Management Accounting in the Age of Digitalization – Selected Studies on the Future of Finance and the Role of Trust in Artificial Intelligence and Algorithms

Inaugural-Dissertation

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List of Abbreviations

AI	Artificial intelligence
B	B Coefficient
CapEx	Capital expenditures
CEO	Chief executive officer
CFO	Chief financial officer
CI	Confidence interval
CO2	Carbon dioxide
EBIT	Earnings before interest and tax
e.g.	exempli gratia / for example
ERP	Enterprise Resource Planning
ESG	Environmental, Social and Governance
et al.	et alii / and others
HR	Human ressources
ICS	Internal control system
i.e.	id est / that is
IT	Information technology
KI	Künstliche Intelligenz
KPI	Key performance indicator
M	Mean
ME	Marginal effects
M.Sc.	Master of Science
n	Sample size
Obs	Observations
OLS	Ordinary least squares
p	Significance level
p.	Page
PhD	Philosophiae doctor / Doctor of Philosophy
P&L	Profit and loss statement
R^2	R-squared
R^2 *adj.*	R-squared adjusted
SD	Standard deviation
SE	Standard error

SQL	Structured query language
US...	United States
USD..	US Dollar
XAI...	Explainable artificial intelligene
z.B.	zum Beispiel

A Research Framework

1 Introduction

The professional and substantive focus of management accounting is subject to constant change and is characterized by trends and innovations in global business relations as well as the associated changes in regulatory requirements and a multitude of technical innovations that are increasingly being integrated into management accounting. Although fundamental finance and accounting knowledge remains the basis of the profession, the new demands on the specialist area are also reflected in changed requirements for the accountants, who must be able to deal with new professional topics, integrate them into accounting and in some cases even develop them further. A significant driver of change and the rapid transformation of accounting is digitalization, which has altered the accounting field and the accounting profession in numerous ways and will continue to exert a profound influence in the future (Möller et al., 2020; Yasinska, 2021).

Nevertheless, an increasing number of digital solutions are also contingent upon potential users utilizing them. This phenomenon can only occur if the new technologies are also accepted by the users. To date, existing technology acceptance models have provided initial insights into potential mechanisms of action as to when and why users accept technologies, reject their use or make their use more difficult. One such acceptance model is the Theory of Reasoned Action, as proposed by Fishbein and Ajzen (1975). This theory posits that behavior is influenced by a person's intention, which in turn is influenced by attitude and subjective norm. However, in the case of completely new technological innovations, normative models are often unavailable, and attitudes and opinions have not yet been formed about the new technology, limiting the applicability of the model. In addition to the theoretical explanatory approach, the Theory of Planned

Behavior according to Ajzen (1991) also provides a further research approach, supplementing the aforementioned model with perceived behavioral control as an influencing factor on intention and thus acceptance behavior. Nevertheless, the validity of this model is also limited, particularly in the context of artificial intelligence. Perceived behavioral control is only present to a limited extent, especially with new technologies and complex underlying models that are not technically tangible. This is due to the uncertainties that arise from the high complexity and low predictability of the consequences. The Theory of Interpersonal Behavior, as proposed by Triandis (1977), is frequently referenced in the context of acceptance research. This theory also draws upon previous explanatory approaches and integrates the determinants of habits, facilitating conditions and affect. However, the influence of factors such as habits is similarly absent in new applications. Additionally, facilitating conditions are frequently absent in the context of artificial intelligence, as a lack of introductions, explanations, and comprehension tends to promote uncertainty and aversion. The Technology Acceptance Model (TAM) proposed by Davis (1989) is a well-known model in the field of technology acceptance. It posits that two key factors, perceived usefulness and perceived ease of use, drive user acceptance of technology. Extensions of this model, such as the Technology Acceptance Model 2 according to Venkatesh and Davis (2000), demonstrate these influences and also consider social influences and cognitive instrumental processes. Nevertheless, it is also the case that systems based on artificial intelligence are often much more complex, less comprehensible and less tangible than other new technologies. Consequently, knowledge about pure functionality may no longer be sufficient for acceptance behavior. In order to make artificial intelligence truly tangible, it is necessary to have an in-depth technical understanding. Furthermore, ethical concerns, data protection issues and security concerns, among other factors, can also contribute to uncertainty and low acceptance, which cannot be mapped using previous models. The rapid development of artificial intelligence and corresponding applications also make this field of research an exciting new complex that requires constant investigation, particularly in the context of digitalization in management accounting.

The digitization of management accounting should result in enhanced process efficiency and greater accuracy in the generation of outputs. Furthermore, process efficiency should create space for employees to address new matters and foster innovation and the generation of novel ideas (Parviainen et al., 2017). Conversely, this process efficiency is also increasingly demanded by the market and business environment, and also ensures the competitiveness of companies and their ability to keep up with the latest developments (Roberts and Grover, 2012). Concurrently, digitization provides the foundation for novel communication and exchange possibilities, which have become increasingly crucial, particularly in the context of remote and novel work (Miklosik et al., 2021; Wang et al., 2022). Furthermore, process optimization through digitalization and the omission of manual minor processes can also reinforce the accountant's role as a business partner, enabling them to fulfil their role as a managerial advisor with financial and accounting knowledge (see also Möller et al., 2017; Weißenberger et al., 2012b; Wolf et al., 2015). As a consequence of these developments in management accounting, some of which have yet been briefly outlined in research, a number of subsequent research questions have emerged regarding the most effective and targeted manner in which digitalization in management accounting can be handled in order to achieve the desired usage, transformation and trust (Verhoef et al., 2021). On the one hand, employees are a central factor in successful digital transformation (Frankiewicz and Chamorro-Premuzic, 2020). Conversely, it is pertinent to consider the extent to which employees, who are afforded greater scope for addressing novel matters as a consequence of enhanced process efficiency, are adequately equipped to navigate and address these topics. Concurrently, this prompts the question of altered core competencies and role profiles, as delineated by Schäffer and Brückner (2019). An equally significant issue is the question of whether management accounting professionals would be willing to embrace these innovations and work with the technical novelties. This initial field of research therefore developed into an investigation of the trust placed in new technical systems and algorithms, as well as an examination of whether employees may have a tendency to form negative preconceptions about new algorithms, a phenomenon known as algorithm aversion (e. g. Berger et al., 2021; Castelo et al., 2019; Dietvorst et al., 2018, 2015; Filiz et al., 2021; Jussupow et al., 2020). Concurrently, more extensive research questions emerge. These include whether an understanding of new algorithms and systems in the sense of reducing a 'black box' can promote the acceptance of algorithms and whether, in this case, explanations have a particularly positive influence on the trust behavior of employees (Adadi and Berrada, 2018; Asatiani et al., 2020; Wischmeyer, 2020; Zednik, 2021). These and other principal research questions are also addressed in this dissertation, with supplementary factors influencing trust behavior placed in a comprehensive framework on the future of management accounting as part of the finance function.

2 Research Gaps and Overview of Studies

2.1 Overview of Studies

In the context of my research, I have addressed pertinent questions regarding the future of the finance function and management accounting, as integrated here, and at the same time examined the role of artificial intelligence and the algorithms behind it, as well as the trust of employees in these new technologies. Artificial intelligence is therefore defined as a digital system that can solve complex tasks and problems similar to those that can normally be solved by humans. This is based on comprehensive data analysis, pattern recognition, and corresponding conclusions, which can be displayed in forms such as machine learning or neural networks

(Kokina and Davenport, 2017). In accordance with the aforementioned proceedings, five papers were produced for this dissertation. Each paper builds on the preceding one in terms of content, ultimately providing a comprehensive overview of future influencing factors and the role of digitization and trust. At the same time, the papers present implications for further research and practice.

In the initial paper, a case study on the future of the finance function, I conducted interviews with a listed German postal and logistics company with the objective of examining the factors that will be particularly relevant in management accounting and the finance function in the future. In this study, the influencing factors that have already been presented in research were compared with the company-specific influencing factors. The initial study demonstrated that, in light of the increased digitization, the trust of finance employees in the data systems must be robust in order for the data outputs generated by the systems to be utilized. However, this trust is not always forthcoming. Consequently, the second study examines algorithm aversion and the factors that cause a rejection of new technologies. Building on this, the trust behavior of individuals was further investigated in three additional papers, each comprising experimental studies. Consequently, I conducted an investigation into the impact of performance, explanations, the origin of forecasts, performance cues, and framing in various contexts, including the accounting setting. The following table provides an overview of my studies, including the respective methodology, contribution, and publications, conferences, and discussion platforms where the results were discussed and presented.

Table A-1 Overview of Studies

Number of Paper	Paper 1	Paper 2	Paper 3	Paper 4	Paper 5
Title	Future of Finance - the Influence of Digitalization, Business Model Understanding and Trend Disruptions on Strategy, Competence Fields and Role Profiles	Never change a running (human) system? Abbau von Algorithmus-Aversion im Digital Reporting	Behavioral Mechanisms underlying Algorithm Aversion in Management and Managerial Accounting	Trust in Artificial Intelligence - the Role of Occupation and Explanations	The Effect of Framing on Trust in Artificial Intelligence: An Analysis of Acceptance Behavior
Topics	Future of Finance, Digital Transformation, Sustainability Accounting, Compliance and Governance, Competence Fields, Role Profiles	Digital Transformation in Management Accounting, Trust in Artificial Intelligence and Algorithms, Algorithm Aversion, Algorithm Appreciation	Trust in Artificial Intelligence, Forecasting, Algorithm Aversion, Predictive Analytics, Forecasting, Decision-marking, Origin, Accuracy, Explanations	Trust in Artificial Intelligence, Occupational Effects, Professional Setting of AI Usage, Decision-making, Origin, Performance, Explanations	Trust in Artificial Intelligence, Private Setting of AI Usage, Decision-making, Origin, Performance, Explanations, Framing
Methodology	Interviews with senior managers and CFOs of all divisions of the finance function at listed postal and logistics group	Literature overview and conceptual contribution through aggregated facts	Multi-method approach: Interviews with professionals from Schmalenbach working group 'Digital Reporting', two experimental studies conducted via respondi	Multi-method approach: Short interviews for pre-study, experimental study conducted via Amazon Mechanical Turk	Experimental study conducted via Amazon Mechanical Turk
Contribution	· Overview of future topics in Finance and Management Accounting ·Translation of new focus areas into competence fields and role profiles · Identification of areas for development and the future role of Management Accounting within the Finance function	· Overview of factors leading to algorithm aversion presented in research · Classification and condensation of factors based on stylized facts · Comparison of the influencing factors of Algorithm Aversion to research approaches on Algorithm Appreciation	· Indication of a trust handicap towards algorithms in forecasting · Assessing the role of human vs. AI based decision basis · Influence of performance and accuracy on trust behavior	· Overview of occupational group effects on trust behavior towards AI · Classification of the effects of performance and origin in professional decision-making context · Influence of explanations in professional settings on trust behavior regarding AI and human decision basis	· Indication of framing effects on trust behavior regarding AI · Classification of the effects of origin and performance in private decision-making context · Influence of explanations in private settings on trust behavior regarding AI and human decision basis
Publications, Conferences and Presentations	Presentation to CFO Group Functions and discussion at CFO level in the company	"Digital Reporting - Transformation des Controllerbereichs durch den digitalen Wandel" (Vahlen, 2023)	Conferences: ERMAC (Vienna, 2021) and EAA (Bergen, 2022) Publications: Submitted to Schmalenbach Journal of Business Research (First Round Major Revisions)	Submitted to SSRN (5008350 WPS)	Submitted to SSRN (5008348 WPS)

2.2 Study 1: Future of Finance - the Influence of Digitalization, Business Model Understanding and Trend Disruptions on Strategy, Competence Fields and Role Profiles

The initial study of this dissertation seeks to address the following research questions:

- Which strategic and substantive aspects will be of particular importance for the future of the Finance function?
- Which new fields of competence and role profiles are emerging here?
- Which position will Management Accounting take within the Finance function?

The field of finance and accounting research has already identified different key areas that could potentially influence the future of the finance function. However, these insights have not yet been consolidated into a comprehensive overview and subjected to rigorous validation through practitioner interviews. This paper aims to address this research gap. Previous studies have identified digitization as a significant driver of change in finance and accounting. This encompasses the management of substantial quantities of data, commonly referred to as Big Data, as well as the assurance of appropriate data quality for the targeted preparation of the data (Cockcroft and Russell, 2018; Emeka-Nwokeji, 2012; Xu, 2009). Furthermore, the implementation of automated data processing in a multitude of systems will be of particular significance (Brands and Smith, 2016). These include systems pertaining to the domains of robotics, analytics, and even artificial intelligence (Ionescu, 2020; Korhonen et al., 2020). This raises the question of the extent to which artificial intelligence is already being used in companies, and whether management accountants are more likely to be concerned with predictive analytics and have not yet adopted self-learning algorithms and artificial intelligence. In addition, the future of accounting within the finance function will be discussed. This raises the question of the extent to which management accounting will continue to exist as an independent area within the finance function and whether the boundaries between the two disciplines are more likely to merge in the future (Bommer and Gruber, 2021; Neundörfer and Wiltinger, 2022; Schäffer, 2022). Research also identifies a number of role profiles and areas of competence (Schäffer and Brückner, 2019). However, these role profiles and areas of expertise must also be subjected to critical review and expansion in light of the emergence of new specialist topics in management accounting. The advent of new sub-areas, such as sustainability accounting, has led to the emergence of new challenges and the necessity for the recruitment of additional experts who are conversant with and able to address such specialized topics (see also Arroyo, 2012; Maas et al., 2016; Soderstrom et al., 2017; Solovida and Latan, 2017). This study critically reviews the approaches outlined in research based on interviews with senior managers and CFOs of a German listed postal and logistics group. The results indicate that digitization is a relevant focus with influence on all areas of the finance function. It is evident that there is a greater need for digitization knowledge, particularly in smaller processes, as management accounts must be able to act independently and without permanent IT support. Furthermore, there are indications that data quality and data maintenance are becoming more important, and that finance AI development is to be driven forward. New specializations through topics such as sustainability or dealing with crises are also emerging. This also reveals an updated picture of accounting, which will be integrated more closely into the finance function through greater data interlinking but will continue to exist as an independent field within the function. Concurrently, the expectations of young accountants have also evolved. It is evident that a profound comprehension of business models and a comprehensive professional foundation are highly sought-after, with the potential for subsequent specialization in various domains. This paper presents a comprehensive overview of the future finance function, categorizing trend topics within the specialist divisions and emphasizing the pivotal role of management accounting in the evolution of the finance function.

2.3 Study 2: Never change a running (human) system? Abbau von Algorithmus-Aversion im Digital Reporting

The second study primarily addresses the following research questions:

- What are the patterns of behavior that occur in the context of an algorithm aversion?
- What factors may cause algorithm aversion?
- How can algorithm aversion potentially be addressed and overcome?

A number of studies have been conducted on the phenomenon of algorithm aversion in the field of research (e. g. Berger et al., 2021; Castelo et al., 2019; Dietvorst et al., 2015; Filiz et al., 2021; Jussupow et al., 2020; Reich et al., 2022). Nevertheless, there is no comprehensive examination of the factors that may influence algorithm aversion. Moreover, existing reviews do not make comparisons to the opposing body of literature, namely algorithm appreciation (see also Logg et al., 2019; You et al., 2022). This paper aims to address the existing research gap regarding the factors that can cause algorithm aversion, with a particular focus on management accounting and the transferability of such factors. Additionally, this overview aims to contribute to the handling of a trust handicap in organisations, ensuring that employee trust and the effective use of digital solutions can be achieved. In the context of digital transformation, the use of algorithms and new digital systems is also increasing in management accounting. Consequently, it is of paramount importance to be able to deal with algorithms and systems and to trust them. However, this trust in the new digital solutions and algorithms is not always forthcoming (Eschenbach, 2021). It is possible that there may be a trust handicap with regard to algorithms, which cannot always be rationally justified (Dietvorst et al., 2015). This phenomenon is known as algorithm aversion. It can manifest in various forms. On the one hand, algorithm aversion indicates a greater trust in one's own intuition and judgement than in an algorithm or its output (Castelo et al., 2019; Dietvorst et al., 2015). Conversely, an aversion to algorithms can manifest as a preference for the input of human decision-makers and experts over that of algorithms (Dietvorst et al., 2015; Önkal et al., 2009; Promberger and Baron, 2006). Furthermore, an algorithmic aversion can be expressed in such a way that even other decision-makers are subjected to greater scrutiny and criticism if they place greater trust in an algorithmic decision-making process than they do in a human expert (Shaffer et al., 2013).

The reasons for an aversion to algorithms are numerous and diverse. This study indicates that experience can influence an aversion to algorithms (e. g. Alexander et al., 2018; Burton et al., 2020; Carey and Kacmar, 2003; Goodyear et al., 2016; Highhouse, 2008a, 2008b; Lodato et al., 2011; Sutherland et al., 2016; Thayer, 2008). A lack of experience can lead to a lack of trust in the competencies of new systems and an association with inadequate performance. Conversely, first contact and training with and about algorithms can reduce this potential driver of algorithm aversion. Furthermore, this study also shows other factors, such as perceived subjectivity of the decision bases, lack of incentivization, or lack of intervention and modification possibilities with regard to the algorithmic output (Castelo et al., 2019; Dijkstra et al., 1998; Lee, 2018; Mahmud et al., 2022). All these factors are aggregated in this study and brought into an inter-relationship of effects. In addition, this study compares the results with findings from research on algorithm appreciation. Here, partially contradictory findings become apparent, so that, for example, a lack of experience and inexperience are associated with excessive trust, since the user assumes that the system can perform better than he or she can (Logg et al., 2019). Finally, the results are also transferred and interpreted with regard to management accounting and digital reporting, thus enabling a comprehensive understanding of the topic.

2.4 Study 3: Behavioral Mechanisms underlying Algorithm Aversion in Management and Managerial Accounting

The third study aims to address the following research questions:

- Can an algorithm aversion in the accounting field be experimentally proven?
- What are the factors that lead to algorithm aversion in this case?
- What influence do performance and explanations have on trust behavior?

The objective of this study is to conduct a critical review of the topic of algorithm aversion and trust in artificial intelligence in management accounting. Previous studies have examined trust in artificial intelligence and digital transformation in management accounting and in the finance function (e. g. Alexander et al., 2018; Glikson and Woolley, 2020; Hasija and Esper, 2022; Schmidt et al., 2020; Siau and Wang, 2018). Nevertheless, the phenomenon of algorithm aversion has not yet been sufficiently investigated with regard to accounting, so that implications for companies are not yet possible. This is where this paper comes in and examines, in the context of two experimental studies, whether a trust handicap of an artificial intelligence compared to a human expert can be proven and to what extent an algorithm aversion can exist in management accounting. In addition, further effects are analyzed, which can have an influence on the trust behavior. One aspect of this research is to ascertain the extent to which respondents recognize and take into account the superior performance of digital systems or human decision-makers. Another objective is to examine whether explanations have an influence on trust behavior, for example by reducing the black box effect often described in research, which implies a trust handicap towards an AI. The experiment relates to the field of forecasting.

Forecasts represent an essential component of accounting, serving as a fundamental aspect of the work of accountants (Mouritsen and Kreiner, 2016). The advent of digital transformation has also transformed the landscape of forecasting and the manner in which forecasts are generated. A growing number of companies are striving to enhance the utilization of automated forecasts that operate on sophisticated algorithms and have been programmed, tested, and trained using a substantial amount of training data. While the inclination is towards automated forecasts and a considerable number of companies have already begun to utilize artificial intelligence, the actual implementation of automation or even artificial intelligence is not yet prevalent in many companies (Verstraete et al., 2020). Currently, however, a significant number of companies are in the initial stages of implementing automated forecasting solutions. These solutions are typically introduced in a way that allows the automated output to run in parallel with the traditional forecasting processes, giving management accountants the option of selecting which results they wish to work with or even manually adjusting the algorithm-based results (Hussein, 2021). As automated solutions become increasingly prevalent, companies anticipate a correspondingly high output quality and economic advantages. Consequently, the introduction of automated solutions is being accelerated (Ardia et al., 2019; Baranes and Palas, 2019; Blattberg and Hoch, 1990; Dietvorst et al., 2018; Elliot et al., 2020; Schweitzer and Cachon, 2000). Concurrently, it is essential to consider the phenomenon of algorithm aversion, as a rejection of algorithms, which may be irrational, can result in automated forecasts being rejected and not used (Dietvorst et al., 2015). Consequently, an aversion to algorithms and a lack of trust can impede the successful implementation of digital solutions, automation and AI (Gsenger and Strle, 2021; Jussupow et al., 2020; Prahl and van Swol, 2017). This study provides the first evidence that algorithm aversion cannot be assumed or measured in every case. Instead, selective perception or psychological ownership can have a significant influence on the decision-making behavior of accountants. Furthermore, the results suggest that explanations are not as effective as previously thought and that there may be a lower importance attached to understanding about AI.

