a meaningful way, the answer options consisted of groups of ten indicators/KPIs each, ranging from "1–10" to ">50" indicators/KPIs.

4.2.2 Dependent Variables

Satisfaction with Forecasting (*SATIS_FC*) To assess satisfaction with forecasting, we asked respondents to state their satisfaction with the forecasting process during the crisis on a scale ranging from "1" (very dissatisfied) to "7" (very satisfied). To capture the forecasting process with all its aspects in a holistic and coherent manner, we specifically asked the respondents about the forecasting process in its entirety, which means that *SATIS_FC* is a single-item variable.[3] Taking satisfaction as an overall measure is commonly done in management accounting research to capture a thorough picture and multiple facets of the process investigated (Bergmann et al. 2020; Hansen and van der Stede 2004).

Effectiveness of Countermeasures (*COUNTEREFF*) In addition to specific countermeasures and their extent taken, we assessed the effectiveness of these measures for crisis management purposes. We thus asked the respondents a number of questions relating to risks and chances with respect to the crisis and the measures implemented, the sufficiency of these measures and the timing of the implementation. These questions are in line with findings from the literature showing that crises often have a dual character in that they bear not only risks but also chances (Ezzamel and Bourn 1990), and a timely reaction is crucial in times of crisis (Hertati et al. 2020). We thus specifically asked to what extent companies (1) have been able to cope with the negative consequences of the crisis thus far, (2) have taken advantage of the crisis situation to seize new opportunities, (3) have taken measures that are sufficient to combat the crisis, and (4) have taken measures to combat the crisis faster than competitors. Answers were recorded on a scale ranging from "1" (not at all) to "7" (to a very high degree).

[3] Where appropriate due to the unidimensionality and objectivity of the question at hand, we used single-item constructs. However, for issues prone to more subjectivity and for a greater leeway of possible answer options, we used multiple-item constructs to account for the embedded complexity.

Economic Situation during a Crisis (*INCRISIS*) Last, the impact of the crisis on the companies was assessed by the three-item latent variable *INCRISIS*, comprising the liquidity situation, the profit situation and the ratio of assets to liabilities. The latent variable accounts for various consequences of the crisis on the economic situation. Thus, the respondents were asked to assess whether their liquidity situation, their earnings situation and their ratio of liabilities to total assets during the crisis were better than the corresponding situations of their competitors. Agreement with the given statements was measured on a scale ranging from "1" (does not apply at all) to "7" (does fully apply).

Cost-saving Measures (*COSTSAVING*) As cost-saving measures are an important means during crisis management (Milic 2011), we asked the respondents to state the extent to which various cost-saving measures were implemented as a reaction to the current COVID-19 crisis conditions. To capture the effects of the COVID-19 crisis on firms and their reactions, we specifically asked to what extent firms (1) reduced wages and salaries, (2) reduced inventory costs, (3) reduced R&D spending, (4) reduced G&A expenses, (5) reduced marketing and sales spending, and (6) postponed major projects planned. Answers were recorded on a scale ranging from "1" (not at all) to "7" (to a very high degree).

Liquidity-saving Measures (*LIQSAVING*) In addition to cost-saving measures, firms often implement liquidity-saving measures to combat acute crisis conditions (Wright 2020). Therefore, we asked respondents to express the extent to which specific liquidity-saving measures were implemented to react to the current crisis conditions. Specifically, respondents were asked to what extent (1) receivables were collected faster, (2) inventories were reduced, (3) liability payments were postponed, (4) new funds were borrowed, (5) existing loans were renegotiated, (6) governmental subsidies were used, and (7) wage and salary payments were delayed/reduced using a scale ranging from "1" (not at all) to "7" (to a very high degree).

4.2.3 Control Variables

In addition to our main variables, we controlled for several other variables in our research models. First, we refer to two forecasting-related control variables: forecasting accuracy and the timeliness of forecasts. The accuracy of forecasts (*ACCUR_FC*) was measured by forecast error and, thus, the difference between the predicted and actual values. In the literature and in practice, there is still no consistent measure of forecasting error (de Gooijer and Hyndman 2006; Mahmoud 1984). The measurements discussed and used most widely are the mean squared error (MSE), the root mean squared error (RMSE) and the mean absolute percentage error (MAPE) (de Gooijer and Hyndman 2006; Mahmoud 1984). We followed the literature but slightly adjusted the measurement to ensure good response quality (Danese and Kalchschmidt 2011a). To obtain answers efficiently, we asked the respondents to state the percentage deviation between the forecasted and actual values for the second half of 2019 in percentage points, which means that *ACCUR_FC* is a single-item variable. The timeliness of forecasts (*TIME_FC*) is also a single-item variable and is based on the question of how important forecasts were to react quickly to new developments, with the respondents using a scale ranging from "1" (not important) to "7" (very important).

Second, we included the individual characteristics of the respondents. As the position in the company can influence the point of view on the forecasting process, we asked the respondents which position they hold in the company, letting them choose between "management accountant", "director of management accounting", "CFO", "CEO" or "other", and we separately controlled for each of the categories (*POSITION*). We also included how long the respondent had already been working for the company (*DURATION_POSITION*), capturing the level of experience and knowledge of processes in the company, which could influence the respondent's evaluation of forecasting. We therefore asked respondents an open-item question about how many years they had already worked for the company. Third, we asked respondents to indicate their level of IT affinity (*AFFINITY_IT*) on a scale ranging from "1" (very low) to "7" (very strong). We included this control variable to detect possible confounding effects on the level of digital and methodological sophistication of forecasting and the corresponding level of expertise of the respondents. Finally, we controlled for personal experience with COVID-19 (*COVID*) to account for possible biases in the assessment of the questionnaire. Therefore, we used a variable consisting of the respondents' answers to whether they or persons in their close personal environment had fallen ill with the coronavirus.