2.5 Study 4: Trust in Artificial Intelligence - the Role of Occupation and Explanations

The fourth study covers the following research questions:

- Do different professions exhibit different trust behaviors regarding artificial intelligence?
- How do forecast origin and performance affect trust behavior?
- Do explanations have an influence on trust in algorithms?

The objective of this study is to ascertain whether different professional groups exhibit disparate acceptance behaviors towards algorithms and artificial intelligence. It will examine whether individuals with diverse professional backgrounds respond differently to results when they are presented by a human or an artificial intelligence. Furthermore, this study will examine the role of explanations during the decision-making process. To this end, the effect of the explanation itself will be examined, as well as the effect when these explanations concern results from humans or machines. In addition, this study aims to examine the effect of performance on the acceptance process and to determine whether human or machine performance is a key driver of acceptance behavior, in general or for specific occupational groups.

The preliminary findings of the research indicate that performance may be a significant factor influencing trust and acceptance behavior (e. g. Alexander et al., 2018; Glikson and Woolley, 2020; Siau and Wang, 2018; You et al., 2022). Nevertheless, the emphasis on the performance of artificial intelligence appears to be at odds with research findings indicating that it is not the focus on performance per se that is crucial for trust behavior, but rather the reduction of artificial intelligence as a black box (e. g. Adadi and Berrada, 2018; Asatiani et al., 2020; Eschenbach, 2021; Rai, 2020; Wischmeyer, 2020; Zednik, 2021). This paper will investigate this aspect accordingly. It will examine the effects of performance and explanations for the reduction of the perception of an artificial intelligence as a black box. Additionally, research is focusing more on the question of what role professional groups have on people's behavior and how corresponding behavioral science approaches can be applied here. This question is particularly pertinent in the context of artificial intelligence, given that different professional groups have varying levels of contact with AI and may therefore hold disparate impressions and concerns about it (Långstedt et al., 2023). For instance, data protection concerns in professions with a heightened responsibility towards human life, such as in medical fields, may influence acceptance behavior in a manner that differs from that observed in business fields, where, for example, performance is often seen as a relevant factor for new innovations (e. g. Lennartz et al., 2021; London, 2019; Longoni et al., 2019). These discrepancies have not yet been sufficiently investigated in research, and thus are included in this study.

The results of this study indicate a surprising uniformity in the acceptance of new algorithms and artificial intelligence. First, it was demonstrated that although different performance is generally perceived by test subjects, it is not a decisive factor in the acceptance of artificial intelligence or the preference for a human advisor. The picture is similar for explanations. Although explanations have a slightly positive effect on acceptance behavior, they have no significant influence on whether artificial intelligence is adopted or rejected. This effect can be observed across occupational groups, with no significant differences in acceptance behavior observed between them in this study. Consequently, this study demonstrates that acceptance behavior can have universal reasons but is not solely driven by reduced black box explanations and pure performance factors. This study thus contributes to the research question of whether professional groups require different introductions and approaches to artificial intelligence and shows that acceptance theories can be applicable across professional groups.

2.6 Study 5: The Effect of Framing on Trust in Artificial Intelligence: An Analysis of Acceptance Behavior

The fifth study addresses the following research questions:

- What role does performance play in the acceptance of artificial intelligence?
- Do explanations have an influence on the acceptance of artificial intelligence?
- What role does the framing of a situation play in the acceptance of an artificial intelligence when introducing such a technology?

The objective of this study is to examine trust and acceptance research on artificial intelligence in a novel setting and with consideration of novel influencing factors. The concept of trust is explored in the context of a private application, specifically in the context of an investment scenario. This study aims to identify the determinants of trust that could potentially influence both the pre-contact phase with artificial intelligence and the application process itself. This study aims to demonstrate the influence of framing a situation before the application of artificial intelligence and before the processing of an output of an artificial intelligence. It also intends to illustrate the significance of managing expectations. Furthermore, the study seeks to illustrate the influence of performance and explanations in the subsequent course of the application on user behavior and acceptance behavior. This will provide a comprehensive view of the acceptance process.

Previous research from other disciplines and fields of application has already investigated the influence of framing, for example in a political context, and demonstrated its influence on opinions and behavior (Crow and Lawlor, 2016). To illustrate, framing can influence expectations prior to action, which may subsequently influence acceptance through expectations (Kim and Song, 2022). The initial research approaches are also influencing the framing of situations in which artificial intelligence is used and are investigating the influence of humanized and auditory representations on human behavior (Liao and Sundar, 2021). However, research approaches in management accounting are still rare in this area. The impact of performance and explanations has been explored in several research papers, with findings indicating that explanations can influence trust behavior (Du and Ruhe, 2009; Giboney et al., 2015; Miller, 2019; Pieters, 2011). Nevertheless, it remains unclear how these factors operate if the situation has previously been framed.

The findings of this study indicate that explanations and performance are not the primary drivers of trust in the application process of artificial intelligence. Instead, a significant effect of framing was demonstrated, which had a significant positive influence on the trust of the test subjects. The positive framing of an artificial intelligence was associated with greater trust and more readily accepted results. This advancement in trust generated by framing was so pronounced that the human advisor was even distrusted in the study, despite delivering superior results. This study not only demonstrated a positive influence on trust in artificial intelligence, but also an excess of trust, which can be generated by framing and must be observed and, if necessary, controlled accordingly.

This study contributes to the recent body of research on algorithms and artificial intelligence and expands previous research approaches to include the factor of framing. The study demonstrates that it is particularly important to offer an adequate introduction to artificial intelligence, which, however, still explains the possibilities, applications and functionalities as well as the possible limits within a realistic framework. In this way, acceptance behavior can be influenced by positively highlighting possibilities and potentially reducing barriers to application. Concurrently, this study demonstrates that communicating the limitations of artificial intelligence is also crucial to prevent overtrust and irrational behavior following a framing of the situation.

B Study 1: Future of Finance – the Influence of Digitalization, Business Model Understand and Trend Disruptions on Strategy, Competence Fields and Role Profiles

Authors, affiliation, and share of contribution:

Sonja Gabriele Prinz, Heinrich Heine University Düsseldorf: 100%

Author contributions:

Sonja Gabriele Prinz reviewed the literature, conducted the interviews and wrote the paper.

Publications, conferences and presentations:

Presentation to CFO Group Functions and discussion at CFO level in the company

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1 Introduction

Management accounting has been subject to a constant state of flux in recent years, driven in particular by new technical innovations and changes in the economic, political and regulatory environment. One of the main drivers of innovative new developments in management accounting is digitalisation, which within just a few years has evolved from an opportunity for global networking to an opportunity for comprehensive process optimization (Alam and Hossain, 2021; Yasinska, 2021). In addition to the advent of digitalization, other topics have also broadened the scope of management accounting. For instance, the emergence of new professional areas such as sustainability and the management of crises and uncertainties has led to the creation of new domains within the field of management accounting (e. g. Arroyo, 2012; Bennett et al., 2013; Soderstrom et al., 2017; Solovida and Latan, 2017). The areas of expertise in management accounting have also undergone adaptation in accordance with the changes in professional requirements and subject areas. The professional expansions and their effects on the competence fields and role profiles, as well as the influence of further trend topics, have not been adequately addressed in research to date. This study therefore aims to address this research gap and provide an overview of future subject areas that will be of importance for finance and management accounting. In addition, it will present several potential influences on the competence fields and role profiles. To explore the future of the finance function, I adopted an explorative approach based on the finding of the grounded theory (see Glaser and Strauss, 2017). This approach permitted an iterative process of data collection and analysis, thereby ensuring that insights emerged directly from the data itself. In this study, I engaged with experts from a major German postal and logistics company to reflect on and discuss their perspectives on the future of the finance function. The insights gained from these discussions have provided a comprehensive understanding of the evolving landscape of financial operations and strategy.

2 Historical Development of Management Accounting

The role of management accounting has undergone a series of changes and developments in recent years. The integration of management accounting within the finance division is also subject to change, with different approaches being employed in different companies. Of particular importance in the transformation process of management accounting is the shift in the role of the accountant towards that of a business partner of management (see figure House of Controlling as decribed in Weißenberger, 2007 and e. g. Weißenberger and Löhr, 2008), who is on the one hand responsible for the original and derivative fields of action, such as reporting an development of relevant finance IT but also supports strategic decisions with financial knowledge and stands alongside the company's top management (Weißenberger et al., 2012b).

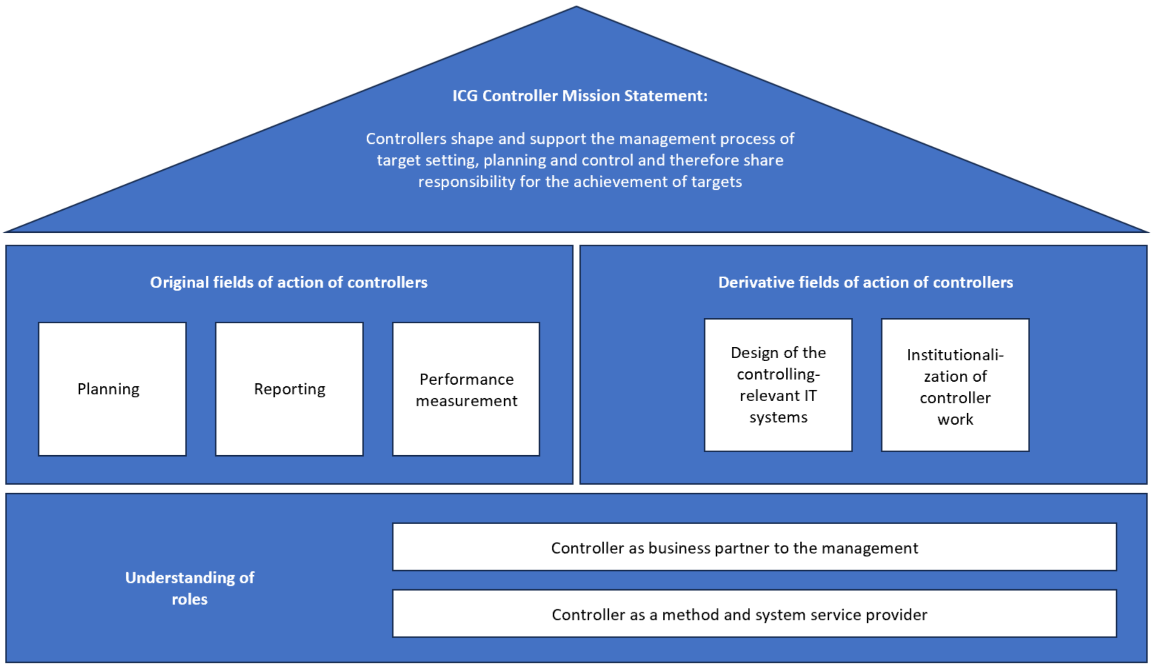

Figure B-1 House of Controlling

To describe the development, it is first necessary to refer to the role of the management accountant in the middle of the 20th century. During this period, the role of management accounting was strongly geared towards a purely financial orientation and a very focused view of financial figures. The monitoring of key financial figures and the transfer of financial data into corresponding financial reports was the main task of the management accountant, alongside cost and budget control. Strategic decisions were rarely discussed together with accounting (Kaplan, 1984; Ovunda, 2015). In the 1970s, this profile was already undergoing a gradual transformation, and the role of management accounting within the finance function and within the company was confronted with new challenges in the context of an already growing globalization, which demanded a higher and faster responsiveness of management accounting. In conclusion, the impact of management accounting on strategy and corporate success became increasingly evident, leading to a gradual integration into corresponding processes and a greater acceptance of the finance-based strategic exchange between management and management accounting (Johnson, 1981). As part of the initial digitization processes at the beginning of the 1990s, the responsibility for data management within the field of management accounting also increased. This, in turn, led to a further role adjustment and the emergence of new task profiles. The advent of digital evaluation systems and the possibility of faster data processing meant that recommendations for action could also be passed on to management more quickly and in a more up-to-date manner. In addition to newly acquired digital skills, the foundation was also prepared for the expansion of the accountant role as a business partner (Caglio, 2003; Wolf et al., 2020). In accordance with these developments, the role of the business partner in management accounting has been further developed and consolidated over the years. Currently, management accountants are responsible for monitoring the company's financial performance, as well as market developments and strategic decisions with corresponding financial implications for the company. Consequently, they have become an indispensable part of the leading management team in companies. Consequently, the role of the management accountant has evolved from merely dealing with financial flows to comprehensively mapping the real economic business model and simultaneously supporting innovations that are crucial for the finance sector (Samanthi and Gooneratne, 2023). Consequently, the contemporary exemplar of the management accountant is also, to a certain extent, engaged in the provision of counsel on and the promotion of the digitalization of the financial sector and digital change within companies (Yigitbasioglu et al., 2023). Accordingly, the ongoing evolution of management accounting is contingent upon the legitimacy theory or license to operate. This implies that not only financial decisions are supported and validated, but also that actions are aligned with social, ethical and regulatory frameworks. These frameworks are increasingly included in decisions. The growing responsibility and demands placed upon the role model of the management accountant necessitate a rethinking of the interdependencies between the organization, finance and accounting, as well as legitimacy and ethical responsibility (Banker et al., 2023). The skills required of management accountants may continue to evolve. In addition, to reinforce the legitimacy of accounting in the finance sector, it is necessary to consider the implications of new global trends and influencing factors, such as the role of sustainability and the implications for the finance structure in companies. Furthermore, it is essential to demonstrate an openness to new topics (Garanina and Kim, 2023; Xu and Woo, 2023). Consequently, the role of management accounting within the finance sector and the structure of finance within organizations remains subject to constant change in line with market fluctuations, global social, ethical and economic currents and trends. However, it is essential that the fundamentals of management accounting always form the basis of commerce and the foundation of knowledge. This study will critically examine and review the changing structure and requirements of management accounting and the future of the finance function. A case study will be used to inform this analysis.

3 Transformation of Management Accounting Through Digitization

3.1 Adequate Database as a Crucial Precondition for Digital Systems

Digitization has had a significant impact on the design and processes of management accounting and will continue to be of great importance for progress in this discipline within the company. However, in order to take advantage of opportunities offered by digitization, especially new tools for data processing, it is first necessary to create an adequate data basis so that the new tools can deliver the desired data-based result. Consequently, the efficacy of data processing is contingent upon the establishment of a data foundation that can be effectively processed by digital systems. The centrality of large and comprehensive data sets, commonly referred to as Big Data, in this process is evident (Hui, 2019; Warren Jr et al., 2015). Furthermore, an increasing number of data sets are incorporated into managerial accounting decisions, necessitating the preparation of data for use by digital accounting systems. In this context, the quality of data has become a significant challenge in management accounting (Emeka-Nwokeji, 2012; Xu, 2009). The quality of the data must be sufficient to permit its input into digital systems (Emeka-Nwokeji, 2012). It is important to note that in many cases, structured data must be created from a large amount of unstructured data. This step is often missing in many companies, which results in a lack of ability to process the data further due to its heterogeneity. Consequently, the data cannot be included in data-based decisions (Cockcroft and Russell, 2018; Eberendu, 2016; Vasarhelyi et al., 2015; Zhang et al., 2020). The heterogeneity of large amounts of different data sets is also reinforced by the fact that in management accounting, not only internal company and financial data are brought into decisions, but that it is increasingly observed that external (market) data are also brought into management accounting decisions

(Appelbaum et al., 2017; Brands and Holtzblatt, 2015). For instance, studies have demonstrated that the utilization of previously unused external data can facilitate the drawing of conclusions regarding the economic behavior of competitors, the general market movements, and the changes in production locations. Even conclusions about the fluctuations in production volumes can be reached through the use of external data. Such external data encompasses, for instance, satellite data, such as that from Orbital Insight, which enables the tracing of economic movements globally and the strategic utilization of such data by companies. The insights gained can then be translated into implications for the internal planning of the company in question (Kang et al., 2021).

3.2 Automated Data Processing of Internal and External Data Sets

Once the internal and/or external data has been prepared for further processing in the respective system, automated data processing processes are typically initiated, representing a significant innovation in management accounting that has emerged in recent years. The implementation of automated processes in the background also raises the question of how to prepare and present the results at the end of data processing (Brands and Smith, 2016; Ionescu, 2020; Korhonen et al., 2020). Some studies have indicated that the increased automation of systems may also result in a loss of trust in the sense of algorithm aversion and a trust handicap. Such trust losses can be alleviated, for example, through interaction and independent decision-making regarding the output of those systems, which are not simply imposed on one and need to be accepted and used for further work (Gsenger and Strle, 2021; Jussupow et al., 2020; Prahl and van Swol, 2017). The advent of self-service applications has enabled a new approach to the integration of users' needs, their own interaction and intervention capabilities, and automated data processing. A case in point is the widespread adoption of self-reporting tools, such as ‘PowerBI’, in the field of management accounting. These tools are already in use in numerous companies and are undergoing continuous development (Arnaboldi et al., 2021). The future of such automated systems in management accounting is contingent upon the increasing utilization of artificial intelligence, which can facilitate self-learning processes and thus pave the way for the development of completely independent systems and robotic process automation. Through self-learning processes, queries from employees may be anticipated at an early stage and mapped directly without their intervention. Furthermore, data can be processed in a more targeted manner in order to present results in the most efficient manner possible, which can inform further decisions in management accounting, as well as at the strategic level in management (Almagtome, 2021; Binkow, 2015; Leitner-Hanetseder and Lehner, 2022; Riggins and Klamm, 2017).

3.3 Digital Services as Part of the Finance Function

In addition to automated processes and new data, new digital services are also playing a role, both as a separate part of the finance function and in the outsourcing of various other processes. On the one hand, it is evident that new digital solutions are being developed within the companies themselves as a consequence of the digital transformation, which in some cases also result in changed business models (Bican and Brem, 2020; Frank et al., 2019; Priyono et al., 2020; Sebastian et al., 2020). Furthermore, a countervailing trend can be observed with regard to the outsourcing of processes (Lacity et al., 2011). In examining the standalone digital solutions, two primary movements can be discerned. On the one hand, there is a pervasive internal pressure, also evident in management accounting, to incessantly assess novel digitization solutions and to guarantee enhancement and augmented efficiency of the systems. However, due to the proliferating intricacy of the systems and the mounting number of solutions, the further advancement and comprehension of such systems in the finance functions and in management accounting is also becoming considerably more intricate and challenging (Beerbaum et al., 2019). It can be observed that some companies have already established a separate IT service function as a new area within the finance functions, which deals with the review and further development of digital solutions in the finance area. Consequently, it can be seen that there is a new scope of responsibilities and new roles within the finance functions that has been triggered by digitalization (Coman et al., 2022; Möller et al., 2020). Accordingly, the frequent reference here to job losses due to digital solutions (e. g. Dengler and Matthes, 2018) is at least partially refuted and weakened, as digital transformation can also act as a creator of new jobs and new task profiles (Frankiewicz and Chamorro-Premuzic, 2020). In addition to the new function within finance functions, there are further changes, many of which affect shared service centers. In some cases, shared service centers have evolved to the point where they can offer bundled solutions and processes on the market as their own product or service. In other cases, shared service centers are increasingly becoming independent and no longer play a merely secondary role in companies (Klimkeit and Reihlen, 2022). The increasing independence of shared service centers can also facilitate the opening up of new market segments. It should be noted, however, that while companies tend to outsource processes that are relatively straightforward to standardize to shared service centers, this is not always beneficial (Ulbrich, 2012). In the context of uncertain political environments, the central consolidation of corporate functions with high priority for the course of the company has once again become a matter of importance. In particular, when dealing with sensitive data and critical management accounting processes, which may have previously been outsourced in parts, those are being reintegrated into the core of the company so that no disruptions can occur due to changes in the political and/or regulatory conditions of the country to which outsourcing was operated. In light of recent developments, it can be posited that the future will see a re-emergence of internalized processes, with digital solutions and services, as well as management accounting services, assuming an increasingly pivotal role within the core of the company (Banham and He, 2014; Everaert et al., 2007).

3.4 The Influence of Changed Communication Through Digitization

Another issue that must be considered in the context of future developments in management accounting and finance functions is the aspect of changed communication and interaction, driven by increased exchange between humans and machines (Stavrova et al., 2021). In the context of altered communication, new digital offerings play a supporting role. On the one hand, it is important for the future of the financial divisions to promote interaction despite the prevalence of automation and the takeover of activities by robotics (Hanna, 2016). One method of introducing a personal touch to the exchange process is to engage in linguistic interactions with the system (Seaborn et al., 2021). While in the private application context, voice control via systems such as Siri have become the norm (Verhoef et al., 2021), they still play a subordinate role in companies today, but are becoming increasingly important in the further development of systems. the utilization of direct exchange via chatbots can be encouraged (Miklosik et al., 2021; Wang et al., 2022). The humanization of machines, whether through the use of human robots or human-rendered assistants on computer screens, may also improve human-machine interaction. However, studies have indicated that it is questionable to what extent such humanization, particularly in important financial areas, actually prevails. Furthermore, the representation of a robot as a human being may have a deterrent and frightening effect, which could result in a reduction in acceptance behavior on the part of the provider (Fratczak et al., 2021; Spatola and Wudarczyk, 2021).