Third, we controlled for basic company characteristics. In line with related forecasting studies, we controlled for the possible effects of company size based on revenues (*REV_HIGH*) (Chronopoulos and Siougle 2018; Danese and Kalchschmidt 2011b), as firm size could have an impact on the specification and sophistication of the forecasting process in general. For example, in Knauer et al. (2020), firm size was operationalized in terms of annual revenue. We coded the variable *REV_HIGH* as 1 if the respondents stated an annual revenue of at least €250 million and 0 otherwise, splitting the sample into two comparably large groups. We further controlled for how long the company has existed (*COMPANY_EXISTENCE*), accounting for possible effects on the sophistication and standardization of internal processes, especially in forecast generation. In an open-item question, we thus asked the respondents to state for how many years their company already existed. Due to the sample consisting of companies from a wide range of industries with possibly different conditions, we additionally controlled for industry effects (*INDUSTRY*) for each single industry. For that, respondents were asked to indicate the industry in which their company is operating, having to choose from 12 different industries.

Hence, our regression equations for Models 1, 2 and 3 are given as follows:

$$\begin{aligned} \mathrm{SATIS}_{\mathrm{FC}} = \beta_0 &+ \beta_1 DIGI + \beta_2 METHSOPH + \beta_3 DATA_{FC} + \beta_4 ACCUR_{FC} \\ &+ \beta_5\, TIME_{FC} + \beta_6\, POSITION + \beta_7\, DURATION_{POSITION} \\ &+ \beta_8 AFFINITY_{IT} + \beta_9\, COVID + \beta_{10} REV_{HIGH} \\ &+ \beta_{11}\, COMPANY_{\mathrm{EXISTENCE}} + \beta_{12} INDUSTRY + \varepsilon \end{aligned} \tag{1}$$

$$\begin{aligned}\text{COUNTEREFF} = {} & \beta_0 + \beta_1 DIGI + \beta_2 METHSOPH + \beta_3 DATA_{FC} \\ & + \beta_4 ACCUR_{FC} + \beta_5 TIME_{FC} + \beta_6 POSITION \\ & + \beta_7 DURATION_{POSITION} + \beta_8 AFFINITY_{IT} \\ & + \beta_9 COVID + \beta_{10} REV_{HIGH} + \beta_{11} COMPANY_{\text{EXISTENCE}} \\ & + \beta_{12} INDUSTRY + \varepsilon\end{aligned} \tag{2}$$

$$\begin{aligned}\text{INCRISIS} = {} & \beta_0 + \beta_1 DIGI + \beta_2 METHSOPH + \beta_3 DATA_{FC} + \beta_4 ACCUR_{FC} \\ & + \beta_5 TIME_{FC} + \beta_6 POSITION + \beta_7 DURATION_{POSITION} \\ & + \beta_8 AFFINITY_{IT} + \beta_9 COVID + \beta_{10} REV_{HIGH} \\ & + \beta_{11} COMPANY_{\text{EXISTENCE}} + \beta_{12} INDUSTRY + \varepsilon\end{aligned} \tag{3}$$

4.3 Reliability and Validity of the Survey Constructs

To test our hypotheses, we first performed a confirmatory factor analysis (CFA) to extract our constructs from the questionnaire items and tested the reliability and validity of the derived factors (Tabachnick and Fidell 2014). This theoretical model was then used to test our hypotheses concerning the associations between our variables and constructs by applying OLS regression. All of the factors used in the regression models, that is, *DIGI, METHSOPH, DATA_FC, COUNTEREFF, INCRISIS,* as well as *COSTSAVING* and *LIQSAVING*, which are used in the additional analysis, led to only one factor with an eigenvalue >1; thus, no rotation was necessary (Hair et al. 2019). To ensure construct validity, we tested for convergent validity, i.e., the degree to which the measures of a single construct converge (Bryant 2000). For that reason, factor loadings, i.e., the contribution of an item to the respective construct (Yong and Pearce 2013), were checked. All factor loadings exceeded the generally proposed threshold of 0.5 (0.4) (Hair et al. 2019), with the lowest factor loading showing a value of 0.576 (*text mining*) loading onto the factor *METHSOPH*. As with all other measures of reliability and validity, the precise values of the factor analysis are presented in Table 2. We further validated convergent validity using the average variance extracted (AVE), which measures the convergence among the set of items of a construct (Fornell and Larcker 1981). Except for *METHSOPH*, all factors exceeded the commonly applied threshold of 0.5, with *METHSOPH* being close to the proposed threshold (0.459). However, Fornell and Larcker (1981) pointed out that if the AVE is less than 0.5 and the composite reliability (CR) is at least 0.6, the relevant construct is convergently valid. This condition holds for our construct. To verify the reliability and, thus, the internal consistency of our applied constructs (Mooi et al. 2018), we assessed CR[4] (Cronbach 1951; Raykov 1997a). Applying the common threshold of 0.7 (Hair et al. 2019), all of our constructs exceeded the required thresholds to presume general reliability.

[4] We use CR instead of Cronbach's alpha because the latter measure mistakenly assumes equal factor loadings of all items in a factorial model (tau-equivalence) (Raykov 1997b). CR, on the other hand, considers standardized loadings for each item and is thus considered a superior measurement tool (Shook et al. 2004).