3.5 Processing Real-time Data as a Goal in Digitization

In addition to communication, the handling of real-time data will also be a relevant topic in management accounting and finance functions in the future. Currently, real-time data is not adequately implemented in companies, yet it will become increasingly important for controlling and reacting quickly to global and local events (Byström, 2019; Geddes, 2020; Schmitz and Leoni, 2019). The development is supported by the increased use of smartphones and the growing demand for mobile finance applications that accountants and other users from finance functions can use and access data on the go. Furthermore, the increased use of mobile phones also highlights the existing gap with real-time data (Kwilinski, 2019). External data, in particular, such as news, readily arrives on smartphones as near-real-time push notifications, and in principle, can also have an impact on further behavior, for example, of investors (Clor-Proell et al., 2020). Consequently, erroneous strategic conclusions may be drawn from purportedly independent or neutral external real-time information, which is not supplied or processed by the company itself. Consequently, the objectivity and relevance of such information may be questionable, and it may even be misleading. Consequently, the availability of real-time data, even on mobile devices, could take on a decisive role.

3.6 Changing Role of Management Accounting in the Finance Function

In the context of the emerging changes and transformation processes, it is evident that the role and responsibilities of the CFO will undergo a transformation in the future. On the one hand, the CFO will assume greater responsibility for the data used and for its handling by the individual departments reporting to him/her. Furthermore, he/she will have to intensify the exchange with other leading managers regarding data exchange and usage (Sandner et al., 2020). Furthermore, the business partner role will be expanded to include new areas of expertise, such as sustainability or ESG, which will be discussed in greater detail later in the paper. The emergence of new trends in the financial sector and the associated changes also raise the question of what role management accounting itself will play in the company in the future and to what extent the two areas of finance and management accounting will move closer together in the future or can be more clearly distinguished from each other (see also Bommer and Gruber, 2021; Neundörfer and Wiltinger, 2022; Schäffer, 2022). This also prompts the question of the extent to which digitization has ensured that processes and departments tend to be expanded with new functions or even overlap more in terms of content in the future. It is often stated in the course of changes through digitization that efficiency advantages can be achieved (Parviainen et al., 2017). This is accompanied by the aforementioned process optimization. This can result in management accountants, for example, being able to focus more strongly on management activities, core tasks and strategic aspects, and even on their role in business partnering (see also Möller et al., 2017; Weißenberger et al., 2012b; Wolf et al., 2015). Consequently, the implementation of new digital process innovations may result in a corresponding streamlining of management accounting tasks. However, this is counterbalanced by an increase in complexity, which is fostered, for example, by larger volumes of internal and external data, as well as the general advance of digitalization (Knudsen, 2020). Furthermore, the expansion of data sets and the general digitization of information may necessitate increased interdepartmental exchange, as there may be instances where the content of one department is dependent on that of another (Roberts and Grover, 2012; Ruiz-Alba et al., 2019). In light of this, it is possible that departments such as finance, divisions, or even insurance and risk departments could be brought together. However, it is important to note that this does not necessarily imply a reduction in the number of departments, but rather a concentration of activities that can be re-organized in different ways within the company due to the proximity of content.

4 Areas of Competence in Management Accounting

4.1 Existing Fields of Competence in Management Accounting

The latest advancements in management accounting and the finance function demonstrate that the scope of expertise among management accountants has undergone a transformation in recent years (Wolf et al., 2020). It is first necessary to note that some originally defined fields of competence continue to exist in this way but can be expanded to include new aspects. Among the predefined areas of competence that continue to exist in management accounting is, of course, the very fundamental area of competence of finance and management accounting (knowledge), which also includes, for example, knowledge of financial ratios, financial and management accounting processes, and non-financial aspects and ratios. It is noteworthy that in the definition of this competence field by Schäffer and Brückner (2019), the aspects of finance and management accounting are already closely linked and almost combined. It is evident that although elements of finance are part of the competence field, classic finance functions such as treasury cannot be found here. Instead, content is based on traditional management accounting knowledge. In addition to the competence field of management accounting and finance, the competence field of management remains consistent. The content-related aspects of this competence field, such as the introduction and development of agile management methods or adequate change and project management, remain of significant importance. Furthermore, the competence field of communication continues to be relevant (Schäffer and Brückner, 2019). The global pandemic has highlighted the crucial role of effective communication in maintaining business operations. The shift towards digital communication has necessitated a more meticulous approach to meetings, with extensive preparation required to ensure smooth and productive exchanges. The evolving role of the management accountant, moving towards a more consultative and collaborative approach, has also brought to the fore the importance of leadership, negotiation skills, and effective communication and storytelling abilities. Furthermore, the competence field of analysis and technology continues to be an area of significant interest for the management accountant (Schäffer and Brückner, 2019). In particular, the relevance of this competence field is reinforced by the emergence of new data volumes and the associated issues of data protection and data security, as well as the topic of data quality and the development of adequate data analysis models. This is particularly evident in the context of accounting. Furthermore, personal skills such as analytical thinking, the capacity to comprehend and resolve issues, and a certain receptivity to innovations remain pertinent for management accountants. A fundamental comprehension of the business model, as delineated by Schäffer and Brückner (2019), also designated as a competence area, remains pertinent to controller work and the prospective evolution of the finance function. In this context, the term 'business model understanding' refers to the comprehensive capture of the core business activity at the operational level. In this manner, the accountant is in a position to adequately manage the company financially. This entails, for instance, identifying value drivers and success factors of the business model and the individual entrepreneurial sub-preparations, as well as translating them into financial key figures and strategies (Schäffer and Brückner, 2019). Furthermore, it is evident that these existing areas of expertise can be further developed. For instance, in recent months, additional topics have been addressed in business, corporations, and finance and management accounting that require greater focus and contribute to the development of entirely new areas of expertise.

4.2 New Developments of Competence Fields in Management Accounting

In the context of current developments, in particular those pertaining to sustainability aspects and ESG, it has become evident that managers and management accountants are assuming a greater role in crisis management (e. g. Arroyo, 2012; Bennett et al., 2013; Hörisch, 2021; Jasch and Stasiškienė, 2005; Latan et al., 2018; Maas et al., 2016; Padovani and Iacuzzi, 2021; Pavlatos and Kostakis, 2018; Soderstrom et al., 2017). Upon examination of the inaugural potential domain of ESG, it becomes evident that certain elements within the domain of management accounting have emerged as pertinent, despite their absence from previously delineated competence fields. For instance, controllers are becoming increasingly involved in matters pertaining to the formulation of a green strategy and the development of an ESG roadmap (Cokins and Căpușneanu, 2020). his strategic aspect of the new area of expertise is linked to more financially significant topics, such as green budgeting, the definition of ESG metrics across the different dimensions, compliance with legal obligations and their monitoring in the context of green compliance, and the introduction or monitoring of green audits, which require adequate green data management (e. g. Chan et al., 2014; Eny and Rum, 2019; Moorthy and Yacob, 2013; Rounaghi, 2019; Solovida and Latan, 2017).

In addition to the sustainability focal points that have led to the emergence of a new field of competence, the management accountant as a crisis manager or the field of competence of crisis and risk management may also be relevant. General uncertainties and global crises, be they health crises or geopolitical disputes, require companies and accountants to deal with uncertainties and, at the same time, require strategic adaptation, flexibility and robust crisis management (Bobryshev et al., 2015; Iershova et al., 2021). Against the backdrop of the necessity for rapid adaptability, scenario analysis and flexibility in planning have also assumed greater importance. In addition, the topic of internal control systems also plays a role in the field of adapted risk management (Adegboyegun et al., 2020). In light of the adjustments and innovations, it is imperative to guarantee the correct execution of ICS within the company. Consequently, within the scope of the accountant's competence field, the role of risk manager is emerging. This encompasses, in particular, the development and monitoring of the implementation of new and existing internal controls, particularly in the context of ICS. The prevention of fraud, compliance with regulations, cybersecurity and data security also play a role in risk management and are linked to existing areas of expertise such as technology and analysis. Overall, risk management in management accounting is gaining more relevance, which supports a development that has already become apparent in studies in recent years (e. g. Bhimani, 2009; Rasid et al., 2014; Soin and Collier, 2013).

5 Role Profiles in Management Accounting

5.1 Existing Role Profiles in Management Accounting

The emergence of new competence fields and the evolution of existing ones indicate a shift in role profiles of finance and management accounting professionals and the respective perception of needed competencies (e. g. Kokina et al., 2021; Tiron-Tudor and Deliu, 2021; Vlačić et al., 2021). This evolution should be taken into account when planning the future development of the finance function. However, it is important to note that the current role models, which have already been defined, continue to exist, at least in their central definitions. Existing role profiles by Schäffer and Brückner (2019) include the Service Expert, who is responsible for basic accounting processes, especially their execution and improvement. Furthermore, the Functional Lead is responsible for ensuring technical and methodological expertise and for communicating new strategic adjustments. The Change Agent, as a driver of procedural change, is tasked with advancing new processes, whereas the Scorekeeper, in contrast, is responsible for recurring, routine tasks. With regard to the role profiles, the Guardian is responsible for steering and controlling the achievement of defined goals, while the Business Partner, as previously mentioned, acts as strategic support for the management. Furthermore, the aspect of data and analysis competence is also important in the role profiles. In light of the ongoing demand for data competence, the role profiles regarding digitization are further subdivided into the Data Engineer, the Data Scientist, and the Decision Scientist. The Data Engineer ensures high-quality data and is also responsible for implementing new digital solutions. The Data Scientist focuses more on data analysis and the development of new data-driven solutions. Ultimately, the responsibility falls upon the shoulders of the Decision Scientist to draw the most appropriate conclusions from the processed and analyzed data, and subsequently to pose the most effective questions to the system in order to be able to incorporate the findings holistically into strategic aspects and approaches (Schäffer and Brückner, 2019).

5.2 Potential Expansion of Role Profiles

In accordance with the newly defined areas of competence, the existing role profiles of accountants may also be expanded in the future. For instance, in light of the new competence field of sustainability and ESG, the role of a 'Green Controller' may become increasingly important. This role profile may be further broadened to highlight the various focal points of this role profile. On the one hand, the role of the ‘Green Business Partner’ could be defined as one in which the individual is responsible for defining new sustainability strategies in collaboration with the company management and identifying potential opportunities for implementation within the financial framework. In addition, a further differentiation of the Green Controller as a ‘Green Budget Manager’ could become relevant. In this context, the Green Budget Manager is responsible for defining and managing investment or ecological budgets, as well as supporting the definition and implementation of the Green Roadmap in allocating the budgets for the respective implementation steps. Additionally, the Green Performance Auditor could be considered a subgroup of the Green Controller. The Green Performance Auditor is tasked with monitoring the implementation of the green strategy, with a corresponding focus on key performance indicators. In addition to ESG indicators, the individual in question is also responsible for the management of strategies in the context of green compliance and for accompanying the green audit and carbon accounting. They act as a technical contact person within the company, with financial expertise.

In addition to the Green Controller, another new role model may also be of importance in the future. Against the backdrop of growing uncertainties, which also affect management accounting, the finance functions, and the associated competencies, a ‘Risk and Crisis Manager’ may become important. Like the Green Controller, this role profile can also be further subdivided. An 'ICS Agent' may be defined as a role responsible for defining internal controls, control systems and their correct implementation by employees, as well as ensuring that controls are documented in accordance with regulations. Additionally, the ICS agent is tasked with defining measures and further steps if controls indicate that action is required. Subsequent adjustments and renewed checks are also accompanied by the ICS agent. Furthermore, in the capacity of a role model for the Risk and Crisis Manager, the Compliance Guardian can be a subdivision. It is of particular importance that the Compliance Guardian monitors and checks compliance with (new) legal framework conditions and also communicates the corresponding changes within the company. Additionally, the Risk and Crisis Manager may be further subdivided into the 'Uncertainty Steward'. The individual in question is responsible for reviewing the risks defined by the various departments and classifying them via a risk map into financial key figures and potential effects. This is done in order to then work together with the management on strategies for risk minimization. In addition, the Uncertainty Steward may be tasked with new focus activities, such as increased scenario analysis and integration of adjustment modalities into planning. The Uncertainty Steward should be able to identify risks at an early stage and incorporate external and internal developments into corporate planning. Furthermore, they should be able to assess the consequences of these developments for the company and its financial performance. Finally, the Risk and Crisis Manager could also be subdivided into the ‘Supply Chain

Guardian'. Due to changes in legislation and increased transparency requirements for supply chains and suppliers, the Supply Chain Guardian can allocate and manage risks to supplies and procurement. It is of paramount importance to ensure cost-effective and efficient supply chains, while at the same time adhering to legal and compliance regulations. Furthermore, alternative plans can also ensure flexibility in planning in case of crisis. Thus, the Supply Chain Guardian, as a subdivision of the Risk and Crisis Manager, can ensure the financially secure, cost-effective, and efficient supply chain (control).

6 Further Trends in Finance and Management Accounting

6.1 Increased Talent Development and Talent Acquisition

Furthermore, in the context of future financial development, it is important to consider additional trends and focus topics that are also important in addition to innovation topics, competence profiles and role models. Compared to innovation drivers such as digitalization or new areas of competence such as ESG, trend topics are usually already addressed in the company to a certain extent, but become more relevant in the future. The initial trend to be discussed is the growing emphasis on the acquisition of new talent, as well as the development of existing talent within the company (Alashmawy and Yazdanifard, 2019). It is becoming increasingly evident that in order to attract new talent, companies must devise new strategies and expand the scope of their activities. Furthermore, employers are attempting to engage with students at an early stage, introducing their company and development and career opportunities during their studies, particularly at prestigious universities (Hamza et al., 2021). In principle, a number of factors can be identified as potential measures that companies may wish to consider in order to attract new talent in the fields of finance and management accounting. One such factor is the establishment of early dialogue opportunities with students and young professionals. These may take the form of career fairs, conferences held at universities, or guest lectures, through which students can gain an understanding of the initial focus of the company in question, as well as engage in professional exchange with the company in question (Gebreiter, 2019; Zaharee et al., 2018). Furthermore, early collaboration with students through student business consultancies, internships and student traineeships can assist the company in gaining an early understanding of the working methods of potential high performers, thereby facilitating their integration and retention within the company upon completion of their studies. The introduction of new and flexibly designed trainee programs represents an attractive proposition for potential new employers of students, as they provide a comprehensive insight into the company (Baum and Kabst, 2014; Jonsson and Thorgren, 2017). In addition, young talents also perceive internal development opportunities, values, and work practices of the potential employer through reviews of the employer on relevant portals, contacts, or articles. These external sources of information can also influence the choice of their own employer. This goes hand in hand with internal aspects of employee retention, which are particularly important for the future of finance. Such initiatives include, for instance, a comprehensive development and training programs from which employees are free to choose and for which they are also given appropriate freedom of action (Elnaga and Imran, 2013; Sal and Raja, 2016; Zahra et al., 2014). Furthermore, diversity, including the proportion of women in managerial roles, is also perceived by external stakeholders and students (Backhaus et al., 2002; Perna; Schäpers et al., 2021). Furthermore, the signal to provide employees with greater flexibility in their work or general conditions, whether through expanded home office options or a four-day week or parent-child offerings, is regarded as valuable both internally and externally (e. g. Sánchez-Hernández et al., 2019). Furthermore, these flexibility aspects also facilitate the recruitment process. Previously, the recruitment of new employees was conducted exclusively at the respective location. However, with the advent of home office contracts, it is now possible to work independently of location, allowing for a much wider reach and simplifying the acquisition of new talent. Furthermore, employee benefits, such as company pensions, are of significant importance to some employees, as is the fact that the company defines and lives its purpose and values in an appropriate manner (Gartenberg et al., 2019; Spisakova, 2019). The advent of greater transparency on the Internet has facilitated the dissemination of information about companies, thereby enabling new and existing employees to assess the ethical and value-oriented conduct of the organization. The current global and political crises have heightened the importance of this topic, which is also pertinent when attempting to persuade future finance and accounting employees of the company's credibility and ethical actions.

6.2 Influence of Increased Cash Orientation

In addition to the search for new finance talent and the focus on employee retention, the issue of cash orientation has also become a stronger focus for companies. This is due to deficits in the real economy and the sharp rise in inflation and interest rates in recent months, which have made the availability of cash more important. Indeed, initial studies conducted in 2014 indicated that cash orientation is becoming more important again among companies (Schäffer and Weber, 2015). The financial crisis also precipitated this development, as did the growing significance of chapter markets. In the face of prevailing uncertainty, this development has been reinforced accordingly and is designed to guarantee a certain ability of companies to react promptly. This also demonstrates that the nexus between finance and management accounting, between internal management and the chapter markets and treasury, is becoming increasingly crucial and that exchange is essential. For instance, cash is becoming a more significant control variable, necessitating greater attention from management accounting and inclusion in decisions and planning (Schäffer and Weber, 2015). Furthermore, it seems that cash is becoming increasingly important for the company's success. Consequently, initial studies have indicated a positive correlation between the intensity of the use of cash ratios and the respective company's success (Schäffer and Weber, 2015).

6.3 Agile Management Accounting and Supply Chain Accounting

Agile management accounting and supply chain management accounting also play a role in the context of trend development. In agile management accounting, the focus is increasingly on formulating goals in an agile manner, for example using the 'Objective Key Result' method, and at the same time also implementing agile performance measurement (Stormi et al., 2019). Furthermore, the implementation of agile approaches in management accounting should facilitate communication with management, who often also work with agile target structures and agile project management. With regard to supply chain management accounting, it should be noted that this trend has been promoted by the 'Supply Chain Due Diligence Act'. In the context of supply chain accounting, which has now become more important, the objective is to provide financial support to management in anticipation of and avoidance of supply bottlenecks, while ensuring a cost-efficient and fair supply chain. Risk monitoring and risk minimization play a central role and have become more important due to current global developments (Doktoralina and Apollo, 2019; Möller et al., 2020; Taschner and Charifzadeh, 2020; Velayutham et al., 2021). The role of accountants in supporting management as a business partner in new strategy or alternative strategies with regard to supply chains, as well as scenario analysis and new forecasting models, has become increasingly important in light of this development. It is likely that this will continue to complement the range of tasks of this professional field.

It can be observed that a number of factors are having a significant impact on the future of management accounting and the future of finance divisions. These include digitization, current trend developments such as cash orientation, and the associated new competence profiles, such as ESG, and new role profiles. In the following section, the future topics identified in the research are compared to the future strategy of a company that currently focuses on defining future finance and accounting roadmaps and prioritizing topics in their finance department. Accordingly, the aspects presented here are subjected to critical review, with the issues prioritized in practice.

7 Case Study on the Future of Finance

7.1 Methodological Approach

As part of the methodology of this case study, the aspects concerning the future of the finance function were reviewed and expanded through interviews. The interviews were conducted with seven contacts from a listed logistics and postal company, all of whom held a management position related to finance and management accounting. In this explorative approach (see also Glaser and Strauss, 2017) interviews were semi-structured, with the main questions prepared in advance, but with flexibility to react to aspects and issues raised by the interview partners during the course of the interviews. Consequently, the interview questions were further differentiated and expanded during the course of the interview. The interviews lasted between 40 and 80 minutes and were each digitally recorded. The interview partners were selected by the company. Each interview partner was selected and assigned according to a key area of the internal finance strategy in which he or she had particular expertise. Consequently, the areas of focus for the finance strategy and the corresponding interviews were defined as business model understanding, finance employee (development), cash orientation, compliance/governance/aspects around process security, sustainability, digitalization, and the future role of management and the CFO. However, due to the extensive finance and management accounting knowledge of the interviewees, it was also possible to discuss and critically review the other aspects presented in the research beyond these focus areas.

7.2 Analysis of the Results

7.2.1. Data Processing, Process Efficiency and the Development of Artificial Intelligence as Future Focal Points in Digitization

The initial area of analysis is digitization, which will continue to play a pivotal role for the finance function in the future. Efficiency can be defined as a key driver for the implementation of new digital solutions within the finance environment. Efficiency in this context refers to process efficiency, which is ensured by new solutions. However, cost efficiency is also a significant factor, as investments are amortized and there is more room for employees to devote themselves to new tasks and hand over standardized tasks to digital systems. Consequently, the advancement of digitization will also facilitate the allocation of resources to new tasks and focal points that were previously constrained by the demands of day-to-day management accounting and finance activities. Furthermore, this will provide opportunities for further development and the emergence of new specializations.

The current focus in the digitization of the finance and management accounting function is often precisely in the area of process automation, as well as in data analytics and the harmonization of a previously often very heterogeneous ERP system landscape. This raises the question of the extent to which accountants, who increasingly have to work with digital systems and digital analysis methods, also need to have a digital understanding. As previously stated, digital competence is regarded as a core competence of accountants in research (see also Schäffer and Brückner, 2019). In the context of the case study, it can be posited that digital knowledge remains a core competence. However, a more granular analysis reveals that this is less important for accountants and the finance function. Instead, there must be a basic understanding of digital solutions and how they work. However, it is not necessary for every accountant to be an expert in data analytics, as it is possible to develop expertise in such fields over the course of one's career in the company. Furthermore, it should be noted that the degree of digitization as a core competence of accountants also varies and fluctuates depending on the size of the process. It can be posited that in-depth knowledge is less important for large-scale, group-wide or global processes. This is because such finance and management accounting processes often involve numerous experts and interdisciplinary teams, meaning that computer scientists or finance employees with a focus on data analytics can act directly with knowledge of digital systems, negating the need for the less specialized accountant or finance employee to possess such expertise. Nevertheless, the smaller the digital finance processes are, the fewer digitization experts or digitization specialists are automatically involved. Consequently, the accountant must continue to handle and resolve digital issues independently, necessitating a correspondingly greater depth of knowledge about the digital foundations and systems with which they must work.

The role of big data and the handling of structured and unstructured data volumes in the company and in the finance functions were also analyzed. It can be said here that the importance of dealing with large volumes of data will remain in the future, but that this will become easier. Indeed, this has already become easier in the present.

"*I believe that this has become much easier, in the sense that the technology that is available can simply handle much larger amounts of data*." (Key Informant #1)

The digitization of the finance function has placed a particular emphasis on data security and data cleanliness, with these issues being given increasing priority and attention in recent years. The targeted, improved evaluation of large data volumes, data markers, Power BI and SQL has also played a role in this process. In conclusion, the digital evaluation systems for large data volumes have been specifically enhanced and will be even more capable of processing unstructured data volumes in the future. This will facilitate the incorporation of a greater volume of data into financial decisions and strategic decisions. Although data quality remains a concern in certain instances, it is no longer a significant obstacle to the digitization of the finance function. This issue has been effectively addressed through proactive measures.

Another topic that will be discussed in the context of future finance developments is the handling of external data sources and external market data. During the course of this analysis, it became apparent that external data is increasingly being incorporated into corporate decisions and finance decisions. One example of this is forecasting, which also incorporates external data as factors relevant to decision-making. In addition to the internal updating of historical data as a basis for future forecasts, external developments such as the oil price or inflation are also constantly analyzed and included. The external factors that have to be included in a decision are constantly growing, and the systems that have to process such external data are also being developed rapidly and are becoming more capable of incorporating new volumes of data. In conclusion, the finance function is still in its infancy, and external data sources represent a relevant future topic within the finance function.

The development of business process outsourcing and the role of shared service centers for the finance function in companies were also considered within the context of the interviews. In the case of business process outsourcing, it was found that this topic is less relevant for the future development of the finance function. In recent years, simple, highly standardized finance processes have been increasingly outsourced, but this has been accompanied by a decline in the quality of the results. Furthermore, the high turnover of employees at the selected service providers made it impossible to ensure consistent quality of the results or processes, thus rendering outsourcing untenable. With regard to shared service centers, it can be observed that these are being further promoted and built up, but only from within the company itself, which rules out working with external shared service centers. In the context of global changes, there is a reduction in the number of location-related issues in the future. However, the effects of labor market dynamics also play a role in the context of shared service centers, with high employee fluctuation potentially leading to quality issues in processes and their outputs. In conclusion, it is advisable to reduce the company's dependency on third parties and external parties, particularly in the finance function, in order to avoid the creation of dependencies that could potentially lead to failures due to global changes that cannot be compensated for directly by internal areas. Furthermore, digitization will also impact the field of communication in the future, which has also undergone a transformation through digital solutions. Overall, digital applications for communication will become increasingly important. The humanization of systems and voice control of applications are becoming more relevant. One example of this is the fact that voice comment generators are already being used in companies to provide voice comments on sales changes and similar issues. Currently, this linguistic function is merely descriptive; however, in the future, it is to be increasingly integrated into analysis activities. For this to occur, however, it is elementary that accountants and finance employees also trust the digital systems, which can still be a hurdle in some cases. With regard to the issue of trust in new digital systems, it can be stated that employees in the finance sector currently have the option of continuing to work with the output of digital systems and to utilize them. However, in the future, this choice will become less or even disappear altogether, with accountants, for example, being required to rely on the digital outputs fully, for example for forecasts, and to deal with them in a decision-oriented manner.

"*This is still a very young discipline, so I think we have already struggled in many places to deal with the results and to trust them. [...] Predictive topics like this are already being used for very important key figures and you have to get some degree of acceptance for what comes out of it. Frankly, I can't really estimate what will happen yet, but only the future will really show when this topic becomes more widespread and trust has to grow even more. After all,* *there is a difference between using data analytics or predictive analytics to manage two or three small parts of a company today and saying at some point, 'Well, 70-75% of my key figures run on something like this'. This is a completely different area of risk that I am entering than is the case today, where we are still a bit experimental.*" (Key Informant #2)

Nevertheless, it is perceived within the company that the decisions are not attributed to the system itself, but rather to the human who worked with the system. Consequently, digital systems do not appear to provide a basis for justification, but rather serve merely as a means to an end for the finance staff. However, the decision is then attributed to them. This issue can also reinforce a trust handicap. In order to facilitate the adoption of new digital solutions, it is necessary to address the trust handicaps that currently exist. This will require the implementation of measures that encourage employees to engage with the development of new solutions and ensure their scalability, for example, in the case of new digital voice and communication solutions.

The case study also addressed the development of artificial intelligence in the finance function. This demonstrated that solutions based on artificial intelligence will also play a pivotal role in the finance function. There is also considerable scope for developing solutions in the finance function. The initial approaches for digital solutions based on artificial intelligence have already been established. Here, the first solutions are being created and designed in areas where there is a substantial quantity of training data that can be used to train an artificial intelligence. For instance, the domain of sales forecasting represents a significant area of research and development, employing extensive training data and novel statistical models that facilitate the emergence of artificial intelligence. Ultimately, patterns in the data are discerned, upon which an artificial intelligence develops a decision or a finance output. During the interviews, it was also observed that such solutions based on artificial intelligence are predominantly developed internally within the company. It is rare for suitable AI solutions to be found through purchasing, which is why internal teams are commissioned with developments and can then work with internal data volumes. Experts from the field of data science have become increasingly important. Consequently, this specialization has been expanded internally to a greater extent and will continue to be expanded in the future. One avenue for pursuing data science education is through a course of study that lasts half a year. This option is available in collaboration with a university and has been well-received by employees in the finance department. It is anticipated that this initiative will continue in the future. Additionally, the Center of Excellence is undergoing continuous expansion. This center brings together experts from various fields to provide specialized knowledge and expertise. In the event that a finance department requires the input of a data science specialist to establish an interdisciplinary team, the Center of Excellence can be contacted, which will then send experts to transfer the relevant knowledge to the finance function. Furthermore, the Centers of Excellence are to be further expanded and focused on digital applications and solutions. The impact of uncertainties and crises on the development of digitization in the finance function was also discussed as part of this case study. It can be said that various past crises have not slowed down any internal development, but that the development of new digital applications for the finance function has been steadily expanded and has even become more important.

"*I don't see that that has slowed us down. [...] How do we deal with the fact that our divisions are affected by any [...] crises? So these are all things that had priority for us, of course. Nevertheless, we have continued our digitalization projects on the one hand. On the other hand, we have actually used them to improve in the area of risk management, for example. In other words, with the help of digitalization, with the help of these tools, be it dashboarding or prediction, we have also achieved that we are better able to assess our risk in certain areas. So that has actually helped us to improve in this area and respond to this crisis*." (Key Informant #1)

Consequently, novel digital solutions, such as those pertaining to risk management, were accorded greater significance and employed with greater frequency, thereby facilitating accelerated development. All domains pertaining to prediction also became increasingly pivotal, with digital solutions being increasingly utilized and expanded in this regard.

Overall, digitization in the finance function indicates that the demands on the finance function will continue to grow. On the one hand, the quality of data and decisions is becoming increasingly important, as is the increased speed and efficiency of processes. At the same time, however, completely new content-related topics are also entering the finance function, such as sustainability/ESG and new subareas in the internal control systems. These new topics must then be addressed by the same number of employees who have to handle other day-to-day accounting and finance tasks. Consequently, the scope for familiarizing employees with new topics and taking them on is correspondingly limited. This is where digitization and the associated process efficiency will become particularly important. Digitization should ensure that processes can run automatically and autonomously. At best, internal and external data can be pulled and processed automatically for this purpose. Consequently, employees can then transfer processes to digital solutions, thereby creating the opportunity for them to familiarize themselves with new subject areas in which they may later specialize. However, in addition to the development of suitable digital components and solutions, one challenge that remains concerns the question of the qualifications of finance employees. It must be ensured that employees are willing to deal with the new topics and that they can grasp and understand their content. This may necessitate the implementation of new training programs to equip employees with the requisite competencies and knowledge in the future.

7.2.2. Management Accounting as an Independent Unit within the Finance Function

The case study on the future of the finance function also addressed the question of the role that management accounting will play in the company. This raises the question of whether management accounting will be regarded as an integral part of the finance function and will move closer to finance tasks in terms of content, or whether management accounting will continue to exist and operate as an independent department alongside traditional finance tasks. A clear picture emerged. In essence, it can be posited that the conventional notion of management accounting is on the decline. This is substantiated by the fact that management accounting is often associated with rather negative characteristics, such as those of a controller and supervisor or a bean counter. This is particularly evident due to the German terminology, whereas the English version of the professional term mitigates these language-related effects. Consequently, the term 'controller' is employed less frequently at lower hierarchical levels, particularly at the outset of a career, and is instead replaced by the term 'business analyst'. However, the latter still performs management accounting-related tasks. Nevertheless, the term 'business analyst' also conveys a distinct characterization and transformation in management accounting, which is becoming increasingly important in companies. For instance, young controllers are being sought who are less likely to commence their careers in a specific area of specialization or with a specific set of skills, such as sustainability accounting, within the company. Instead, they are seeking individuals who can develop into generalists capable of assuming roles in various specialist areas within the company and subsequently becoming experts in a number of key areas during their careers. The controller should initially act as a generalist, serving as a navigator or critical counterpart and developing a broad knowledge of the business model and the various divisions within the company. It is also essential that they possess a basic understanding of financial key figures and processes. Nevertheless, the controller is not primarily a 'controller' of numbers; rather, he possesses a depth of numerical expertise that can be leveraged to assume a more expansive role within the company. This could include becoming a data expert, sustainability expert, or ICS expert. At the management level, however, the term management accounting persists, as the negative associations associated with it are less prevalent in this context. Here, a certain degree of independence from operational departments is more appreciated. The accounting manager or management accounting director acts as a sparring partner, providing advice and expertise independently of hierarchical levels in operational areas. They also provide support for number-based corporate management or management of departments. In addition to the aspects already mentioned, it also became apparent that management accounting is an independent, but at the same time interrelated area within the finance function. On the one hand, the tasks of management accounting, for example forecasting, will always continue to exist and will also exist separately alongside other finance functions and be performed by accountants/business analysts. Nevertheless, management accounting is linked to other finance functions, which can be explained in particular by the increased exchange of data between departments. It is becoming increasingly evident that there are interdependencies between treasury, risk management and management accounting. In order to perform their tasks comprehensively and act with foresight, all three functions rely on the mutual exchange of financial data. In conclusion, it can be posited that the term 'management accounting' is being replaced at lower hierarchical levels by other job titles that have as few negative associations as possible and at the same time do justice to the accountant as the generalist, he/she is supposed to start out as. At management level, the term 'management accounting' will continue to exist, and thus management accounting also stands for independence, neutrality, and business partnering for the operational areas. It is anticipated that management accounting tasks will remain in the future unless they are automated and further developed by digital process solutions. Nevertheless, the increased exchange of data between the finance departments also encourages them to move closer together, since interdependencies exist on a data basis and only by exchanging information with each other can well-founded decisions be made and measures be taken.

7.2.3. Business Model Understanding and Extended Specifications as Factors Influencing Competence Fields and Role Profiles

Evolving role profiles and areas of competence for the future of the finance function were analyzed as well. With regard to role profiles, it is evident that controllers should initially adopt a generalist approach before progressing to the various specialization.

"*So you initially look for someone, a controller or business analyst, whatever title they are given, who starts out more as a generalist and, let's say, has to gather a general understanding of the company and the fundamental processes in controlling in the world of finance and can then go into this specialization in the next step.*" (Key Informant #4)

In general, the monitoring of strategic topics in management accounting has become more important. However, this also requires a basic operational understanding or a basic understanding of the company's business model. Currently, accountants often lack the time to familiarize themselves with novel issues because routine operational tasks restrict their time. As previously mentioned, this should be replaced and superseded to a greater extent by digital process efficiency and process automation, so that the service expert will become less important. The role of the scorekeeper in accounting is also set to undergo a significant transformation in the future, as the outsourcing of certain routine tasks to focus centers becomes increasingly prevalent. As evidenced by the interviews, reporting is set to become more concentrated in an internal reporting factory in the future, with a particular focus on specialization within the finance function. It was posited that the service expert may increasingly become a supporting service line expert who communicates with operational levels within the company and expands his understanding of the business model, especially at the beginning of his career. Furthermore, it was suggested that the Functional Lead will become more important. As financial governance and compliance have become increasingly important, the Functional Lead is seen here as the controller who ensures appropriate implementation and target achievement in the areas. With regard to the role models of the Guardian and the Change Agent, it was stated that for the future of the Finance function, the Change Agent will bear a large and separate responsibility. Change processes in the Finance function will continue to be a daily part of the role. The change must be managed and coordinated in a targeted manner and implemented successfully. The accountant, acting as a change agent in the finance function, requires an extensive skill set to manage these changes. In addition, the accountant must be able to leave their own perspective and put themselves in the perspective of other people and departments. As a consequence of the challenging nature of this change management task, it was further proposed that this role profile might be regarded as a discipline in its own right within the context of management accounting and the finance function. This is because it requires a broad knowledge base, control competence and foresight, which must first be built up. Furthermore, the role profile of the business partner remains important and is further present in management accounting. Nevertheless, the career path may have undergone a slight modification. Initially, accountants commence their careers as generalists, subsequently specializing in a particular field, before assuming the role of operational partner within their respective areas of expertise. Finally, they become business partners and managers for the executives. Nevertheless, this development remains to be observed, as the role of business partner may also be assumed much earlier. This is because the accountant as a generalist has early contact with the specialist departments and is already active here in an advisory and supportive capacity, thus already exercising part of the business partner role at an early stage. With regard to the role profiles of the data engineer, data scientist and decision scientist, it is evident that although accountants possess a rudimentary understanding of digital systems, they are not typically required to comprehend them to the granular level of individual algorithms. In the case of larger processes, accountants are typically supported by digital experts. Conversely, for smaller processes, a more comprehensive understanding of digital systems can be advantageous, as controllers themselves interact more frequently with digital systems and may be required to make changes. Nevertheless, it is not essential for the accountant as a generalist or for the accountant's general area of responsibility to possess in-depth information or data science knowledge in order to function effectively within their professional field. However, they must be able to interact with and comprehend the outputs of the systems in a targeted manner. In this context, it can be posited that the role profile of the decision scientist may become increasingly important in the future of both finance and management accounting. As work will and must increasingly be done with digital outputs, it will be necessary to transfer these outputs into decisions in a targeted manner. Furthermore, it is important to avoid the build-up of a trust handicap, which was already addressed in the analysis of digitization. With regard to the newly defined role models of the 'green controller' or 'green accountant' and the accountant as risk and crisis manager, it can be stated that these role models exist in principle, but that they exist more in the context of specializations. This will also be addressed in the context of the (core) competencies in the further course. For example, specialization as a green accountant becomes more important when working in internal areas that have a high carbon footprint. The controller as risk and crisis manager is also a specialization that is expressed through internal risk management, which continues to gain importance. Role models have also evolved in line with changing areas of expertise, which continue to be in flux for the finance function and require continuous development of finance staff and accountants.

The definition of the competence fields for accountants is preceded by the question of which areas are elementary for holistic corporate management. These areas then represent the relevant core competencies for (future) accountants. In principle, a basic methodological competence in finance and management accounting is particularly important and forms the basis of knowledge for every accountant. However, other topics are then also included with regard to holistic accounting and, depending on the focus, further weighted. This weighting can deviate accordingly in specializations or shift in one direction, for example, towards the management and measurement of sustainability or the creation and review of internal control systems. With regard to the competence fields defined as examples in the research, namely finance and management accounting, management, communication, technology and analysis, personal skills and an understanding of the business model, it is evident that the competence field of finance and management accounting forms the basis. However, all competence fields remain important and also gain in relevance at certain points. In the context of the case study, it was stated that the competence fields of technology and analysis are not gaining as much relevance. However, this cannot be attributed to the diminished relevance of data analysis for accounting and finance. As previously stated, data facilitates the integration of finance departments and enables process efficiency through digitalization. The reference here is to the development of the underlying technology for accountants. As a consequence of the expansion of IT departments that are able to act independently on behalf of the finance function within the company, digital tasks can be outsourced to such departments or a center of excellence and are no longer necessarily within the core competence area of accountants. A particular emphasis was placed on the understanding of business models in the context of this case study. The understanding of the business model, which accountants should also possess, has been culturally neglected in the past. Finance and management accounting were strongly isolated within the company, acting and reporting only in their service line and to the respective management and CFO. At the same time, however, the approval of finance and management accounting from the operational levels was required for financial decisions and investments. These approvals were only given if the finance employees understood and thought through the underlying facts. This process required a lengthy, case-specific training period in each case and held up progress overall. In light of the growing demand for management accounting to not only approve decisions but also to provide advisory services, a re-evaluation of the organizational structure, development and training of accountants within the company became imperative. To fulfil this advisory role (in the capacity of a business partner), it is essential to ensure an in-depth understanding of the business model from the outset and to continuously expand and develop this understanding. This encompasses, on the one hand, an understanding of operational functions and the core business, but also, for example, the ability to identify the success factors of the respective areas. This was particularly evident when non-financial data played a role. Deriving trends from the ancillary costs was important for accountants, but also for operational areas. However, this was only possible if the accountant understood the business model and the business very well. The development of CO2 key performance indicators (KPIs) and the audit-proof mapping of KPIs demonstrated once again the importance of interaction and exchange between finance, management accounting and operational areas of the company. This is accompanied by the requirement for the accountant to start as a generalist, who first builds up a broad base of knowledge in the company and about success factors. In the future, the accountant as a generalist must also rapidly establish a network within the company and be able to communicate their findings to other (non-specialist) individuals in a compelling manner, including through the use of storytelling and presentation skills. Additionally, they must be able to interact effectively with management and superiors. Understanding the business model will also be a correspondingly high priority for the future of the finance function and will be pursued further. This includes guiding this topic at the level of the (Group) CFO, i.e. at the level of management. In addition, the strengths and weaknesses of this implementation process will continue to be subject to an iterative review, supported by the HR function as an outside perspective. At the same time and in this case, there is an implementation survey conducted three times a year, which is then discussed at management offsites. In conclusion, this topic remains highly relevant within the framework of the competence fields and will continue to be pursued with intensity. With regard to the newly defined areas of competence in crisis and risk management as well as green accounting/sustainability accounting, a differentiated picture emerges from this study. In principle, these areas of competence are present in the finance function and also play a key role. However, these areas of competence are not so much focal points that an accountant needs to know directly upon joining the company and in which he or she needs to have knowledge. Rather, they are competencies that are required in later specializations. Nevertheless, risk and crisis management has become a more fundamental specialization, given that dealing with crises has assumed greater significance and market trends must be monitored more closely overall. New tools for risk identification and differentiated internal control systems will also become particularly important here. However, in the context of this case study, risk management/crisis management is defined as a field which in part goes beyond holistic control and is therefore, as already mentioned, more in the context of a specialization into which the controller can develop in the later course of his career.

Furthermore, the field of green accounting or sustainability accounting is of significant importance in the context of specializations. This area has gained greater significance in recent years and will also play a decisive role in the future of the finance function. In the context of this case study, it was asserted that with a rudimentary understanding of the requisite methodology, it is relatively straightforward to gain proficiency in this specialized field. Nevertheless, it is beneficial for young accountants to have had some initial contact with this topic, as this allows them to become more familiar with the issues more quickly and to classify certain terminology and processes. In the company, sustainability accounting and sustainable management are regarded as integral components of the organization's identity.