Table 3 Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) *DIGI*	1.000	–	–	–	–	–	–	–	–	–	–	–	–	–	–
(2) *METHSOPH*	**0.3176*****	1.000	–	–	–	–	–	–	–	–	–	–	–	–	–
(3) *DATA_FC*	**0.3165*****	**0.2303*****	1.000	–	–	–	–	–	–	–	–	–	–	–	–
(4) *SATIS_FC*	**0.6513*****	**0.2661*****	**0.3079*****	1.000	–	–	–	–	–	–	–	–	–	–	–
(5) *COUNTEREFF*	**0.2280*****	**0.2071*****	0.0333	**0.3184*****	1.000	–	–	–	–	–	–	–	–	–	–
(6) *INCRISIS*	**0.1471***	**0.1498***	0.0351	**0.2474*****	**0.5688*****	1.000	–	–	–	–	–	–	–	–	–
(7) *COSTSAVING*	0.0393	0.0319	0.1022	–0.0206	**–0.2976*****	**–0.2630*****	1.000	–	–	–	–	–	–	–	–
(8) *LIQSAVING*	–0.0543	0.0149	0.0480	–0.0379	**–0.2517*****	**–0.3899*****	**0.7123*****	1.000	–	–	–	–	–	–	–
(9) *ACCUR_FC*	**0.2472*****	**0.2210*****	0.0718	**0.3048*****	**0.3304*****	**0.3138*****	**–0.1939****	**–0.3017*****	1.000	–	–	–	–	–	–
(10) *TIME_FC*	**0.3936*****	**0.2736*****	**0.2519*****	**0.3837*****	**0.1977****	**0.1617****	–0.0442	0.0191	**0.2187*****	1.000	–	–	–	–	–
(11) *DURATION_POSITION*	**0.2063*****	0.1219	**0.2195*****	**0.1546****	0.0266	0.0811	**–0.1329***	**–0.2390*****	**0.1461***	**0.1281***	1.000	–	–	–	–
(12) *AFFINITY_IT*	**0.2283*****	0.0561	**0.1292***	**0.2053*****	**0.2802*****	**0.1708****	**–0.1750****	**–0.1679****	**0.2027*****	**0.1729****	0.0379	1.000	–	–	–
(13) *COVID*	0.1147	0.0621	0.0042	–0.0162	–0.0201	–0.0646	0.0052	–0.0494	**0.2420*****	0.0830	0.0523	–0.0403	1.000	–	–
(14) *REV_HIGH*	**0.2663*****	**0.1571****	**0.3382*****	**0.1833****	**0.1534****	0.0383	**0.1500***	0.0314	0.1008	**0.2062*****	**0.1571****	0.0667	0.0023	1.000	–
(15) *COMPANY_EXISTENCE*	**0.1644****	**0.1669****	**0.1627****	0.0407	0.0962	0.0755	**–0.2169*****	**–0.2883*****	**0.2084*****	0.1022	**0.2958*****	**0.1406***	0.1068	0.1062	1.000

Note: This table presents the Spearman correlation coefficients.
* $p \leq 0.10$
** $p \leq 0.05$
*** $p \leq 0.01$

Table 3 presents the bivariate correlations between our variables using the Spearman correlation coefficient at significance levels of 1, 5 and 10%. Regarding our first set of hypotheses, the results of the correlation matrix reveal that all three determinants of the digital maturity of forecasting, namely, *DIGI, METHSOPH,* and *DATA_FC,* which are our independent variables, are significantly correlated with *SATIS_FC*, indicating initial support for our hypotheses. In line with our second set of hypotheses, referring to the effectiveness of countermeasures, *DIGI* and *METHSOPH* are also significantly correlated with *COUNTEREFF.* Additionally, the three determinants are weakly correlated with *INCRISIS* and, thus, the economic situation during crises.

Furthermore, all but one of the significant bivariate correlations are below the commonly proposed threshold of 0.7, meaning that multicollinearity is unlikely to affect our results (Hair et al. 2019). The only significant correlation exceeding this threshold refers to our additional analysis and is a positive association between cost-saving measures (*COSTSAVING*) and liquidity-saving measures (*LIQSAVING*), indicating that both instruments are taken complementarily to combat a crisis situation. As both variables are not used in the same regression but rather as distinct dependent variables in different regressions, it does not affect our inferences.

5 Empirical Results

5.1 Descriptive Statistics

We provide the descriptive statistics for the variables and factors used in our model in Table 4. Concerning the components of *DIGI*, the mean values for various aspects of digital transformation indicate average progress regarding the diffusion of digitalization and automation in firms, with digitalization aspects being slightly more advanced (mean = 4.06, median = 4.00) than aspects of automation (mean = 3.75, median = 4.00). With respect to the forecasting methods used (components of *METHSOPH*), time series analysis is applied most broadly (mean = 3.82, median = 4.00), whereas text mining is applied the least (mean = 1.49, median = 1.00). Regarding the input and output data of forecasts (*DATA_FC*), as indicated by a category mean of 2.21 and a category median of 2.00 (category 2: 11 to 20 forecasting indicators), companies use on average 11 to 20 forecasting indicators, with none of the companies surveyed stating the use of more than 50 indicators as input to the forecasting process (max = 6.00, category 6: >50 forecasting indicators). Additionally, firms mostly forecast 1 to 10 KPIs (median = 1.00 with category 1: 1 to 10 KPIs), supposing a focus on a limited number of KPIs used for planning purposes.

Answers to how satisfied respondents were with forecasting during the crisis show a high level of satisfaction with processes involved in forecasting (mean = 4.79, median = 5.00). Regarding the effectiveness of the countermeasures taken, the results show overall satisfaction with and confidence in firms' management during the first months of the COVID-19 pandemic. When asked about coping with the negative consequences of the crisis thus far, 4 out of 5 respondents stated that they were more satisfied than not (not tabulated). Moreover, regarding firms' economic situation

Table 4 Descriptive statistics

Item	Mean	Median	SD	Min	Max
DIGI					
Degree of digitalization	4.06	4.00	1.60	1.00	7.00
Degree of automation	3.75	4.00	1.64	1.00	7.00
Degree of maturity	4.35	4.50	1.52	1.00	7.00
METHSOPH					
Regression analysis	2.41	1.00	1.89	1.00	7.00
Outlier analysis	3.06	3.00	1.96	1.00	7.00
Time series analysis	3.82	4.00	2.04	1.00	7.00
Cluster analysis	2.64	1.50	1.93	1.00	7.00
Text mining	1.49	1.00	1.12	1.00	7.00
Classification methods	2.28	1.00	1.76	1.00	7.00
DATA_FC					
Indicators	2.21	2.00	1.35	1.00	6.00
KPIs	1.91	1.00	1.28	1.00	6.00
SATIS_FC	4.79	5.00	1.47	1.00	7.00
COUNTEREFF					
Coping with the consequences of the crisis	5.38	6.00	1.43	1.00	7.00
Taking advantage of new crisis opportunities	4.37	4.00	1.72	1.00	7.00
Sufficient measures taken to combat the crisis	4.96	5.00	1.52	1.00	7.00
Taking measures faster than competitors	4.47	4.00	1.53	1.00	7.00
INCRISIS					
Liquidity situation	4.59	5.00	1.64	1.00	7.00
Income situation	4.56	5.00	1.61	1.00	7.00
Debt situation	4.47	4.00	1.92	1.00	7.00
COSTSAVING					
Reduction in wages and salaries	3.60	4.00	2.32	1.00	7.00
Reduction in inventory costs	3.30	3.00	2.07	1.00	7.00
Reduction in R&D spending	3.09	2.00	2.19	1.00	7.00
Reduction in G&A expenses	4.03	4.00	2.04	1.00	7.00
Reduction in marketing & sales spending	4.41	5.00	2.05	1.00	7.00
Postponement of projects planned	4.31	5.00	2.06	1.00	7.00
LIQSAVING					
Faster collection of receivables	4.08	4.00	2.14	1.00	7.00
Reduction in inventories	3.67	4.00	2.05	1.00	7.00
Postponed payment of liabilities	2.81	2.00	2.00	1.00	7.00
Borrowing of new funds	2.72	2.00	2.11	1.00	7.00
Renegotiation of existing loans	2.48	1.00	2.00	1.00	7.00
Use of governmental subsidies	3.27	3.00	2.28	1.00	7.00
Delayed/reduced payment of wages and salaries	1.67	1.00	1.58	1.00	7.00

Table 4 (Continued)

Item	Mean	Median	SD	Min	Max
ACCUR_FC	14.38	10.00	14.36	0.00	72.00
TIME_FC	4.92	5.00	1.59	1.00	7.00
POSITION	2.23	2.00	1.14	1.00	5.00
DURATION_POSITION	10.46	8.00	8.23	0.50	34.00
AFFINITY_IT	5.58	6.00	1.10	2.00	7.00
COVID	1.82	2.00	0.38	1.00	2.00
REV_HIGH	0.37	0.00	0.48	0.00	1.00
COMPANY_EXISTENCE	80.98	60.00	152.27	12.00	413.00
INDUSTRY	7.26	7.00	4.23	1.00	13.00

during the crisis, the respondents assessed their liquidity, income and debt situations as being slightly better than those of their direct competitors, with minor differences between the three financial facets.

Additionally, regarding cost-saving measures to combat crisis effects, companies have used a wide range of specific measures complementing each other (overall mean = 3.79). Nevertheless, companies reported having reduced marketing and sales spending the most often (mean = 4.41, median = 5.00), whereas R&D spending was reduced the least (mean = 3.09, median = 2.00). With respect to liquidity-saving measures, a faster collection of receivables was used the most often (mean = 4.08, median = 4.00), whereas only a minor number of companies reported having delayed or reduced the payment of wages and salaries (mean = 1.67, median = 1.00).

5.2 Hypotheses Tests

Tables 5, 6 and 7 report the results of our hypotheses tests. Models 1, 2 and 3 (i) and (ii) contain the associated relationships with our independent variables *DIGI*, *METHSOPH* and *DATA_FC* on (1) *SATIS_FC*, (2) *COUNTEREFF* and (3) *INCRISIS* (i) without and (ii) with the control variables, respectively. To address the fact that the three determinants of digital maturity cannot be changed in the short term, we used the surveyed items as of *before* the crisis as our independent variables and calculated their effect on our dependent variables *during* the crisis in Models 1, 2, and 3 (i) and (ii). Doing so should additionally decrease any potential issues regarding causality, as the different points in time questioned within the questionnaire allow for a causal explanation of our independent variables on our dependent variables but not the other way round.

The first set of hypotheses (H1a to H1c) presented in Table 5 concerns the potential effects of the three determinants of the digital maturity of forecasting on satisfaction with forecasting during crises. In H1a, we predict a positive association between digitalization and automation and satisfaction with forecasting during crises. Model 1 (i) and (ii) confirm the predicted association (i: $\beta = 0.8047$, $p < 0.001$; ii: $\beta = 0.5524$, $p < 0.001$), showing that more digitalized forecasts are advantageous and lead to higher satisfaction with forecasting during crises. We also predict a positive association between methodological sophistication and satisfaction in H1b. While

Table 5 Results of regression (Model 1(i)/Model 1(ii))

Dependent variable/Hypothesis	Independent variable	Model 1 (i): Main effects Coefficient (p value)	Model 1 (ii): Control variables included Coefficient (p value)
SATIS_FC			
H1a (+)	*DIGI*	**0.8047*** (<0.001)**	**0.5524*** (<0.001)**
H1b (+)	*METHSOPH*	0.0855 (0.393)	0.0652 (0.534)
H1c (–)	*DATA_FC*	**–0.1656* (0.100)**	**–0.2894*** (0.010)**
	ACCUR_FC	–	**0.0139* (0.081)**
	TIME_FC	–	**0.1248* (0.078)**
	POSITION	–	Included
	DURATION_POSITION	–	–0.0058 (0.671)
	AFFINITY_IT	–	0.1165 (0.223)
	COVID	–	0.1260 (0.616)
	REV_HIGH	–	0.2859 (0.198)
	COMPANY_EXISTENCE	–	0.0009 (0.171)
	INDUSTRY	–	Included
	R^2	0.2927	0.4338
	Adjusted R^2	0.2805	0.3362
	n	179	171

Note: This table presents the results of the regression with the dependent variable *SATIS_FC*. Significant results are presented in bold.
* $p \leq 0.10$
** $p \leq 0.05$
*** $p \leq 0.01$

the association is positive, the results are not significant (i: $\beta = 0.0855$, $p > 0.10$; ii: $\beta = 0.0652$, $p > 0.10$). Hence, a large variety of methods does not seem to drive satisfaction with forecasts during crises. Finally, H1c examines how the data volume and satisfaction with forecasting during crises are related. Here, our results show that a low data volume is actually advantageous during crises and that less (input and output) data increase satisfaction with forecasting (i: $\beta = –0.1656$, $p = 0.100$; ii: $\beta = –0.2894$, $p = 0.010$). This is consistent with empirical and anecdotal evidence from firm practice revealing that more focused forecasting facilitates forecast generation and enhances the quality of the forecasts generated (Stratigakis and Kallen 2017; Vieweg Verlag Wiesbaden 2016; Claus and Rüthers 2017). Regarding our control variables presented in Model 1 (ii), our two forecasting-related control variables, namely, forecasting accuracy and timeliness, reveal significant positive associations with satisfaction with forecasting (*ACCUR_FC*: $\beta = 0.0139$, $p = 0.081$; *TIME_FC*: $\beta = 0.1248$, $p = 0.078$). Hence, during crises, higher accuracy and the possibility of reacting quickly increase satisfaction. This confirms that more accurate forecasts also lead to a better decision base and the possibility of taking appropriate and precise courses of action on the basis of the forecasts generated. With respect to timeliness, a quick generation of the forecasts frees up time of the forecast preparer and makes the forecasts more readily available for the forecast user. Furthermore, the position the respondents hold in the company (*POSITION*) is slightly significant, with the