"*It's 100% already part of our company's objectives strategy, who we are. And I think more and more companies are moving that way if they have not already. And the whole push on the* *agenda, that's the point of it, it's to make it a part of how we'll be and how we will work.*" (Key Informant #6)

Consequently, the integration of sustainability into the finance function or management accounting was a natural process. Due to the reporting requirements, the exchange of data to be collected, as well as the targeted evaluation and preparation, became more important and represented an elementary link, which will also be lived and expanded in the future. Overall, the field of sustainability was accompanied by a lot of investments, which was also seen as a hurdle by the finance department and slowed down the process. In the medium and long term, however, it became evident that the investments had been worthwhile, thus enabling the field of sustainability to be advanced more effectively through the implementation of sustainability accounting. Employees from the operating units but also from the finance division, were able to identify strongly with this new topic, which contributed to a more positive corporate culture. In general, however, it will be challenging to find individuals who may initially be generalists but who subsequently specialize in this field, which is constantly evolving due to new requirements. The role profile of the green accountant will also have to be further differentiated and adapted to developments in the future. Currently, this role profile is characterized by fixed areas of responsibility within the scope of specialization. These include, for example, the development and measurement of key performance indicators (KPIs), the derivation and monitoring of industry standards in collaboration with peers and governance bodies, the preparation of data for business decisions and its evaluation in a targeted manner, and the provision of advice to management in the company as a 'green business partner'. However, in the future, these areas of responsibility are expected to be expanded. In the future, the finance function will also have to address other issues in this area of expertise that currently pose greater challenges. For instance, in comparison to conventional finance and market data, the quality of ESG data remains a challenge, particularly in terms of measurement, tangibility, and integration. Furthermore, there are additional complexities associated with mapping, namely the delineation of responsibilities for the various sustainability and ESG data. It is therefore essential to define these responsibilities in the future.

7.2.4. Transformation of the CFO's Role

The role of the Chief Financial Officer (CFO) and the role of managers in the finance function as a whole are undergoing a transformation as a consequence of recent developments in areas of competence and a changed corporate environment. From a technical standpoint, it is evident that the requirements that have been introduced by new areas of competence and special issues must also be documented and made tangible in terms of content for the CFO. For instance, the ability to apply business analytics, comprehend ESG, manage risk, adhere to standards and policies has become crucial. Concurrently, it is evident at the CFO level that an understanding of the business model has assumed a pivotal role in finance-oriented corporate management. Proximity to operational management, in particular, will play a pivotal role and become increasingly important for the future of the finance function. In addition, the ability to manage crises and deal with uncertainties plays a role and will also become more important for CFOs. Furthermore, the CFO must continue to drive cultural change within the company and live the company's cultural values and proactively integrate them into the subdivided levels. This includes, for example, a culture of open communication, which also implies an open approach to failure and mistakes. It is evident that the role of the CFO has undergone a significant transformation. The traditional image of the CFO as a risk-averse, process-compliant number cruncher has been supplanted by a more dynamic profile, encompassing the responsibilities of a business partner and leader, with a focus on financial and numerical expertise, innovation, and driving change. This shift has profound implications for the demands placed on management and accountants. Consequently, the business partner role (with expanding financial expertise) should also be fulfilled here. In the context of this case study, this combines the roles of a 'Credible Business Leader' and a 'Valued Financial Expert'.

"*I need to understand how operations is subsequently reflected in my financial figures. [...] The CFO of the 21st century has to cover both areas. They have to be the Valued Financial Expert and at the same time the Credible Business Leader*." (Key Informant #7)

In this context, it is assumed that the accountant/manager, within the scope of their role, drives financial topics forward and promotes exchange at the operational level, while at the same time ensuring a macroeconomic view of the topics, has leadership skills and conducts relationship management within the company and with external partners and interest groups, and is characterized by an open mindset and an interest in innovation. In conclusion, the transformation of the CFO role demonstrates that the increasing demands on the finance function have a far-reaching impact on the role profile. However, this does not merely imply professional gains in knowledge required of the CFO or management. Concurrently, cultural change, communication skills and the reconciliation of operational and financial as well as macroeconomic perspectives become crucial, and should contribute to value-oriented, holistic corporate management.

7.2.5. Prioritization of Trend Topics

Furthermore, the case study discussed other trend topics that could potentially impact finance and management accounting in the future. On the one hand, these included agile management accounting, the increased focus on supply chain accounting, the increasing cash orientation, and the topic of talent development and talent acquisition. Additionally, another trend topic emerged here, which relates to compliance, governance and (IT) security. The initial observation regarding agile approaches in management accounting is that they have become less significant in the context of the future of the finance function. While several managers in management accounting implemented agile approaches over the past two years, employees lacked sufficient time and resources to pursue new agile goals, leading to the discontinuation of this management method.

In contrast, supply chain accounting remains a highly relevant and important trend topic. It is of particular importance to maintain constant transparency, including the potential for disruption to the supply chain. It is crucial to anticipate potential disruptions as early as possible to prevent bottlenecks. However, this topic is again addressed as part of an internal specialization and is not a broad topic or core competence area in the management accounting and finance function. Consequently, young accountants will have to bring this knowledge base with them in the future. Furthermore, as in research, the increasing cash orientation was addressed as a trend topic in the company.

"In general, this is a topic which will be further accentuated in the finance function. The topic of cash is, in my opinion, probably even more important and is now particularly important in the company I work for, or it is particularly emphasized. Furthermore, it is treated in the same manner as the topic of profit, which is not the case in all companies. This demonstrates that cash is a highly significant topic within the company in question. It is not a novel topic, but one that has been of great relevance for many years. It is reasonable to conclude that the topic of cash is perhaps more prominent in this company than in some of the other companies I have previously worked for. [...] I believe that it has simply been understood that although earnings or EBIT are of course very important, there is a divergence between cash generation and earnings development. Achieving greater consistency is therefore an important objective." (Key Informant #5)

In general, EBIT, capex and cash flow are the key performance indicators considered. However, in line with this trend, the view tends to move away from the EBIT orientation to the cash flow orientation. It will also become important that P&L and the balance sheet are considered more for management purposes. This is also driven by the requirement for a stronger process view, as explained in the further course.

In addition to this change, another trend topic plays a crucial role for the future of the finance function. As previously stated in this case study, the business model and the link between the finance function and the operating levels and divisions in the company will be of great importance in order to enable a holistic view and thus also to ensure the most value-oriented, efficient corporate management possible. Up to now, management and the CFO have often focused primarily on output KPIs for analysis. This will have to change in the future, also in light of the interlocking between finance and operational business. Instead, a holistic process view will be required, which will also necessitate the consideration of more input KPIs. These will also have to be included and reconsidered for optimized management, and the implications of the KPIs will have to be examined in terms of content. In conclusion, the process view, and not just the consideration of output KPIs, is becoming increasingly important for the integration of purpose into the finance function. Only through a holistic process view and changes along the entire process chain can holistic management be ensured, and the purpose be anchored in all elements of the value and process chain. Furthermore, the budgeting aspect must also be improved in the future and be driven more strategically by those responsible. Budgeting should not be a rigid construct; rather, it should provide direction and facilitate operational implementation. This driving of progress through budgeting must become even more important in the future of the finance function.

Another priority and trend topic is the trend topic defined as 'Keep the House in Order’ around risk management, prevention of fraud, compliance, governance, IT security, business continuity management and critical review of the basic functions in the company. In light of the ever-increasing governance and compliance requirements, it is imperative that all departments maintain a constant focus on these matters and implement them adequately within their respective organizations. At the same time, in a more digitalized finance function, the importance of cyber security has increased, given that data has become the basis of all actions and hacker attacks have simultaneously increased.

"*Continuity management, with the example of cyber attacks, would be an issue for me where we need to ensure that we can still handle these basic processes in a stable manner, even in the event of any major incidents*." (Key Informant #3)

In the context of this topic, it is therefore important to ascertain whether all areas are familiar with the security basics, implement this internally and exchange information on this across departments. Furthermore, external factors such as embargoes, sanctions, new tax and reporting regulations must be continually reviewed and prepared for implementation by the relevant areas. This trend field has made the exchange of professional expertise within the finance function particularly important, and this will continue to be a priority in the future, for example, within the framework of 'Townhall Meetings'. In order to ensure transparency, the current catalogue of measures is discussed and further developed internally. Concurrently, a shared understanding of this topic must be cultivated through ongoing discourse. In addition to this trend field, the development and acquisition of talent in finance and management accounting also play a special role in the future of the finance function. This topic has once again become a focal point in the context of the shortage of skilled workers and the 'War for Talents'. In this context, the defined goal of establishing the "Best Finance Team" should also serve as a message and promote a sense of belonging and identity. In the future, the optimal team in finance and management accounting will be distinguished by highly trained personnel engaged in the finance function, ensuring the highest level of expertise. In addition, internal satisfaction should be a priority, as evidenced by high satisfaction ratings, positive feedback, a sense of belonging and pride, a commitment to the team spirit, and the presence of diverse role profiles that contribute to high-quality work. In the future, young talents will be required to possess a combination of hard skills, soft skills, and social/intercultural skills. The hard skills that are prioritized are those related to technical qualifications, methodological skills, and knowledge of holistic corporate management. In terms of soft skills, problem-solving abilities, the capacity for independent and structured work, the ability to tell a story, and the ability to monitor and develop one's own tasks are particularly important. In terms of social skills, it is important to consider teamwork, communication skills, openness, and the ability to engage in global, intercultural exchange. Furthermore, young talents should be encouraged to cultivate a spirit of inquiry and a willingness to inquire further, as this approach can facilitate the accumulation of knowledge through the exchange that it encourages. Internally, a variety of trainee programs and role profiles should then be implemented in order to facilitate the aforementioned development. It is recommended that young accountants and finance employees be permitted to devise their own trainee programs. The role profiles should highlight new opportunities within the finance function and be defined in collaboration with the prospective employee, taking the form of a career path or roadmap. Furthermore, a range of internal opportunities for the advancement of finance and management accounting professionals will continue to be accessible in the future. These include online and offline training, the promotion of networking and exchange through support programs and events, and the accountant starting out as a generalist in the company. Furthermore, the company should continue to offer international opportunities, while simultaneously implementing a more robust hybrid working model to ensure that employees retain the desired flexibility. Furthermore, the emphasis is on the transparency of individual performance. This entails ensuring that finance employees are able to present their own performance and work independently, and that their work is not merely transferred to superiors, who then present it in management meetings and pass on the feedback in a top-down manner. Furthermore, visibility and the associated direct praise and feedback should also signal confidence in the individual's performance and abilities. This should, in turn, facilitate the establishment of an open and trusting corporate culture, which should continue to be present in the finance function.

8 Discussion

The results of the case study have already demonstrated a corresponding transformation in the function of management accounting, in conjunction with the respective role profiles and areas of responsibility of management accountants. In order to revisit the analyzes and results of the case study in a focused manner, four theses are presented below, which represent the developments and are discussed accordingly in terms of content.

T1: The number of new areas of expertise in management accounting is constantly increasing and requires new training, new job profiles and divisions within the finance function.

The ever-increasing number of new areas of expertise is clearly demonstrated in this case study. New areas of expertise can be in the field of digitalization but can also extend to completely new and not yet fully standardized topics such as ESG or sustainability and their measurement and mapping in reporting. This necessitates a corresponding adaptation of knowledge within the finance function so that these new topics can be addressed, and the competitiveness of the company can be maintained simultaneously. Furthermore, it sends a signal to relevant stakeholders that new topics are being addressed, innovations are being recognized, understood and internalized, and that the finance function is constantly evolving. One potential solution to this problem is to ensure that employees are adequately trained in new content. However, as the case study revealed, this can be challenging due to the time constraints and the need for employees to integrate and become familiar with new topics in addition to their ongoing day-to-day responsibilities.

One alternative is to create new positions within the finance function that are dedicated to these new topics. This approach can provide relief for existing employees while ensuring that they are adequately familiarized with the new content. In conclusion, the creation of new positions within new subject areas can also facilitate inter-divisional exchange, as more consultation, including with operating units, is required. However, this presents a challenge, as this exchange must also be practiced within the finance function and in management accounting. For instance, it would be advantageous to define a standard process for regular exchanges between relevant departments and divisions. This would ensure that consultation takes place at regular intervals and interdisciplinary and cross-divisional discussion is maintained, especially in times of increased digital conversation. It is also important to consider the increased cost base when creating new positions. This is due to the new positions themselves and the associated recruiting costs. Furthermore, the creation of numerous specialized positions also reduces the flexibility of the finance function, as employees are generally only able to work in their limited field. This may result in a lack of understanding of other finance topics, strategic or operational issues. Nevertheless, it cannot be denied that new subject areas will enter management accounting and the finance function, which will result in a corresponding change in jobs. This will also have an impact on management. Accordingly, the further thesis is as follows:

T2: The role of the CFO will be expanded and will be aligned and extended to new divisions and subject areas.

The expansion of the CFO role is also based on the expansion of subject areas, job profiles and divisions within the finance function. For example, it is conceivable that new topics relating to sustainability and ESG could be covered by a dedicated CFO with the corresponding specialization. As a consequence of this development, the House of Controlling may also be expanded to include a new basis that deals with the management function and control of non-financial objectives, measurement and integration into the corporate strategy. This basis may also perform this function in addition to the purely financial view, for example, the role of business partner, or may be covered and considered in management accounting (see figure below).

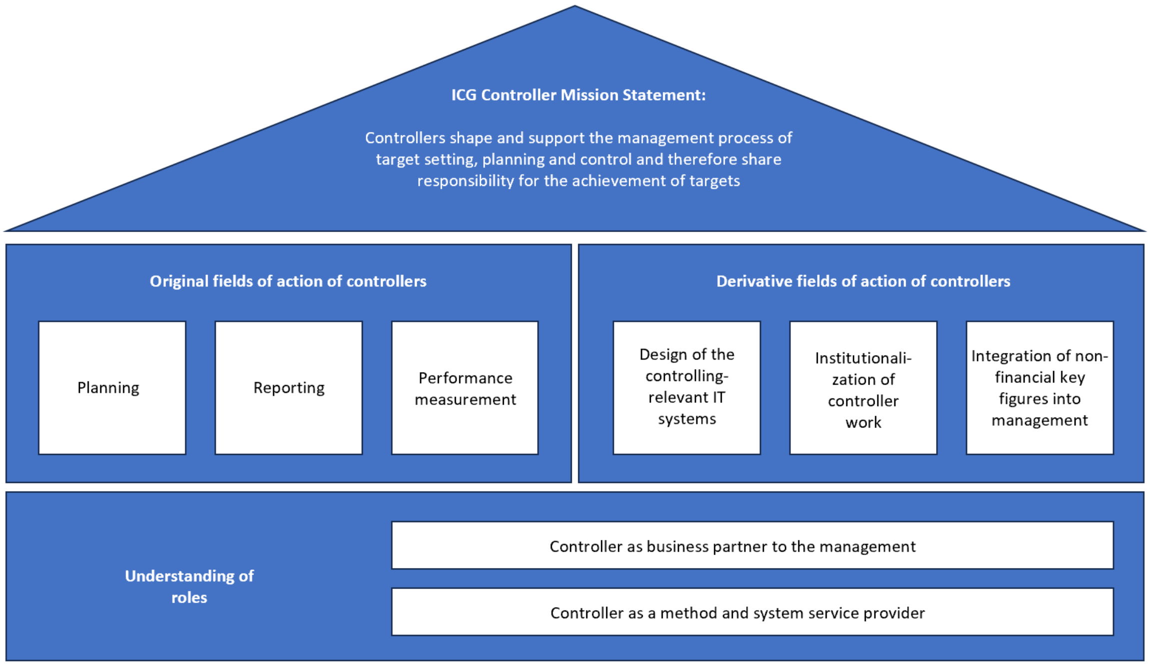

Figure B-2 Extended House of Controlling

An appropriate management position with a dedicated CFO for new specialist topics such as ESG can ensure a comprehensive view and control of the topic at management level and at the same time guarantee leadership for new employees in new positions and divisions below. The necessary combination of financial expertise, which was also repeatedly mentioned in this case study as a necessary basis for all management accounting activities, and non-financial topics with corresponding management and reporting are also ensured. This could again strengthen stakeholder trust and ensure or even improve a positive corporate image. At the same time, however, there could also be possible overlaps in competencies, which could lead to potential conflict due to a lack of demarcation of responsibilities. In addition, new CFO positions are also likely to result in an increased cost base due to salaries and recruiting costs, which must be taken into account and factored in accordingly. In addition, potential conflicts with the planned budget framework should be clarified in advance, as new positions relating to sustainability, for example, will also require more investment volume, which will be with-drawn and shifted from other divisions, for example. Possible conflicts and shifts in investment volumes should be considered in advance and discussed and planned together with the relevant managers. At the same time, sustainability issues are not the only area that creates new challenges within the finance function. Accordingly, the following statement is:

T3: Artificial intelligence is being driven forward in the finance function and is creating new efficiency benefits.

As evidenced by this case study, the role of artificial intelligence in the finance function is set to become increasingly significant in the future. It is already a driving force behind innovation in the sector. By continuing to invest in the development of specific AI capabilities within companies and within the finance function, it may be possible to create evaluations and forecasts with greater speed and accuracy, using real-time data. Routine work in the finance function and in management accounting could be replaced, thus enabling the role of business partner to be fulfilled more effectively. This development is also supported by the fact that, as this case study also showed, storytelling, presentation and communication skills are becoming increasingly important and must be present in order to fulfil the role of business partner at an early career stage. It is possible that artificial intelligence may be used even more specifically in the future for critical issues such as cyber security and improved automatic defense against cyber attacks on the company or the finance function. This would not only generate efficiencies but also ensure the protection of the company and its data sources and data volumes, while at the same time improving the company's image and strengthening stakeholder trust. Conversely, the advent of artificial intelligence may also result in job losses, particularly in those roles that can be automated and digitally taken over. Another significant challenge is the discussion of data use and the definition of ethical boundaries and limits for the use of artificial intelligence, with corresponding responsibility and liability when using AI-based results. These issues are often not sufficiently clarified, which can result in uncertainty, lack of use, or incorrect use of new digital and AI-based systems. In this context, it is similarly important to establish clear communication and clear guidelines to ensure that employees are adequately informed and have access to appropriate resources. This includes identifying avenues for seeking guidance and discussing challenges or innovative ideas with relevant stakeholders. In light of these considerations, the final thesis of this case study is as follows:

T4: Communication skills and storytelling ensure cross-divisional exchange and promote an innovative corporate culture despite advancing digitalization and increased digital exchange.

It is imperative that communication be further strengthened and prioritized within the finance function, particularly in the context of the digital age. By prioritizing direct exchange, an open corporate culture can be simultaneously promoted, which has the potential to generate more innovation and further development. Conversely, the identification and resolution of issues, queries and challenges can be more effectively managed, thereby reducing the incidence of errors. Effective communication, which is also encouraged by management, can also enhance employee satisfaction, which can subsequently lead to an enhanced corporate image. Additionally, the importance of storytelling is increasing, and this is a skill that must be introduced to young talent within the finance function through targeted training and promoted at an early stage. Ultimately, this will enable the role of business partner to be fulfilled effectively. Concurrently, in an environment where data is increasingly pivotal, it is imperative that the factual basis is not overlooked. In particular, within the finance division, it is crucial to emphasize that decisions are not solely based on a compelling narrative and persuasive communication skills, but also on a foundation of reliable financial information. Otherwise, there is a risk that the use of storytelling and skillful presentation will lead to an overly positive distortion of facts, resulting in poor and unprofitable decisions with negative consequences for the company and thus also for the staff in the finance function and other departments.

In conclusion, it can be observed that the emergence of new topics such as artificial intelligence and sustainability will necessitate the creation of novel roles, divisions, and a management team with expanded responsibilities within the finance function. A willingness to innovate and the ability to make sound strategic decisions, in conjunction with business partners who are adept at effective communication and narrative construction, facilitate the advancement of new developments within the company. This, in turn, engenders an enhanced corporate image and elevated levels of employee satisfaction. Furthermore, it facilitates the retention of new, young talent within the company, thereby further promoting this positive development.