Table 6 Results of regression (Model 2(i)/Model 2(ii))

Dependent variable/Hypothesis	Independent variable	Model 2 (i): Main effects Coefficient (p value)	Model 2 (ii): Control variables included Coefficient (p value)
COUNTEREFF			
H2a (+)	*DIGI*	**0.3110*** (<0.001)**	**0.1544* (0.055)**
H2b (+)	*METHSOPH*	0.1258 (0.101)	**0.1205* (0.086)**
H2c (–)	*DATA_FC*	–0.1014 (0.185)	**–0.1577** (0.034)**
	ACCUR_FC	–	**0.0265*** (<0.001)**
	TIME_FC	–	0.0045 (0.925)
	POSITION	–	Included
	DURATION_POSITION	–	**–0.0153* (0.099)**
	AFFINITY_IT	–	**0.1402** (0.028)**
	COVID	–	–0.2724 (0.104)
	REV_HIGH	–	**0.3196** (0.031)**
	COMPANY_EXISTENCE	–	0.0003 (0.414)
	INDUSTRY	–	Included
	R^2	0.1236	0.4777
	Adjusted R^2	0.1084	0.3870
	n	178	170

Note: This table presents the results of the regression with the dependent variable *COUNTEREFF*. Significant results are presented in bold.
* $p \leq 0.10$
** $p \leq 0.05$
*** $p \leq 0.01$

results indicating that directors of management accounting are more satisfied with the forecasting process than the other respondents are ($\beta = 0.6795$, $p = 0.098$). Controlling for potential industry effects on satisfaction with forecasting (*INDUSTRY*) revealed that satisfaction with forecasting is higher for companies operating in the industries "Chemicals/Pharmaceuticals/Health Care" and "IT/Telecommunication" ($\beta = 1.1935$, $p = 0.054$; $\beta = 1.7326$, $p = 0.032$).

The second set of hypotheses examines the effect of the determinants of digital maturity on the effectiveness of countermeasures during crises. The results are presented in Table 6, Model 2 (i) and (ii). Regarding H2a, the results strongly confirm the predicted effect and reveal a significant positive association between digitalization and automation and the effectiveness of countermeasures (i: $\beta = 0.3110$, $p < 0.001$; ii: $\beta = 0.1544$, $p = 0.055$). Hence, digitalization not only increases satisfaction with forecasting during crises but is also relevant for implementing effective countermeasures. When considering the control variables (Model 2 (ii)), we find significant effects for methodological sophistication and the data volume, supporting H2b and H2c. Specifically, the results in Model 2 (ii) underline a significant positive association between methodological sophistication and the effectiveness of countermeasures, while the data volume is again negatively and significantly associated with countermeasures (*METHSOPH*: $\beta = 0.1205$, $p = 0.086$; *DATA_FC*: $\beta = –0.1577$, $p = 0.034$). This again supports observations from practice showing that focusing the

Table 7 Results of regression (Model 3(i)/Model 3(ii))

Dependent variable/Hypothesis	Independent variable	Model 3 (i): Main effects Coefficient (p value)	Model 3 (ii): Control variables included Coefficient (p value)
INCRISIS			
H3a (+)	*DIGI*	**0.2266*** (0.007)**	0.1028 (0.253)
H3b (+)	*METHSOPH*	0.0908 (0.248)	0.0790 (0.310)
H3c (–)	*DATA_FC*	–0.0818 (0.305)	–0.0742 (0.375)
	ACCUR_FC	–	**0.0248*** (<0.001)**
	TIME_FC	–	0.0276 (0.599)
	POSITION	–	Included
	DURATION_POSITION	–	–0.0150 (0.145)
	AFFINITY_IT	–	0.0364 (0.607)
	COVID	–	–0.2726 (0.146)
	REV_HIGH	–	–0.0007 (0.997)
	COMPANY_EXISTENCE	–	–0.0000 (0.972)
	INDUSTRY	–	Included
	R^2	0.0640	0.3432
	Adjusted R^2	0.0478	0.2292
	n	178	170

Note: This table presents the results of the regression with the dependent variable *INCRISIS*. Significant results are presented in bold.
* $p \leq 0.10$
** $p \leq 0.05$
*** $p \leq 0.01$

forecasting process on only the most relevant KPIs and understanding the underlying causes and effects ensures enhanced decision-making and a sound basis for decisions (Claus and Rüthers 2017; Vieweg Verlag Wiesbaden 2016). Overall, the results provide evidence that digital maturity is highly relevant for implementing effective countermeasures during crises. Additionally, as shown in Model 2 (ii), forecasting accuracy again plays an important role and is highly significant regarding implementing effective countermeasures ($\beta = 0.0265$, $p < 0.001$). This shows that more accurate forecasts help to effectively and precisely adopt necessary countermeasures during crises. Furthermore, regarding individual characteristics, the respondents' position, especially as a management accountant, and the duration in a specific position are negatively associated with the effectiveness of countermeasures during crises, while IT affinity is positively associated (*POSITION*: $\beta = –0.4863$, $p = 0.093$; *DURATION_POSITION*: $\beta = –0.0153$, $p = 0.099$; *AFFINITY_IT*: $\beta = 0.1402$, $p = 0.028$). Finally, regarding company characteristics, company size, as measured by revenues, reveals a positive association with the effectiveness of countermeasures. Hence, it is easier for larger companies to implement effective countermeasures ($\beta = 0.3196$, $p = 0.031$). Additionally, the effectiveness of countermeasures during crises is significantly lower for companies that operate in the industry "Financial Services" ($\beta = –1.2572$, $p = 0.045$).

Finally, the third set of hypotheses, presented in Table 7, investigates whether the determinants of digital maturity also affect the economic situation of firms during crises. Here, we find only partial support for our predictions, which could be traced back to the fact that digital maturity affects satisfaction with forecasting and the effectiveness of countermeasures during crises in a timely manner, while the effect of digital maturity on the economic situation might manifest with a larger time lag not (fully) captured by our survey timeline. Specifically, we find a strong significant positive association between digitalization and automation and the economic situation during crises in Model 3 (i) ($\beta = 0.2266$, $p = 0.007$). While the directions of the effects of methodological sophistication (positive) and the data volume (negative) coincide with our predictions, the results are not significant. With regard to our control variables in Model 3 (ii), forecasting accuracy is strongly positively associated with the economic situation during crises. This implies that more accurate forecasts also have a direct measurable effect on the liquidity, cost, and debt situation of companies during crises and shows that accurate forecasts are important for crisis management ($\beta = 0.0248$, $p < 0.001$). Additionally, the results again reveal a negative association between the respondents' position as a management accountant and the economic situation, as the respondents in this position seem to evaluate the situation more negatively than respondents in different positions ($\beta = -0.6101$, $p = 0.060$). Furthermore, the results reveal that the economic situation during crises is significantly better in companies operating in the industry "Chemicals/Pharmaceuticals/Health Care".

5.3 Additional Analyses

5.3.1 Effects of the Digital Maturity of Forecasting on Cost-saving and Liquidity-saving Measures

We additionally analyze how the digital maturity of forecasting influences cost- and liquidity-saving measures. In accordance with the findings revealing that crisis conditions most often weaken companies' cost and liquidity situations, countermeasures implemented by effective crisis management specifically aim to save on costs and liquidity (Eichholz et al. 2021; Janke et al. 2014; Milic 2011; Wright 2020). However, whether effective crisis management is characterized by a lower or a higher number of countermeasures is ambiguous since good crisis management could either result in the possibility of implementing as many countermeasures as possible or reduce the need to implement such measures. We use Spearman correlation coefficients to determine the relationship and find that both cost- and liquidity-saving measures are significantly negatively correlated with the effectiveness of countermeasures and with the economic situation during crises (significance levels of 1%). These results mean that fewer measures are related to more effective countermeasures and a better economic situation during crises. Building on this, we run the same regressions as those presented in Section 5.2 and use cost- and liquidity saving-measures as dependent variables to determine the influence of the digital maturity of forecasting ((i)/(ii) without/with control variables; not tabulated). With regard to cost-saving measures, we find that the data volume shows a significant association (i: $\beta = 0.1675$, $p = 0.043$; ii: $\beta = 0.2186$, $p = 0.015$). Hence, to reduce the number of cost-saving measures, it seems particularly important to focus on few input and output data in forecasting during crises. Additionally, the respondent's IT affinity and operating in the industries "Construction/Real Estate" and "Utilities/Servicing/Disposal" lower the number of implemented cost-saving measures (*AFFINITY_IT*: $\beta = -0.1660$, $p = 0.024$; Construction/Real Estate: $\beta = -0.8507$, $p = 0.079$; Utilities/Servicing/Disposal: $\beta = -1.1057$, $p = 0.026$). Regarding liquidity-saving measures, higher digitalization and automation of forecasting are beneficial (i: $\beta = -0.1931$, $p = 0.022$). However, when considering the control variables, the association is no longer significant, but forecasting accuracy and the timeliness of forecasting reveal a significant influence (*ACCUR_FC*: $\beta = -0.0216$, $p < 0.001$; *TIME_FC*: $\beta = 0.0962$, $p = 0.073$). Interestingly, higher accuracy reduces the need to implement liquidity-saving measures, while the possibility of reacting quickly increases the extent of such measures. This finding might point to the fact that quick reactions are not necessarily the most effective overall. Additionally, the respondent's duration in a position and IT affinity are negatively associated with liquidity-saving measures (*DURATION_POSITION*: $\beta = -0.0185$, $p = 0.077$; *AFFINITY_IT*: $\beta = -0.1442$, $p = 0.047$).

5.3.2 Characteristics of Forecasting before and during Crises

To further elaborate on features of forecasting and how the generation of forecasts may change due to crisis conditions, we compared specific characteristics of forecasting and the forecasts generated before and during the crisis and conducted statistical tests to determine the magnitude of the observed changes.[5]

A full overview of the items concerned with forecasts and forecasting surveyed in our questionnaire before and during the crisis is presented in Table 8. Concerning the frequency of forecasting, we find that only a very limited number of companies forecast in real time (1.67%; 2.22% (before; during the crisis)). This finding could imply that only a minor number of companies are able to receive data in real time and to retrieve meaningful forecasts from these data. One major obstacle might be the slow advances in digitalization and automatization (Möller et al. 2020). With regard to the forecasting frequency before compared to during the crisis, most companies followed a quarterly forecasting frequency before the crisis, whereas during the crisis, most companies updated their forecasts on a monthly basis. This finding conforms to the literature findings that increased uncertainty in economic conditions is approached by increasing the frequency of forecasting to meet informational needs

[5] As these results are mostly descriptive, no inferences can be made to causalities that may have been caused by the crisis conditions. Nevertheless, the reported findings complement each other and support the idea that forecasting practice during the crisis is mainly altered such that forecasts are updated more frequently, forecasting horizons are shorter, and more emphasis is given to short-term planning and being able to quickly react to volatile environmental conditions. As the ability to make a fast and precise reaction in steering companies is utterly important in every business environment (Morlidge and Player 2010) and as companies manage to alter their forecasting process in a way that is supportive in that means, it can be assumed that the observed changes to forecasting may, on the one hand, last also after the acute COVID-19 crisis, and, on the other hand, may be beneficial for the companies' overall economic performance.