9 Conclusion and Contribution

The case study provides a clear picture of the future of the finance function, which also largely supports and extends the theoretical explanations. Thus, this study contributes to research in depicting the future development of the finance function and the management accounting that is integrated into this finance function. In addition, the study can be used to classify new topics in the areas of competence and role profiles and to prioritize trend topics presented in research and assign them to the developments mentioned. In conclusion, the emphasis on process efficiency will be of paramount importance in the context of digitization in the future. It is of particular significance that digital processes create an opportunity for employees from the finance function to familiarize themselves with new topics, and that standardized routine tasks can be taken over by digital solutions. This will be accompanied by the further development of an internally created artificial intelligence in the respective area, which will be developed in an integrated manner in the corporate divisions and no longer considered a separately considered development topic. In order to achieve this, it will be crucial to provide sufficient training data for artificial intelligence. At the same time, there is the challenge of linking internal and external data and having it evaluated by an artificial intelligence. In essence, external data and information from markets are becoming increasingly significant and must be considered and integrated more rigorously. This is contingent upon the aspects of data quality and data maintenance. Process efficiency as part of the digitization of the finance function should create room for further training and new focus areas. New specializations in finance and management accounting, which have become integrated into the finance world as new competencies, are becoming correspondingly more important. These include the field of sustainability accounting, but also crisis and risk management as well as other sub-areas such as compliance, governance, or data security, which result in differentiated role profiles in the specifications. Concurrently, the field of holistic corporate management remains a pivotal aspect of management accounting and the finance function. This necessitates that young accountants commence their careers as generalists within the company, developing an understanding of the business model and the capacity to classify and prioritize issues within the context of holistic management. This is accompanied by the emergence of a new role for the business analyst and the linguistic differentiation from pure management accounting and the German work 'controlling' at lower hierarchy levels. However, management accounting remains a distinct function and is still referred to as such at management level. Additionally, management accounting is still a separate component of the finance function, which also includes other elements such as tax. Nevertheless, the interaction between the finance departments has become more pronounced, which has been driven in particular by linked data. While data represents a linking element, the technical part is rather decoupled here and outsourced to IT departments. This is because controllers should again concentrate more on new topic areas and the development of the business model and not have to work too much on detailed levels of new technology. The aforementioned changes also reflect a change in the CFO's role model, which has shifted from a risk-averse, process-compliant number cruncher to a business partner with an affinity for numbers, a driver of change and an open communicator and leader. New expertise is becoming just as important as leadership skills and an understanding of the business model, which is also reflected in changed management ratios. Consequently, a process view and the view from pure output to input KPIs, as well as the inclusion of cash flows, P&Ls and the balance sheet in finance-based strategic analyzes and decisions, is becoming increasingly important. Finally, there are other trend areas that have become more important for the finance function. These include, for example, talent development and talent acquisition, as well as topics around compliance and governance and supply chain accounting. Nevertheless, there are several open issues that require further investigation by researchers and the finance function in the future. These include the accelerated development of new digital components, new digital solutions, and artificial intelligence that is more deeply integrated into the finance function, thus enabling further progress in process efficiency in management accounting. This is accompanied by the development of training data, which may in the future extend beyond internally accumulated data sets. Furthermore, there is the challenge of incorporating and integrating external data sources, ensuring data quality and data maintenance, and analyzing data points in order to draw conclusions about the operational business and gain a holistic understanding of the business model. This is accompanied by the issue of mapping and assigning responsibilities, which are not clearly regulated in the case of new data sources and measurements. In order to address these challenges, it would be beneficial to develop guidelines for mapping, as well as a requirements catalogue, which would then imply the mapping to responsible persons. Additionally, the issue of the measurability of ESG data will remain a significant hurdle. For instance, not all soft factors can be clearly measured by operational teams and accountants and may therefore need to be classified into specific thresholds. This must then also be taken into account by finance and accounting in KPI development and the corresponding reporting. Furthermore, the transition to a process-oriented approach in financial management will present a challenge, as the consideration of KPIs that relate more to the initial stages of a process chain is just as novel as the increased focus on the P&L and the balance sheet for management-relevant issues. Additionally, the implications for the training of junior accountants are that a general understanding of holistic (and sustainable) corporate management must be promoted. It is therefore essential that young accountants are able to critically examine new issues in order to identify their overall implications, to embed them in their context and to draw financial and strategic conclusions from them. This is the only way to successfully integrate new specializations into a company and into the finance function and to proactively meet the growing demands on management accounting and finance.

C Study 2: Never change a running (human) system? Abbau von Algorithmus-Aversion im Digital Reporting

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Sonja Gabriele Prinz reviewed the literature and wrote the paper.
Prof. Dr. Barbara E. Weißenberger provided guidance in conceptualizing the content and also wrote the paper.

Additional remark:

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1 Algorithmus-Aversion als Bias im Entscheidungsprozess

Digitale Technologien in Form von Algorithmen Künstlicher Intelligenz (KI) haben in den vergangenen Jahren einen breiten Entwicklungsschub für die praktische Anwendungsreife auch in betriebswirtschaftlichen Anwendungsfällen erfahren (vgl. statt vieler Mahlendorf et al., 2022; Weißenberger, 2020). Die Bemühungen waren dabei insbesondere durch die Motivation getrieben, so genannte selbstlernende, also algorithmenbasierte Systeme einzusetzen, bei denen automatisierte Formen maschinellen Lernens insbesondere mit Hilfe neuronaler Netze zum Einsatz kommen. Hier erhofft man sich Vorteile gegenüber den traditionellen, nicht-automatisierten bzw. manuellen Verfahren der Informationsverarbeitung, die vor allem auf menschlicher Fachexpertise basieren, d.h. auf vom Menschen aktiv ausgewählte und definierte Analyseinstrumente, Bewertungsfunktionen, Dateninputs oder Beurteilungsverfahren. Dabei geht es nicht nur um mehr Effizienz, weil beispielsweise durch algorithmenbasierte KI viel größere Datenmengen ausgewertet werden können,[*] sondern auch um höhere Objektivität und Verlässlichkeit der auf diese Weise generierten Informationen. Die Überlegenheit selbst einfacher Bewertungsalgorithmen, z.B. in Form von quantitativen Ratingfunktionen gegenüber einem gesamthaften, auf persönlicher Intuition beruhendem Expertenurteil wird in der psychologischen Literatur beispielsweise für die Evaluation psychischer Krankheitsbilder bereits seit den 1950er Jahren ausführlich diskutiert (Grove und Meehl, 1996; Meehl, 1954).

Auch im Controlling lässt sich dies inzwischen beobachten. Dort betrifft der Einsatz von Algorithmen beispielsweise die automatisierte Erstellung kurz- bzw. mittelfristiger Prognosen im Planungs- und Reportingzyklus (Deipenbrock et al., 2019; Mahlendorf und Weißenberger, 2021). Es lässt sich zeigen, dass Prognosen mittels selbstlernender KI, die auch als Predictive

[*] Vgl. hierzu den Beitrag „Digital Reporting mittels Text-Mining aus dem Internet: Anwendungsbeispiele für das Controlling“ aus Teil 3 des Sammelbands.

Analytics bezeichnet werden (Mehanna et al., 2016), eine deutlich bessere Prognosegüte besitzen als traditionelle Prognoseinstrumente wie Werttreibermodellen, Zeitreihenanalysen oder Indikatorfunktionen, weil sie größere und diversere Datenmengen präziser und weniger fehleranfällig verarbeiten (Dietvorst et al., 2015; Grove et al., 2000; Roh, 2014).

Interessanterweise neigen allerdings Funktionsträger in Controlling wie Management auch bei einer objektiv besseren Performance dazu, automatisiert generierten, also ‚algorithmischen', Vorhersagen weniger zu vertrauen und die derart bereitgestellten Informationen nicht oder nur in Teilen zu nutzen. Dieses Verhaltensmuster wird ganz allgemein auch als Algorithmus-Aversion bezeichnet (Berger et al., 2021). Longoni et al. (2019) definieren Algorithmus-Aversion als negative Einstellung und daraus resultierend ablehnendem Verhalten gegenüber Informationen, die automatisiert mittels Algorithmen generiert wurden, und zwar unabhängig von deren Performance. Algorithmus-Aversion kann deshalb auch als eine Form der Entscheidungsverzerrung (Bias) eingeordnet werden (Tversky und Kahneman, 1974).

Bei genauerer Betrachtung reduziert Algorithmus-Aversion die Entscheidungsqualität über drei verschiedene Mechanismen (vgl. Abbildung C-1) die sowohl direkt, als auch indirekt wirken. Erstens zeigen Dietvorst et al. (2015), dass Entscheider im Rahmen von Algorithmus-Aversion dazu tendieren, in der eigenen Entscheidung von Menschen bereitgestellte Informationen stärker zu gewichten als den automatisierten Output eines Algorithmus (Önkal et al., 2009; Promberger und Baron, 2006). Deshalb wird in diesem Sinne eine ‚traditionelle' Prognose einer algorithmenbasierten Prognose unabhängig von der Prognosegüte vorgezogen (Diab et al., 2011; Eastwood et al., 2012). Zweitens neigen Menschen bei Algorithmus-Aversion dazu, übermäßig der eigenen Intuition zu vertrauen bzw. gelangen zu einer eher affektiven Urteilsbildung und Entscheidungsfindung (Castelo et al. 2019). Zu diesen beiden Mechanismen tritt ein dritter, indirekter Mechanismus hinzu. Algorithmus-Aversion kann nämlich auch dann entstehen, wenn zwar eine menschliche Expertise als Informationsgrundlage bereitgestellt wird, für die allerdings auch auf automatisiert erstellte Inputs algorithmenbasierter KI zurückgegriffen wurde (Shaffer et al., 2013).

Dieser indirekte Effekt ist im Controlling insbesondere dann relevant, wenn Controller als Business Partner Entscheidungsprozesse im Management unterstützen und begleiten sollen, dies aber erschwert wird, weil seitens des Managements die von Controllern verwendeten Algorithmen Misstrauen in die Qualität der Controllerarbeit auslösen. Derartige Friktionen werden schon seit jeher auch beim Einsatz traditioneller Controllinginstrumente in der funktionalen Beziehung zwischen Management und Controllern beobachtet (Weissenberger et al. 2012; Weissenberger und Angelkort 2011; Weissenberger 1997) und dürfen für das Ziel einer effektiven Zusammenarbeit nicht ignoriert werden.

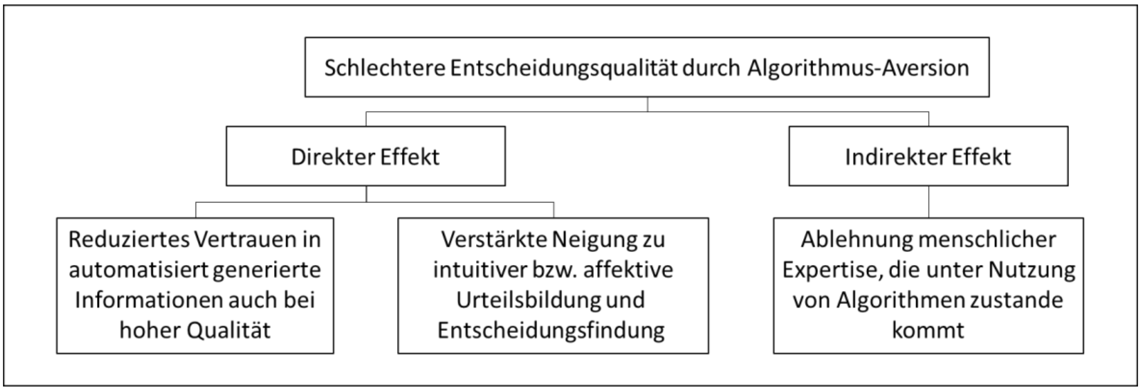

Figure C-1 Schlechtere Entscheidungsqualität durch Algorithmus-Aversion: Die Wirkmechanismen

Auch in der Literatur zur Technologieakzeptanzforschung wird gezeigt, dass die vom Nutzer erwartete Leistungsfähigkeit eine der wichtigsten Determinanten für den tatsächlichen Einsatz einer verfügbaren Technologie darstellt (Venkatesh et al., 2003). Es kann deshalb nicht davon ausgegangen werden, dass für die tatsächliche Nutzung KI-basierter Algorithmen in der Controlling- bzw. Managementpraxis vor allem deren objektive Performance entscheidend ist, z.B. in Form von Verlässlichkeit oder Prognosegüte (z.B. Glikson und Woolley, 2020; Lockey et al., 2021; Siau und Wang, 2018). Wie bei vielen anderen Entscheidungsverzerrungen ist weiterhin nicht zu erwarten, dass sich dieser Bias durch Erfahrungslernen automatisch abbaut, da systematische Entscheidungsverzerrungen von den betroffenen Personen oft nicht selbst erkannt werden (Dunning et al., 2003) bzw. selbst dann weiterhin bestehen bleiben, wenn auf vorliegende Biases hingewiesen wird (Wang und Jeon, 2020). Soll also die Nutzung KI-basierter Algorithmen im Controlling gefördert werden, ist es notwendig zu verstehen, wie Algorithmus-Aversion als Bias tatsächlich entsteht und welche Maßnahmen dagegen in der Gestaltung des Digital Reporting ergriffen werden können

Hierfür wurden für den folgenden Beitrag eine Literaturrecherche im Forschungsfeld „Entscheidungsfindungs- und Vertrauensbildungsprozesse beim Einsatz algorithmenbasierter KI“ durchgeführt, bei der insbesondere themenbezogene Suchbegriffe wie *Algorithm Aversion*, *Algorithm Appreciation*, *Algorithm Acceptance*, *Trust in Artificial Intelligence (AI)*, *Trust in Machine Learning*, *Explainable AI*, *Interpretable AI*, *Information Technology Acceptance* oder *AI-based Decision-Making* einzeln und in Kombination verwendet wurden. Als Suchplattformen wurden Web of Science, EBSCOhost, JSTOR sowie zur Vervollständigung möglicher Lücken Google Scholar verwendet. Ausgeschlossen wurden in einem zweiten Analyseschritt Fundstellen, deren Inhalte sich nicht auf einen betriebswirtschaftlichen Kontext übertragen lassen, sowie Studien, die beispielsweise aufgrund von kulturellen Rahmenbedingungen nur lokale Rückschlüsse zulassen und nicht auf den europäischen oder amerikanischen Wirtschaftsraum übertragbar sind. Ausgeschlossen wurden weiterhin Fundstellen in Büchern, Buchkapiteln, Postern, Fachvorträgen, Konferenz- oder Kurzpapieren ohne wissenschaftliches Begutachtungsverfahren.

2 Grenzen der Automatisierung von Entscheidungsprozessen

Für die Nutzung von Algorithmen im betriebswirtschaftlichen Kontext kann man zwischen zwei Möglichkeiten unterscheiden. Zum einen gibt es Algorithmen, die vollständig automatisiert bestimmte Aufgabenstellungen, wie beispielsweise die Erstellung von Prognosen für bestimmte Variablen und Zeiträume, bearbeiten und damit den menschlichen Problemlösungsprozess vollständig ersetzen, z.B. bei einer KI-basierten Umsatzprognose, die unmittelbar auch Zielvorgabe für den Vertrieb wird. Zum anderen gibt es Algorithmen, die lediglich als Entscheidungsunterstützung dienen, d.h. der menschliche Entscheider führt zwar eine algorithmenbasierte Analyse durch, auf deren Basis das eigentliche Entscheidungsproblem jedoch noch gelöst werden muss (Jussupow et al., 2020; Komiak und Benbasat, 2006; Nissen und Sengupta, 2006). Denkbar ist z.B., dass für eine Vertriebsregion zwar mittels KI wichtige Variablen, wie Marktwachstum oder Inflationsrate vorhergesagt werden, die konkreten Absatz-, Umsatz-, Cashflow- oder Ergebnisprognosen aber weiterhin im Controlling erstellt werden. Ein ähnlicher Fall liegt vor, wenn die mittels KI generierten Prognosewerte für diese Zielgrößen manuell angepasst werden können, weil Sondereffekte, z.B. der Wegfall oder die Gewinnung wichtiger Kunden, der unerwartete Markteintritt eines Wettbewerbers, oder einzel- bzw. gesamtwirtschaftliche Krisensituationen zu einer abweichenden Einschätzung der Situation führen.

Das Auftreten von Algorithmus-Aversion kann insbesondere im ersten Fall, also bei automatisierten Problemlösungsprozessen ohne manuelle Eingriffsmöglichkeiten, beobachtet werden (Jussupow et al., 2020). Liegt die Letztentscheidung dagegen beim menschlichen Nutzer, wird Algorithmus-Aversion weniger häufig beobachtet (Palmeira und Spassova, 2015). Unabhängig von der Eingriffstiefe kann weiterhin gezeigt werden, dass Fehler des Algorithmus wie nachweislich falsche Klassifikationen oder unzutreffende Prognosen bei automatisierten Verfahren von Nutzern deutlich negativer beurteilt werden als vergleichbare Fehler bei manuellem

Vorgehen, und zwar selbst wenn es sich um vergleichbare Fehler handelt bzw. der Algorithmus im Vergleich sogar durchschnittlich besser abschneidet (Dietvorst et al., 2015). Einzelne experimentelle Studien weisen sogar stark emotional gefärbte Reaktionen wie Wut bei Probanden nach, wenn sie auf fehlerhafte Ergebnisse automatisierter Algorithmen aufmerksam gemacht werden (Jussupow et al., 2020; Leyer und Schneider, 2019).

Vor diesem Hintergrund sind die Ergebnisse von Dietvorst et al. (2018) bedeutsam, die nachweisen, dass Algorithmus-Aversion reduziert werden kann, wenn die Nutzer manuelle Eingriffs- bzw. Anpassungsmöglichkeiten haben, selbst wenn deren Umfang vergleichsweise gering ist. Dies lässt vermuten, dass menschliche Interaktion im Sinne eines Zusammenwirkens von Mensch und Maschine im Problemlösungsprozess zum Abbau von Algorithmus-Aversion, mithin also die verbesserte Akzeptanz von Algorithmen, beiträgt. Im Kontext des Digital Reporting lässt sich daraus die Empfehlung ableiten, dass menschliche Entscheidungsexpertise im Controlling nicht vollständig durch automatisiert arbeitende KI ersetzt werden sollte.

Stattdessen sollten automatisierte Algorithmen zwar eingesetzt werden, die Ableitung der zu verwendenden Ergebnisse bzw. Entscheidungsvorschläge aber weiterhin beim menschlichen Nutzer liegen. Im Controlling würde dies für die Erstellung von Prognosen konkret bedeuten, dass Predictive Analytics-Systeme zunächst nur eine Entscheidungshilfe für die Controller darstellen. Beispielsweise ist denkbar, dass Umsatzprognosen zwar automatisiert mittels KI erstellt werden und dann als objektivierte Grundlage für die Monats-, Quartals- oder Jahresplanung verwendet werden, allerdings im Planungsprozess in begründeten Fällen noch manuell korrigiert werden können, bevor sie in die Formulierung verbindlicher Zielvorgaben für Bereiche oder Funktionen übersetzt werden. Die Letztentscheidung bleibt damit bei den Funktionsträgern in Controlling und Management, die Maßnahmen und Ergebnis auch verantworten müssen: Controllability und Accountability fallen weiterhin zusammen und die Problemlösung –

im angegebenen Beispiel die finale Erstellung der Planung – ist Gegenstand einer Kooperation von Mensch und Maschine.

Ein weiterer Faktor, der zur Entstehung von Algorithmus-Aversion beiträgt, liegt in dem technologisch anderen bzw. im Falle neuronaler KI faktisch unbekannten oder nicht nachvollziehbaren Problemlösungsprozess. Dies spielt insbesondere beim stark automatisierten Einsatz von Algorithmen eine wichtige Rolle. Hat der Mensch traditionell beispielsweise bestimmte Routinen im Sinne eines ‚angemessenen' manuellen Problemlösungswegs entwickelt, können selbst geringe Fehler der automatisierten Alternative Algorithmus-Aversion auslösen (Bhattacherjee und Premkumar, 2004; Jussupow et al., 2020). Dies kann adressiert werden, indem beispielsweise in Form von Schulungen die neuen Technologien nicht als umfassend perfekt und ausschließlich fehlerfrei beschrieben werden (Dzindolet et al., 2002; Goodyear et al., 2016; Jussupow et al., 2020; Madhavan und Wiegmann, 2007a). Dabei sollte gleichzeitig über die Funktionsweise, aber auch Limitationen der automatisierten Verfahren aufgeklärt werden, um ein grundlegendes Verständnis für algorithmenbasierte KI und deren Anwendungsbereiche zu fördern.

Abweichende Erwartungen können aber auch durch mangelnde kognitive Kompatibilität zwischen algorithmischer und menschlicher Informationsverarbeitung bzw. Entscheidungsfindung entstehen. Dies tritt u.a. auf, wenn Anwender zwar abstrakt Transparenz z.B. über die Arbeitsweise von Algorithmen wünschen, deren konkrete Ausprägung jedoch nicht mit den eigenen Vorstellungen übereinstimmt (Burton et al., 2020). Da die menschlichen Entscheidungsprozesse in ihrem Zusammenspiel zwischen Kognition und Intuition jedoch schwer abbildbar bzw. in ihren Wirkungsmechanismen noch nicht vollständig verstanden ist, lassen sich die daraus resultierenden psychologischen Prozesse bisher technisch kaum adressieren (Burton et al., 2020; Mullins und Rogers, 2008; Thayer, 2008). Eine Möglichkeit, dieses Problem aufzufangen, besteht darin, die Phasen der Entscheidungsfindung so zu untergliedern, dass

Unterstützung durch algorithmenbasierte KI nicht erst am Ende eines Entscheidungsprozesses, sondern mehrstufig an verschiedenen Stellen, z.B. eigenständig innerhalb einzelner Planungsschritte, geleistet wird (Burton et al., 2020).