Table 8 Comparison of forecasting characteristics before/during the crisis

Characteristic	Unit	n	Before	During	Delta	Significance
Frequency of forecasting	Number of companies[a]	180				
Real-time			3	4	1	–
Daily			4	12	8	***
Weekly			16	50	34	***
Monthly			67	95	28	***
Quarterly			84	48	–36	***
Annually			38	17	–21	***
Forecasting horizon (weeks)	Average	179/178	39.61	31.08	–8.53	***
Importance for levels of planning	Likert Scale[b]	180				
Short-term			6.27	6.44	0.17	***
Middle-term			4.27	4.21	–0.06	–
Long-term			2.65	2.62	–0.03	–
Importance for fulfilling functions	Likert Scale[b]	180				
Forecast of probable business development			5.84	5.94	0.10	**
Possibility of fast reaction to new business conditions			4.92	5.51	0.59	***
Possibility of target setting			4.77	4.41	–0.36	***
Prediction as basis for capital market communication			3.69	3.59	–0.10	–
Use of rolling forecasts	Likert Scale[c]	180	3.88	4.05	0.17	–
Use of flash forecasts	Likert Scale[c]	180	1.72	2.59	0.87	*
Use of forecasts for corporate management	Likert Scale[c]	180	5.14	5.19	0.05	–
Number of indicators (input variables)	Quantity interval[d]	179	2.21	2.23	0.02	–
Number of KPIs (output variables)	Quantity interval[d]	179	1.91	1.98	0.07	*

(Becker et al. 2016; Henttu-Aho 2018). Especially in times of crisis and competitive environments, it has been reported in the literature that a fast and precise reaction to the conditions at hand might be beneficial to the overall economic situation of companies (Morlidge and Player 2010; Vargo and Seville 2011).

Relative to longer forecasting horizons being associated with higher complexity and more time needed for forecast generation (Georgoff and Murdick 1986), the forecasting horizon decreased from 39.61 weeks on average before the crisis to 31.08 weeks on average during the crisis, marking a drop of nearly two months in the forecasting horizon. On the one hand, this result shows that in times of crisis and highly volatile environments, management prioritizes immediate and fast reactions

Table 8 (Continued)

Characteristic	Unit	n	Before	During	Delta	Significance
Accuracy of forecasting	Percentage deviation from actual values	173	14.38	18.87	4.04	***
Satisfaction with forecasting process	Likert Scale[e]	180	4.84	4.79	–0.05	–

Note: The columns "Before", "During" and "Delta" present descriptive results of the most important aspects of forecasting before and during the crisis as well as their change. The column "Significance" presents the results of the two-sided statistical tests performed to determine if the changes observed are significant. Corresponding to the scales of the variables, we used the Wilcoxon signed rank test, the paired t test, or the McNemar test. Significance levels are reported in the following way: * $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$.
[a] The figures before and during the crisis do not sum up to 180 because multiple selection was possible for companies having more than one regular forecasting frequency.
[b] 1 = not important, 7 = very important.
[c] 1 = not at all, 7 = to a very high degree.
[d] Answer options are coded: 1 = 1–10, 2 = 11–20, 3 = 21–30, 4 = 31–40, 5 = 41–50, 6 ≥ 50.
[e] 1 = very dissatisfied, 7 = very satisfied.

over adjusting to middle- or long-term objectives (Becker et al. 2016). On the other hand, this result supports our findings that forecasting is mostly used for short-term planning and needs to provide a certain flexibility to allow companies to adapt quickly to changing business conditions. The stronger focus on short-term planning is further amplified by the slightly increasing importance of short-term planning (+0.17 in mean during the crisis compared to before the crisis) during the crisis compared to before the crisis.

The various functions of forecasts and their development during the crisis also stress a short-term focus as well as the need to provide a certain flexibility in the forecasting process. The highest increase in mean regarding the importance of functions was observed in the possibility of a fast reaction to new business conditions (+0.59 in mean during the crisis compared to before the crisis). This finding again underlines the importance of up-to-date information to steer the business accordingly in volatile times and might be amplified by the special characteristics of the COVID-19 crisis with massive and sudden political interventions, such as lockdowns and the disruption of supply and distribution chains (Donthu and Gustafsson 2020; Verma and Gustafsson 2020). In contrast, the importance of target setting via forecasts decreased during the crisis compared to before the crisis by 0.36 on average. This result is in line with findings from the budgeting literature related to economic crisis situations indicating that the importance of the performance evaluation function of budgets decreases in times of crisis because with increased uncertainty, budget fulfillment can no longer be related to direct managerial actions and may in fact be distorted by uncontrollable crisis factors (Becker et al. 2016).

Regarding the use of rolling as well as flash forecasts, companies reported having used both instruments to a higher degree during than before the crisis (+0.17; +0.87 in mean during compared to before the crisis (rolling forecasts; flash forecasts)) with a higher increase in the use of flash forecasts. These findings support the idea of companies seeking high flexibility in forecast generation as a basis for corporate planning, as is given by the ad hoc feature of flash forecasts.

With respect to the accuracy of forecasts, the percentage deviation between actual and forecasted values increased during the crisis to an average deviation of 18.87 percentage points (14.38 percentage points before the crisis). These results imply that it becomes more difficult for companies to accurately forecast business development in volatile times.

Last, satisfaction with forecasting remains nearly stable during compared to before the crisis (mean = 4.84; mean = 4.79 (before; during the crisis)), showing an overall high level of satisfaction with the process of forecast generation.

6 Discussion and Conclusion

Motivated by the unique crisis conditions of the COVID-19 pandemic, including lockdowns, trade barriers and travel restrictions and the generally increasing volatility of business markets, we investigate how forecasting and its digital maturity help to successfully deal with crises. Specifically, we explore how the three determinants of the digital maturity of forecasting, i.e., digitalization and automation, methodological sophistication, and data volume, influence (1) satisfaction with forecasting during crises, (2) the effectiveness of countermeasures and (3) the economic situation during crises. Last, within our additional analyses, we also relate the digital maturity of forecasting with cost- and liquidity-saving measures. Furthermore, we observe certain aspects of forecasting and how they have changed during the COVID-19 economic environment to obtain a better understanding of how companies react to adverse economic conditions related to forecasting.

We conducted a survey of medium-sized and large German companies, yielding 180 complete questionnaires with which we empirically tested our hypotheses using OLS regression. The applied models provide support for most of our hypothesized associations. First, we find support that a higher level of digitalization and automation of forecasting and a reduced input and output data volume increase satisfaction with forecasting during crises. We argue that more digitalized and automated forecasts help to reduce time resources and are therefore more convenient for those employees who generate forecasts and for those who decide how to react based on them (Bergmann et al. 2020). Hence, it is beneficial to use only as much input data as necessary and to only generate the output data that are crucial for fast decision-making. Our data empirically confirm practice findings showing that focusing on the relevant drivers of business performance during forecasting reduces the effort and time needed of employees, especially in times of crisis (Vieweg Verlag Wiesbaden 2016; Claus and Rüthers 2017). Second, all three determinants reveal significant associations with the effectiveness of countermeasures. Specifically, digitalization and automation, and methodological sophistication in forecasting increase effectiveness. We reason that both are helpful in enhancing the decision base and supporting the quick design and implementation of appropriate countermeasures. Similar to satisfaction, the data volume reveals a negative association, which we trace back to the fact that decision-making on countermeasures is facilitated when only the most relevant data are generated within forecasts and are afterward presented and analyzed. This again supports pratice findings highlighting that an agile accessibility of information based on the forecasts generated is crucial (Stratigakis and Kallen 2017). Third, regarding the effect of the digital maturity of forecasting on firms' economic situation, we find slight support, indicating that digitalization might have a positive influence on the economic situation during crises.

Overall, our results show that forecasting in general and digitally more mature forecasting processes in particular are advantageous for dealing with crises. Therefore, we advise companies to push and adjust to digital transformation to increase the digital maturity of their forecasting and thus enhance forecasting as a tool for crisis management. Additionally, we illuminate how the accuracy and timeliness of forecasts, the individual characteristics of the respondents and basic company characteristics affect the associations described.

Moreover, we scrutinize whether more or fewer cost- and liquidity-saving measures are beneficial, finding that fewer measures are perceived as more effective. On this basis, we again test whether digitally more mature forecasts reduce the need to take actions and find some positive influence. Furthermore, we gain insights into whether the importance of forecasts and their characteristics changes due to crisis conditions. For instance, the analysis reveals that the focus on short-term planning and the possibility of reacting quickly increases during crises, while forecasting accuracy on average decreases. Nevertheless, satisfaction with forecasting remains relatively stable before and during crises, which underlines the importance of this tool to successfully dealing with crises.

Our study links the research fields of forecasting, digital transformation, and crisis management and contributes to the corresponding literature and practice in several ways. First, we answer the call for research that identifies the determinants of effective forecasting (Danese and Kalchschmidt 2011a, b; Morlidge and Player 2010). Second, we transfer this call especially to crisis situations and consider the comprehensive changes due to advancing digitalization (Gulin et al. 2019). Specifically, we apply the general concept of digital maturity to forecasting to illuminate how digital maturity influences whether and how forecasting functions as a tool that facilitates crises management. The positive influences on satisfaction with forecasting and on the effectiveness of countermeasures support the view that digitally more mature forecasts are particularly advantageous during crises, when fast prognoses are required to evaluate future developments and determine how to react (Ezzamel and Bourn 1990). Specifically, the results indicate that forecasting processes should be digitalized and automated as much as possible to reduce the time resources needed and the susceptibility to errors, especially with respect to data entry and consolidation (Armstrong 2001; Danese and Kalchschmidt 2011b). They further indicate that considering the complexity of the tools used, especially regarding the implementation of new, sophisticated methods, is crucial when designing the forecasting process. While the results of research are mixed, our study also reveals that a broad input and output data volume is not beneficial during crises. Conversely, it is beneficial to use only those inputs that are crucial and generate the KPIs that are meaningful in the specific situation.

Due to the study design, our findings are subject to several limitations. First, the questionnaires conducted in our survey may be biased, although we tried to rule out all possible pitfalls beforehand and tested for plausible shortcomings afterward.

Nevertheless, we cannot completely eliminate the threat of potential self-selection bias in a way that companies that were not heavily affected by the COVID-19 pandemic answered our questionnaire. Furthermore, those items that are subject to personal evaluation depend on the subjective perception of the respondent and thus may be biased. We tried to mitigate this effect via explanations of questions in the questionnaire. With respect to the different points in time, i.e., *before* and *during* the crisis, we stated the period of times intended in addition to using the terms "*before*" and "*during*", i.e., the second half of 2019 and the first half of 2020, respectively, to minimize the chance that respondents might confirm a change in forecasting practices and the economic situation. Second, our study considers only a short period. Particularly regarding fast advances in digital technologies and their influence on the field of management accounting, the effects could shift. Thus, with the rise of new technologies, it could be interesting in future research to test for specific advances and their interacting effects with existing techniques. Third, although we believe that our results are (at least partially) transferrable to other types of crises, we can only explicitly illuminate the effects of the COVID-19 crisis with its specific pandemic origin and the described economic consequences. Especially, when referring to the COVID-19 crisis, i.e., characterized as external, nonhuman induced, and global, we believe that our results would also hold for human induced as well as for idiosyncratic crises. Correspondingly, digitally more mature firms should, for example, also benefit from a better forecasting process during the current (human induced) Russian military aggression against the Ukraine. In contrast, when the crisis origin is internal and might have an effect on, e.g., data needed as forecast input data or on internal processes, the benefits of digitally more mature forecasting processes might be reduced. Against this background, it would be interesting to explicitly investigate forecasting related to other types of crises to test whether our results hold. Additionally, it may be interesting to conduct a follow-up study to determine whether the COVID-19 pandemic permanently changed business conditions. Finally, we based our findings on a sample of 180 German mid-sized and large companies, which may limit the generalizability of the results. Future studies should reassess the results using data from other countries or by focusing on country-specific effects.

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Declarations

Conflict of interest J. Eichholz, T. Knauer and S. Winkelmann declare that they have no competing interests.

Ethical standards The survey was conducted in accordance with ethical standards. The participation was voluntary and the personal data collected in the questionnaire is used exclusively for scientific purposes and stored anonymously. For data collection the General Data Protection Regulation was applied. For this article no studies with human participants or animals were performed by any of the authors. All studies mentioned were in accordance with the ethical standards indicated in each case.

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