3 Abbau des Black-Box-Problems durch Erklärbarkeit

Ein zentraler Aspekt für die Entstehung von Algorithmus-Aversion ist das so genannte Black-Box-Problem.* Insbesondere bei selbstlernenden Algorithmen ist für den Nutzer nicht bzw. nur sehr eingeschränkt ersichtlich, wie das konkrete Ergebnis, z.B. eine Umsatzprognose, aus den eingegebenen Daten entsteht. Es fehlt vielfach an Erklärungen (Doran et al., 2017), die über eine Beschreibung der allgemeinen Funktionsweise hinausgehen und tatsächlich auch die konkrete Genese eines bestimmten Results beschreiben (Kayande et al., 2009). Vor diesem Hintergrund überrascht nicht, wenn Nutzer die Einführung KI-basierter Algorithmen zur Entscheidungsunterstützung ablehnen, die sie im Zweifel weder nachvollziehen noch überprüfen können (e. g. Adadi und Berrada, 2018; Taylor und Taylor, 2021; Wischmeyer, 2020; Zednik, 2021). Es fehlt so nämlich bereits an der Interpretationsmöglichkeit des Ergebnisses (Doshi-Velez und Kim, 2017) und damit der Grundlage, die Ergebnisse von algorithmenbasierter KI nachvollziehbar zu plausibilisieren (‚Warum sagt das Predictive-Analytics-System einen überdurchschnittlich hohen/niedrigen Umsatz für das nächste Quarta voraus?‘) und darauf aufbauend zu differenzieren, ob Zufallsfaktoren, Fehlschlüsse oder tatsächlich sinnvolle Indikatoren zugrunde liegen (Kayande et al., 2009; Mahmud et al., 2022; Önkal et al., 2009; van Dongen und van Maanen, 2013). Dies ist auch deshalb bedeutsam, weil Entscheider sachliche Argumente benötigen, mithilfe derer sie die eigenen Entscheidungen begründen und ggf. auch rechtfertigen können (Jingyi und Xuesong, 2018).

* Vgl. hierzu den Beitrag von „Künstliche Intelligenz im Digital Reporting zwischen Strategie und Regulierung“ in Teil 5 des Sammelbands.

Zwar wird bereits an der systemseitigen Bereitstellung von Erklärungen unter dem Stichwort explainable AI (XAI) bzw. interpretable AI geforscht (Doran et al., 2017). Allerdings sind solche Erklärungen grundsätzlich hilfreich (Asatiani et al., 2020; Gunning et al., 2019), aber nicht per se die Lösung, um Algorithmus-Aversion abzubauen. Notwendig ist vielmehr, dass Erklärungen auch verstanden werden können (Yeomans et al., 2019). So kommt es beispielsweise auf den Grad der Komplexitätsreduktion durch die Erklärung bzw. die Anwendbarkeit auf die konkret vorliegende Entscheidungssituation durch die bereitgestellte Erklärung an (Litterscheidt und Streich, 2020; Mahmud et al., 2022; Sharan und Romano, 2020).

4 Die Bedeutung von Merkmalen menschlicher Interaktion

Ganz grundsätzlich spielt für Akzeptanz algorithmenbasierter Analysen eine Rolle, wie stark seitens der Nutzer die Abwesenheit von Merkmalen menschlicher Experteninteraktion wahrgenommen wird, wie beispielsweise die Möglichkeit eines erweiterten fachlichen Austauschs oder die kontextabhängige Einschätzung überraschender oder scheinbar unplausibler Ergebnisse (Bigman und Gray, 2018; Jussupow et al., 2020; Longoni et al., 2019). Aus der Marketingforschung gibt es erste Ergebnisse, die darauf hindeuten, dass durch eine veränderte Darstellung bzw. Kommunikation, die Algorithmen menschlicher erscheinen lässt, Algorithmen-Aversion abgebaut werden kann (Castelo et al., 2019; Madhavan und Wiegmann, 2007b). Man denke hier beispielsweise an die Kommunikation mit einem Chatbot, der so programmiert ist, dass er verzögert, d.h. ‚nachdenklich‘, reagiert. Allerdings stehen diese Ergebnisse im Widerspruch zur Robotikforschung, nach der allzu humanoid konstruiere Robotern eher Misstrauen erwecken (das sogenannte Uncanny Valley, vgl. Mori et al., 2012). Hier besteht noch weiterer Forschungsbedarf.

Hinzu kommt, dass Algorithmen zwar hochleistungsfähig sind, was die präzise Verarbeitung großer Datenmengen betrifft, jedoch die gesamthafte Einschätzung einer Problemstellung beispielsweise unter Berücksichtigung von Normen und Werten vielfach nicht leisten können. Beobachtet wird dies im Kontext sogenannter ‚algorithmischer Diskriminierung' (Weißenberger, 2021a), wenn beispielsweise Algorithmen im Bereich der Personalauswahl trotz anonymer Bewerbungen vorhandene Vorurteile z.B. gegenüber Geschlecht, Alter, Hautfarbe, Herkunft oder bestimmten Bildungsbiografien reproduzieren (Simbeck und Prothmann 2016). Insoweit überrascht es wenig, dass bei einigermaßen objektiviert lösbaren (*well-defined*) Problemen das Vertrauen in algorithmenbasierte Analysen hoch ist, bei wahrgenommener Subjektivität bzw. unscharfen (*wicked*) Problemstellungen dagegen eher niedrig (Castelo et al., 2019; Dijkstra et al., 1998; Lee, 2018; Mahmud et al., 2022). Ein ähnlicher Zusammenhang zeigt sich auch im Hinblick auf die moralische Dimension der Beurteilung: Je mehr moralisches Bewusstsein bzw. moralisches Urteilsvermögen im Rahmen der Problemlösung bzw. Ergebnisevaluation erforderlich ist, umso geringer ist das Vertrauen in algorithmenbasierte Lösungen (Mahmud et al., 2022; Niszczota und Kaszás, 2020).

Daraus lassen sich verschiedene Implikationen für die Controllingpraxis bzw. konkret das Digital Reporting ableiten. So sollte bei der Einführung algorithmenbasierter KI beispielsweise darauf geachtet werden, dass die objektiven Dimensionen in der Aufgabenbearbeitung besonders betont werden. Generell sollte man versucht werden, die Ablösung manueller Prozesse durch algorithmenbasierter KI zunächst bei möglichst objektiv validierbaren Aufgabenstellungen durchzuführen. Das bedeutet im Umkehrschluss, dass Aufgaben, bei denen auch subjektive Urteile eine bedeutsame Rolle spielen, beispielsweise im Bereich der Performance Evaluation und daran anknüpfend die Festlegung von Bonuszahlungen (Fehrenbacher et al., 2018; Luft und Shields, 2010), im Zweifel nicht automatisiert gelöst werden sollten bzw. nur in Verbindung mit umfassenden Erläuterungen (Köchling et al., 2022).

5 Überzeugung prospektiver Nutzer: Schulungen und Showcases

Ein weiterer Faktor, der zur Algorithmus-Aversion beiträgt, ist der vielfach fehlende Anreiz, einen neuen Algorithmus tatsächlich zu nutzen, wenn sich die prospektiven Nutzer erst mit hohem Arbeits- und Zeitaufwand mit einem neuen und unbekannten System vertraut machen müssen, dessen Nutzen sie nicht oder nur eingeschränkt überschauen (Alexander et al., 2018; Brown, 2015; Burton et al., 2020; Eastwood et al., 2012; Highhouse, 2008b; Klimoski und Jones, 2008; Kuncel, 2008; Önkal et al., 2009). Es ist deshalb auch zu prüfen, inwieweit die erforderlichen Anreize gerade in mehrstufigen Planungs- und Entscheidungsprozessen mit vielen Informationsinputs gesetzt werden können (Brown, 2015; Burton et al., 2020; Hafenbrädl et al., 2016). Denkbar sind zunächst sowohl ökonomische Anreize, wie beispielsweise ein Bonus in Abhängigkeit der Forecastqualität, als auch soziale Anreize, beispielsweise über den Zuspruch von Kompetenzen oder besondere Auszeichnungen im Unternehmen (Burton et al., 2020).

Die konkrete Ausgestaltung solcher Anreizsysteme hängt auch vom organisatorischen und sozialen Umfeld ab und muss in Abhängigkeit von Rollen oder Positionen im Unternehmen angepasst werden (Kuncel, 2008); sie erweist sich deshalb oft als schwierig. Vor diesem Hintergrund ist es sinnvoll, die Faktoren näher zu beleuchten, die den Einsatz von Anreizsystemen überhaupt erst notwendig machen und dies durch alternative Ansätze zu ergänzen bzw. zu ersetzen.

Ein erster hindernder Aspekt für die Nutzung algorithmenbasierter Technologien ist vielfach mangelnde Erfahrung und Vertrautheit, die sich in einer grundlegenden Skepsis gegenüber den neuen Technologien äußert (Alexander et al., 2018; Burton et al., 2020; Carey und Kacmar, 2003; Goodyear et al., 2017; Goodyear et al., 2016; Highhouse, 2008a, 2008b; Lodato et al., 2011; Sutherland et al., 2016; Thayer, 2008). Hinzu kommt, dass fehlende fachliche und fallbezogene Erfahrung über Alltagserfahrung bzw. mögliche negative Konnotation von Algorithmen kompensiert und verwechselt werden kann (Kotilainen et al., 2020). Vor diesem Hintergrund spielen Trainingsmaßnahmen bei der Einführung algorithmenbasierter KI im Controlling eine wichtige Rolle (Zhu et al., 2022). Wichtig ist dabei, dass die Trainings und die damit ausgebildeten neuen Kompetenzen in das Schulungsprogramm sowie das professionelle Rollenverständnis integriert werden[*] und dass sowohl Funktionsweisen als auch Leistungsfähigkeit und Grenzen automatisierter Verfahren aufgezeigt werden (Burton et al., 2020).

Ein zweiter Aspekt bezieht sich komplementär auf die Selbstüberschätzung eigener Fähigkeiten und des eigenen Könnens. Generell lässt sich nachweisen, dass Entscheider auch im betriebswirtschaftlichen Kontext dazu neigen, dem eigenen Urteil mehr zu vertrauen als einer dritten Quelle (Gino und Moore, 2007; Keren und Wu, 2015; Logg et al., 2018b; Moore und Healy, 2008). Auch im Controlling kann Selbstüberschätzung der eigenen Fähigkeiten (*overconfidence*), beobachtet werden, die zu Schwierigkeiten und Fehleinschätzungen führt. So zeigen Hribar und Yang (2016) beispielsweise, dass Controller dazu neigen Forecasts zu optimistisch zu gestalten und beispielsweise Umsätze der Zukunft zu hoch zu prognostizieren. Dies führt dazu, dass das Unternehmen sich nicht auf die von Controllern gestellten Prognosen verlassen kann und das Unternehmen nicht adäquat zukunftsgerichtet steuern kann. Auch hier können Schulungsmaßnahmen entgegenwirken (Filiz et al., 2021).

Die in diesem Zusammenhang notwendigen Lernprozesse werden durch Erfolgsbeispiele, beispielsweise in ausgewählten ersten, so genannten Showcases, verstärkt (Venkatesh und Bala, 2008).[**] Dies können kleine Projekte mit limitiertem Umfang sein, die aber gleichzeitig die

[*] Vgl. hierzu den Beitrag „Controller of the Future: Im Digital Reporting macht der Mensch den Unterschied“ in Teil 4 des Sammelbands.

[**] Vgl. den Beitrag „Ausblick: Sechs Thesen zur Transformation des Controllerbereichs beim Einsatz neuer digitaler Technologien“ im Sammelband.

Leistungsfähigkeit der neuen Systeme überzeugend dokumentieren, beispielsweise indem ein Predictive-Analytics-System zunächst nur für eine Prognosegröße bzw. eine überschaubare Region oder Geschäftseinheit eingeführt wird. So zeigen Alexander et al. (2018), dass es das Vertrauen in algorithmenbasierte KI erhöht, wenn es gelingt, prospektiven Nutzern zu verdeutlichen, dass sich ein Algorithmus bzw. ein automatisiertes Verfahren gegenüber manuellen Lösungsroutinen bereits bewährt hat. Verstärkt wird dieser Effekt, wenn Austauschmöglichkeiten zwischen bestehenden und prospektiven Nutzern der Systeme eingerichtet werden.

Schulungen und Austausch können auch dann wichtig sein, wenn demographische Faktoren wie Bildungsgrad oder Alter eine Rolle spielen (Burton et al., 2020). So zeigen Thurman et al. (2019) beispielsweise, dass eine geringe Bildung mit erhöhter Algorithmus-Aversion einhergeht. Weniger eindeutig sind die Studien im Hinblick auf den Einfluss von Alter. So wird teilweise vertreten, dass mit steigendem Alter auch das Vertrauen in neue Technologien abnimmt und Algorithmus-Aversion zunimmt (Mahmud et al., 2022). Araujo et al. (2020) begründen dies damit, dass sich ältere Menschen im Einsatz tradierter manueller Routinen sicherer fühlen, so dass dem Einsatz neuer Technologien kein besonderer Mehrwert zugemessen wird (Mahmud et al., 2022). Ho et al. (2005) vertreten dagegen die Ansicht, dass Algorithmus-Aversion mit steigendem Alter gerade abnimmt, weil Menschen in einem veränderlichen Umfeld mit wachsendem Alter zunehmend weniger Vertrauen in die eigenen Fähigkeiten haben und sich deshalb schneller auf neue unterstützende Technologien verlassen. Ein von Araujo et al. (2020) und Mahmud et al. (2022) vermuteter Einfluss des Geschlechts auf die Stärke von Algorithmus-Aversion konnte bisher nicht nachgewiesen werden (Thurman et al., 2019; Workman, 2005).

6 Ein neues Problem? Übervertrauen in Algorithmen

Insgesamt zeigt sich, dass es eine breite Literatur gibt, die sich mit mangelndem Vertrauen in neue digitale Technologien beschäftigt. Komplementiert wird diese Forschung seit wenigen Jahren durch einen weiteren Forschungsstrang, der sich mit dem gegenläufigen Phänomen der Algorithm Appreciation, d.h. Übervertrauen in Algorithmen, befasst. Eine der bekanntesten Studien wurde von Logg et al. (2019) vorgelegt, die anhand einer Experimentalstudie nachweisen, dass gerade Laien dazu neigen, automatisiert generierte Informationen manuellen Verfahren bzw. der menschlichen Expertise vorzuziehen (ähnlich auch Hou und Jung 2021). Allerdings bezieht sich das Setting dieser Studien auf den außerbetrieblichen Kontext, z.B. auf die Vorhersage der Beliebtheit von bestimmten Melodien oder Liedern, nicht aber für den Einsatz in betriebswirtschaftlichen Settings bzw. in Problemstellungen mit hoher Salienz. Unabhängig davon lässt sich aber festhalten, dass genauso wie Algorithmus-Aversion auch ungerechtfertigtes Übervertrauen in die Leistungsfähigkeit automatisierter Entscheidungsunterstützung und mangelnde kritische Distanz zur Sinnhaftigkeit der auf diese Weise generierten Ergebnisse ein Bias und damit auch eine Herausforderung für das Controlling darstellt, die insbesondere durch Schulungen adressiert werden muss.

Interessant sind in diesem Zusammenhang die Ergebnisse von Kaufmann (2021) und Bogert et al. (2021), die sich beide mit dem Einfluss des Schwierigkeitsgrads einer Aufgabe beschäftigen. Während Kaufmann (2021) bei einfachen und überschaubaren Alltagsaufgaben eher Übervertrauen in Algorithmen beobachtet, konstatiert sie analog zur bestehenden Literatur zur Algorithmus-Aversion bei zunehmend anspruchsvollen und komplexen Aufgaben eine klare Präferenz der Nutzer hin zur menschlichen Expertise. In der Studie von Bogert et al. (2021) ist der Effekt genau umgekehrt: Bei wachsender Aufgabenkomplexität nimmt das Vertrauen in die eigenen menschlichen Fähigkeiten sowie in andere menschliche Expertise ab, so dass sich die

Nutzer gerade mehr auf die Unterstützung automatisierter Entscheidungsunterstützung verlassen. Hier besteht noch weiterer Forschungsbedarf, beispielsweise inwieweit sich Kontextfaktoren wie die Salienz einer Aufgabe für ein bestimmtes Ziel oder der Grad an Haftung bzw. Verantwortung für das Ergebnis auswirken.

7 Verdichtung und mögliche Interdepenzenden

Aus den bereits genannten wissenschaftlichen Erkenntnissen, welche über verschiedene Studien hinweg belegt werden konnten, konnten nun die entsprechenden Zusammenhänge abgeleitet werden (siehe Tabelle C-1).

Table C-1 Faktoren, die Algorithmus Aversion bedingen können

Autoren/ Papiere	Aussagen	Implikationen	Fokussierte Darstellung	Nummerierung
Wang and Jeon (2020)	Verhaltensverzerrungen werden meist nicht direkt von der betroffenen Person selber wahrgenommen und können somit nur schwer selbst reduziert werden.	Eine Algorithmus Aversion ist als Bias nur schwer eigenständig zu reduzieren.	Eine Algorithmus Aversion wird oft als Verhaltensverzerrung nicht aktiv wahrgenommen und kann somit kaum durch eigene Reflektion reduziert werden - somit sollten Externe auf eine mögliche Aversion hinweisen.	FD1
Jussopow et al. (2020) Kombiak and Benbasat (2006) Nissen and Sengupta (2006) Palmeira and Spassova (2015)	Eine Algorithmus Aversion ist besonders in Situationen zu betrachten, in denen Anwender sich auf das Ergebnis verlassen müssen und es nicht nur als Entscheidungshilfe heranziehen können.	Die finale Entscheidung im Umgang mit neuen Systemen und Algorithmen sollte beim Anwender liegen, um eine Algorithmus Aversion abbauen zu können.	Entscheidungsfreiräume und damit nicht vollständige Algorithmus-Ergebnis-Abhängigkeit fördern Vertrauen in neue Systeme und Algorithmen.	FD2
Bhattacherjee and Premkumar (2004) Burton et al. (2020) Dietvorst et al. (2015) Dietvorst et al. (2018) Dzindolet et al. (2002) Goodyear et al. (2016) Jussopow et al. (2020) Leyer and Schneider (2019) Madhavan and Wiegmann (2007a)	Hohe Abweichungen des Algorithmus Ergebnisses zu den eigenen Erwartungen können eine Algorithmus Aversion fördern. Entsprechend wichtig sind Schulungen und Maßnahmen zur besseren, zielgerichteten Erwartungshaltung. Im diesem Sinne führt auch eine Übergewichtung von Fehlern zu irrationaler Ablehnung des Algorithmus.	Fehlendes Erwartungsmanagement schürt unrealistische Ansprüche an Algorithmen und kann in vollständiger, irrationaler Ablehnung resultieren.	Adäquates, frühzeitiges Erwartungsmanagement reduziert unrealistische Ansprüche an Algorithmen und fördert eine zielgerichtete, effektive Algorithmusnutzung.	FD3
Bigman and Gray (2018) Castelo et al. (2019) Jussupow et al. (2020) Longoni et al. (2019) Madhavan und Wiegmann (2007b)	Gesprächs- und Diskussionsmöglichkeiten sowie (dezenzte) Vermenschlichung von Algorithmen und Anschein von Empathie wirken sich positiv auf ein Akzeptanzverhalten bezogen auf Algorithmen aus.	Algorithmen und neue Technologien benötigen teils (dezent) vermenschlichte Oberflächen und sollten auch den verbalen Austausch zwischen Algorithmen und Anwender fördern.	Interaktionsmöglichkeiten und erste menschliche Eigenschaften eines Algorithmmus können das Vertrauen in neue Technologien fördern.	FD4
Castelo et al. (2019) Dijkstra et al. (1998) Lee (2018) Mahmud et al. (2022) Niszczota and Kaszás (2020) Zhang et al. (2021)	Mit höherem Grad an Objektivität steigt das Vertrauen in Algorithmen, umgekehrt sinkt mit steigender Subjektivität in den Entscheidungen das Vertrauen in Algorithmen.	Gerade subjektivere Aufgaben sollten nicht nur und nicht direkt lediglich Algorithmen anvertraut werden.	Die Betonung objektiver Analyseschritte ohne Einbezug von moralischen Fragestellungen können eine Algorithmus Aversion reduzieren und vertrauensfördernd wirken.	FD5
Adadi and Berrada (2018) Asatiani et al. (2020) Burton et al. (2020) Christin (2017) Doran et al. (2017) Doshi-Velez und Kim (2017) Eastwood et al. (2012) Gunning et al. (2019) Kayande et al. (2009) Litterscheidt and Streich (2020) Mahmud et al. (2022) Sharan and Romano (2020) Taylor and Taylor (2021) Wischmeyer (2020) Yeomans et al. (2019) Zednik (2021)	Systeme, die nicht entscheidungsunterstützend sind, sondern die Entscheidung ohne Interventionsmöglichkeit vorgeben, werden stärker als Black Box wahrgenommen und fördern eine Algorithmus Aversion. Abgebaut werden kann eine Algorithmus Aversion hier über Erklärungen - sowohl über die grundlegende Funktionsweise, als auch über den konkreten Output. Als Voraussetzung gilt allerdings, dass die Erklärungen komprimiert sind und komplexitätsreduzierend wirken.	Komplexitätsreduktion und Verständnisförderung sind wichtig, um eine Algorithmus Aversion abbauen zu können.	Erklärungen, die zur Funktionsweise oder zu einem konkreten Output geliefert werden, können eine Algorithmus Aversion reduzieren.	FD6
Jingyi und Xuesong (2018) Kayande et al. (2009) Mahmud et al. (2022) Önkal et al. (2009) van Dongen and van Maanen (2013)	Durch mangelnden menschlichen Bezug kann man Aussagen weder einfach validieren, noch sich Dritten gegenüber gut rechtfertigen, da ein Hinweis, sich auf 'jemanden' verlassen zu haben bei einem Algorithmus häufig nicht glaubwürdig erscheint. Somit ist Rechtfertigung aus Basis von technologischem Output im Vergleich zum Menschen kaum gegeben.	Referenzierungs- und Rechtfertigungsmöglichkeiten müssen bei der Algorithmus Nutzung verstärkt geschaffen werden, damit die Datengrundlage auch in (Management-) Entscheidungen Eingang findet und glaubwürdig ist. Durch Algorithmus basierte Rechtfertigung darf nicht unangenehm oder weniger akzeptiert sein.	Durch mangelnde Rechtfertigungsmöglichkeiten und damit fehlende 'zwischenmenschliche' Validierung, kann die Nutzung von Algorithmen gehemmt und eine Algorithmus Aversion getriggert werden.	FD7
Alexander et al. (2018) Brown (2015) Burton et al. (2020) Eastwood et al. (2012) Hafenbrädl et al. (2016) Highhouse (2008b) Klimoski und Jones (2008) Kuncel (2008) Önkal et al. (2009)	Wenn der Nutzen neuer Systeme nicht klar kommuniziert wird, wird der Anreiz Zeit und Aufwand in die Einarbeitung zu investieren gemindert. Nutzungsincentives, wie ökonomische Anreize durch Boni oder und soziale Anreize wie Anerkennung und Auszeichnungen, sowie Erfolgsbeispiele - am Beispiel der Nutzung anderer - können hier helfen.	Menschliche Interaktionen spielen bei der Akzeptanzförderung neben monetären Anreizen eine entscheinde Rolle. Austausch und Erfolgskommunikation sowie Leistungsanerkennung fördern Algorithmusakzeptanz und gleichzeitig ein offenes Miteinander.	Erfolgsbeispiele (SF8.1) und adäquate ökonomische und soziale Anreizsysteme (SF8.2) fördern die Nutzung und Akzeptanz neuer Algorithmen.	FD8
Alexander et al. (2018) Burton et al. (2020) Carey und Kacmar (2003) Goodyear et al. (2016) Goodyear et al. (2017) Highhouse (2008a) Highhouse (2008b) Lodato et al. (2011) Sutherland et al. (2016) Thayer (2008) Thurman et al. (2019)	Grundlegende Skepsis durch schlechte Erfahrung mit Neuerungen und falsche Ansprüche, auch bedingt durch fehlendes fachliches Wissen, hemmen Algorithmus Akpeztanz.	Schulungsprogramme und erste, ungezwungene und von Experten begleitete Einführungen und Testphasen können Nutzungshemmungen neuer Algorithmen abbauen.	Mangelnde oder schlechte Erfahrung und mangelnde Vertrautheit können die Ablehnung von Algorithmen verstärken.	FD9

Hinweis: Bildung und Alter werden hier außen vor gelassen, da Nichtstrittigkeit der Fakten/ Studien hier nicht gegeben ist

So konnten insgesamt neun Zusammenhänge bzw. fokussierte Darstellungen herausgearbeitet werden. Diese beziehen sich auf die Faktoren der Wahrnehmung der Algorithmus Aversion als Bias, die Entscheidungsfreiheit bei der Weiterverarbeitung von Outputs von Algorithmen, das Erwartungsmanagement im Hinblick auf neue Algorithmen sowie Interaktions- und Kommunikationsmöglichkeiten. Darüber hinaus können die Einflüsse von Objektivität in der Datenverarbeitung, Erklärungen, Rechtfertigungsmöglichkeiten, Anreizsysteme und Erfahrung einen direkten Einfluss auf die Algorithmus Aversion haben.

Insgesamt zeigt sich, dass eine Vielzahl an Studien eine grundlegende Aversion in vor allem neue Algorithmen nachweisen und bestätigen konnte. Da gerade im betriebswirtschaftlichen Kontext jedoch weiterhin verstärkt mit neuen Technologien und Algorithmen gearbeitet wird, ist ein Abbau einer Algorithmus Aversion entscheidend, damit die Technologien auch akzeptiert, angenommen und verwendet werden. Die Sorge, dass die Menschen sich übermäßig auf Technologien verlassen würden und nicht mehr selbständig über Sachverhalte, beispielsweise über Fragestellungen zum Forecasting im Controlling, informieren und nachdenken würden, kann anhand der Literatur nicht bestätigt werden. Stattdessen sollten Unternehmen in Maßnahmen investieren, welche den Anwender mit den Neuerungen vertraut werden lassen und die Akzeptanz fördern, die eben gerade nicht in hohem Maße vorhanden ist. So zeigte sich im Rahmen dieses Literaturüberblicks, welcher im Folgenden durch die fokussierten Darstellungen und Zusammenhänge schematisch dargestellt ist und in einen Zusammenhang gebracht werden kann, dass es zunächst wichtig auf eine mögliche Algorithmus Aversion hinzuweisen, da die Algorithmus Aversion als Bias häufig nicht selbst erkannt und im Laufe der Zeit eher verstärkt werden kann, da keine Reflektion des eigenen Verhaltens stattfindet (siehe Abbildung C-2).

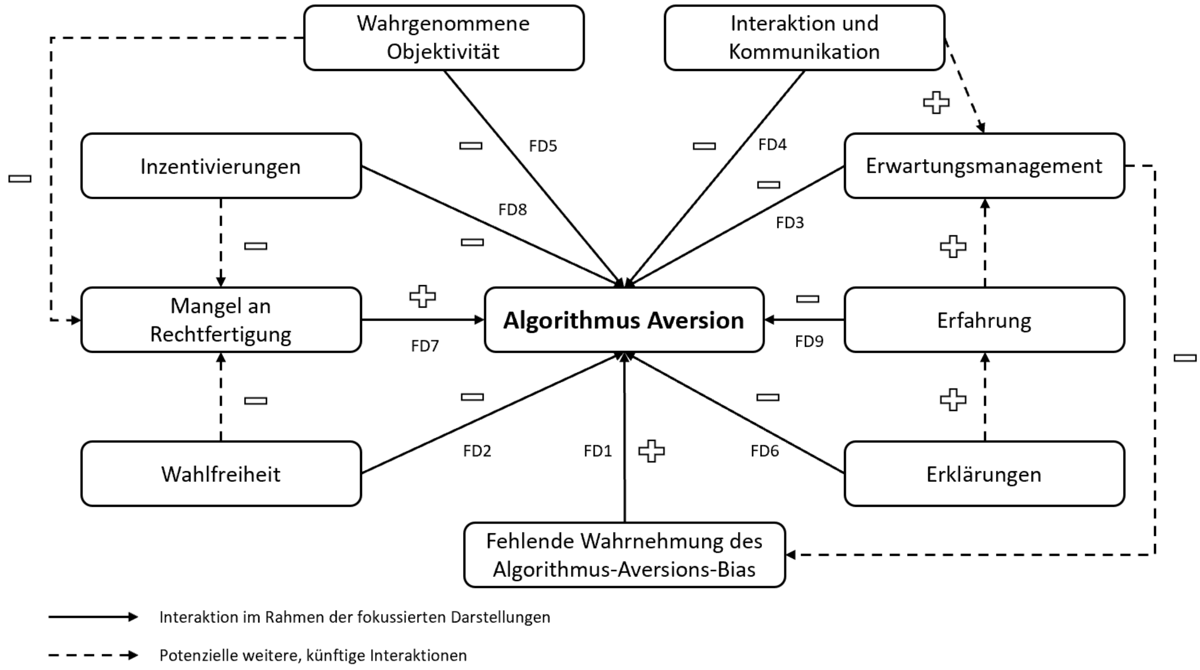

Figure C-2 Wirkzusammenhänge der fokussierten Darstellungen, die zu Algorithmus Aversion führen können

Darüber hinaus wirken sich Entscheidungsfreiräume positiv auf eine Algorithmus Aversion aus und können Studien zufolge diese reduzieren. Durch die Entscheidungsfreiräume fühlen sich Mitarbeiter nicht gezwungen mit einem Algorithmus Output weiterzuarbeiten, was eine positive Einstellung den Algorithmen gegenüber fördert. Zudem kann durch diese Entscheidungsfreiräume auch Vertrauen den Mitarbeitern gegenüber signalisiert werden, was sich ebenfalls positiv auf das Akzeptanzverhalten auswirken kann. Auch ein adäquates Erwartungsmanagement über die Möglichkeiten, aber auch Grenzen der Algorithmen können eine Algorithmus Aversion potenziell reduzieren. Kommunikations- und Interaktionsmöglichkeiten, die auch eine vermenschlichte Darstellung von Algorithmen beinhalten, können sich ebenfalls positiv auf eine Algorithmus Aversion auswirken. So impliziert dies auch, dass Rückfragen an den Algorithmus gestellt werden können und Verständnisfragen ausgeräumt werden können, was ebenfalls positiv zum Akzeptanzverhalten beiträgt. Ebenfalls zeigt sich, dass Objektivität in den Analyseschritten eine Rolle spielt und für ein erhöhtes Vertrauens- und Akzeptanzverhalten sorgen kann. Auch Erklärungen über die Funktionsweise des Algorithmus beziehungsweise zu einem konkreten Algorithmus Output können positiv auf das Akzeptanzverhalten wirken und eine Algorithmus Aversion reduzieren. Auch mangelnde Rechtfertigungsmöglichkeiten können sich auf eine Algorithmus Aversion auswirken. So fühlen Mitarbeiter, dass sie sich nicht umfassend auf Algorithmen beziehen können und diese entsprechend keine Rechtfertigungsgrundlage (zur Entscheidungsfindung) darstellen und entsprechend abgelehnt werden. Anreizsysteme sowie Erfahrung im Umgang mit Algorithmen wirken sich hingegeben wieder positiv aus und könnten eine Algorithmus Aversion reduzieren. Es zeigt sich, dass auch weitere Wirkzusammenhänge vermutet werden können, welche ebenfalls in der Abbildung dargestellt sind. So könnten Erklärungen, je nach Ausgestaltung, auch die (wahrgenommene) Erfahrung im Umgang mit Algorithmen positiv beeinflussen. Bekommt der Anwender beispielsweise eine Auskunft über die Performance eines Algorithmus in der Vergangenheit, so hat er diese zwar nicht direkt erlebt, jedoch bekommt er ein Gefühl für die Performance, welche auch als Erfahrungswert aus der Vergangenheit gewertet werden kann. Darüber hinaus kann sich Erfahrung wieder positiv auf die Erwartungshaltung des Anwenders auswirken. So kann Erfahrung im Umgang mit Algorithmen möglicherweise auch Möglichkeiten und Grenzen der Algorithmen und der Nutzung aufzeigen, wodurch weiterhin realistischere Erwartungen bedingt werden. Auch die Kommunikation und Interaktionsmöglichkeit kann sich gerade hier ebenfalls positiv auf das Erwartungsmanagement auswirken. Da durch Interaktionsmöglichkeiten auch Rückfrage an das digitale System und den Algorithmus gestellt sowie weitere Details erarbeitet werden können, kann auch dies realistischerer Erwartungen positiv beeinflussen. Darüber hinaus könnte das Erwartungsmanagement aber auch über die Wahrnehmung das Algorithmus Aversions Bias positiv zu eben dieser Reduktion beitragen. So soll das Erwartungsmanagement insbesondere Grenzen und Möglichkeiten von Algorithmen auszeigen und realistische Einschätzungen fördern. Durch diese frühzeitige Auseinandersetzung mit dem Algorithmus könnten eigenen

Ansichten und verzerrte Sichtweise frühzeitig reflektiert und potenziell reduziert werden. Diese Wirkzusammenhänge, die sich gerade um Erfahrung, Erklärungen und Erwartungen drehen, müssten künftig in weiteren Studien kritisch überprüft werden, können jedoch aus den bisherigen Studienergebnissen angenommen werden. Weitere potenzielle Wirkzusammenhänge sind darüber hinaus im Hinblick auf das Thema der Rechtfertigung zu prüfen. Entsprechend der dargestellten und vermuteten Zusammenhänge wirkt sich ein Mangel an Rechtfertigungsmöglichkeit negativ auf die Algorithmus Aversion aus beziehungsweise verstärkt diese. Der Mangel an Rechtfertigungsmöglichkeiten könnte jedoch potenziell reduziert werden, sodass der negative Effekt auf die Algorithmus Aversion sich ebenfalls minimiert und gar entfällt. Zum einen kann die Betonung objektiver Analyseschritte eine Rechtfertigungsgrundlage darstellen, da Entscheidern die Sorge genommen werden kann, dass Faktoren möglicherweise in einen falschen, durch Subjektivität bedingten Wirkzusammenhang gebracht werden. Darüber hinaus kann das Bereich der Incentivierungen einen positiven Einfluss auf die Rechtfertigungsgrundlage haben. Dabei sind Incentivierungen hier als breiter gefasster Faktor zu sehen, der im folgenden auch Haftungsfragen mit einschließt. So können beispielsweise geänderte Regeln im Unternehmen dafür sorgen, dass explizit auf Algorithmen verwiesen werden darf, wenn diese für bestimmte Schwerpunktebereiche genutzt werden müssen. Dies kann ebenfalls ein Anreiz sein, sich auf die Algorithmen zu beziehen und diese entsprechend vermehrt zu verwenden. So könnten eine Algorithmus Aversion insgesamt reduziert werden. Auch die Entscheidungsfreiheit kann den Mangel an Rechtfertigungsmöglichkeit reduzieren. Entscheidet sich der Anwender bewusst beispielsweise für die Weiterverwendung eines Algorithmus Outputs, so hat er sich vermutlich intensiv mit dem Ergebnis auseinandergesetzt. Durch diese Auseinandersetzung könnte ein Reflektionsmechanismus angenommen werden, in dem auch Argumente für die Nutzung des Outputs und seine Richtigkeit gesammelt werden. So könnte auch hier eine Rechtfertigungsgrundlage geschaffen werden und eine Algorithmus Aversion reduziert werden.

Insgesamt sind diese Wirkzusammenhänge, die sich insbesondere auf Rechtfertigung und möglicherweise auch Blame-seeking beziehen, ebenfalls in weiteren Studien kritisch zu überprüfen. Insgesamt zeigt sich auch, dass neben den genannten Effekten, alle Einflussfaktoren nicht nur in einen Wirkzusammenhang, sondern in künftigen Studien auch in eine Wirkreihenfolge gebracht werden müssen. Dies impliziert eine Gewichtung der Faktoren, die sich so aktuell aus der Forschung noch nicht ableiten lässt. Gerade diese Gewichtung kann helfen, die besonders großen Einflussfaktoren auf eine Algorithmus Aversion in Unternehmen frühzeitig zu adressieren und damit eine Aversion rasch zu reduzieren oder gar ganz zu vermeiden. Dennoch bietet die derzeitige Forschung bereits eine breite Übersicht über erste Ansätze, die zur Reduktion einer Algorithmus Aversion genutzt werden können und eine Vertrauensbasis in neue digitale Lösungen zumindest in gewissem Maße aufbauen können. Mit dieser Vielzahl von Möglichkeiten und Ansätzen, das Vertrauen in neue Algorithmus-basierte Technologien zu erhöhen, können neue Systeme sicherlich schon in großem Maße erfolgreich im Unternehmen integriert, etabliert und schlussendlich auch akzeptiert und zielführend genutzt werden.

8 Fazit

Die vorliegende Literatur bestätigt, dass gerade beim Einsatz algorithmenbasierter KI in stark automatisierten Entscheidungsprozessen, wie sie im Digital Reporting bzw. generell in einer digitalisierten Finanz- bzw. Controllingfunktion zunehmend eingesetzt werden, die Effektivität durch mangelndes Nutzervertrauen oder Algorithmus-Aversion im Sinne eines Bias eingeschränkt wird. Dieses Phänomen ist nicht nur relevant, wenn Controller oder Manager selbst auf automatisierte Routinen in Form algorithmenbasierter KI zurückgreifen, sondern auch, wenn sie menschliche Expertise einbeziehen sollen, die wiederum auf KI zurückgreift. Konkret bedeutet dies für die Controllerarbeit, dass nicht nur die direkte Algorithmus-Aversion der beteiligten Funktionsträger i adressiert werden muss, sondern dass auch die Counterparts im Management in die entsprechenden Maßnahmen miteinbezogen werden müssen.

Die Literatur zeigt, dass es dabei bedeutsam ist, Entscheidungs- und Problemlösungsprozesse nicht vollständig mit Hilfe algorithmenbasierter KI zu automatisieren, sondern den beteiligten Funktionsträgern immer wieder die Möglichkeit zu manuellen Eingriffen im Sinne von Modifikationen, Korrekturen oder Anpassungen zu geben. Mit anderen Worten: Der Algorithmus soll den Entscheider nicht ersetzen, sondern ihn unterstützen (Weißenberger, 2021a). Die Weiterentwicklung bestehender Systeme hin zur Integration von Erklärungen (XAI) ist sinnvoll, allerdings nur dann, wenn die gelieferte Erklärung tatsächlich einen Mehrwert im Sinne von Komplexitätsreduktion oder besserem sachlichen Verständnis über das Zustandekommen einer Prognose bzw. eines Entscheidungsergebnisses liefert, die intersubjektiv nachvollziehbar ist, d.h. auch gegenüber Dritten begründet werden kann. Ein weiterer wichtiger Baustein für den Abbau von Algorithmus-Aversion sind geeignete Schulungsmaßnahmen, die den Einsatz neuer digitaler Technologien trainieren, aber auch die Nutzung von Showcases bereits in frühen Projektphasen, mit denen die Leistungsfähigkeit von Algorithmen und automatisierten Informationsverarbeitungs- und Problemlösungsprozessen im Controlling, aber auch in anderen betriebswirtschaftlichen Feldern dokumentiert wird.

D Study 3: Behavioral Mechanisms underlying Algorithm Aversion in Management and Managerial Accounting

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Dr. Dr. Peter Kotzian has conceptualized the study, analyzed the data and wrote the paper.

Prof. Dr. Barbara E. Weißenberger provided guidance in conceptualizing the study and also wrote the paper.

Publications, conferences and presentations:

Conferences: ERMAC (Vienna, 2021) and EAA (Bergen, 2022)

Publications: Submitted to Schmalenbach Journal of Business Research (First Round Major Revisions)

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Abstract

Even though algorithms have the potential to improve the quality of managerial decision-making, practitioners are averse to using them. Extant literature provides mixed evidence on robustness and magnitude of algorithm aversion and suggests different underlying behavioral mechanisms for its occurrence. Our study presents two factorial survey experiments using a forecasting task as application that put existing findings into perspective. Our results indicate that if participants simultaneously receive algorithm- and human-made forecasts, they use both in approximately equal manner, indicating no specific aversion to algorithms. This contrasts with findings from studies, where participants are required to abandon a forecast produced by their own in favor of one produced by an algorithm. Instead, we find algorithm aversion results from selective attention. Users tend to pay more attention to the performance of a human than of an algorithm and users follow human but not algorithmic input if they believe it to be more accurate. Probing for additional mechanisms underlying algorithm aversion, we do not find evidence that trust in the source of a forecast is the link by which algorithm aversion operates. Furthermore, neither lack of explanation nor presumed skepticism of superiors constitute obstacles to the use of algorithmic decision-support.

Keywords: Forecasting, Algorithm Aversion, Algorithmic Decision Support, Explainable AI

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1 Introduction

Driven by rapidly advancing development of artificial intelligence (AI)-based information technology, firms invest substantial resources in integrating algorithmic decision-support into managerial accounting information systems (Liu et al., 2012; Rossmann and Wald, 2024; Schmidt et al., 2020) and decision-making. Factually, usage of such systems lags behind as managers are allegedly averse to decision-support provided by algorithms even if it proves to be superior compared to human expertise (Davenport, 2018a; Fildes et al., 2019; Johnson et al., 2021; ; see also review in Raisch and Krakowski, 2021)(Davenport, 2018a; Fildes et al., 2019; Johnson et al., 2021; Polonski, 2018; see also review in Raisch and Krakowski, 2021). In order to address this gap, firms need to know why this is the case.

A highly illustrative example of the issues involved is manager's reluctance of using of algorithmic-based decision-support in forecasting tasks (Mahmud et al., 2022). On the one hand, forecasts are an immensely relevant element in managerial accounting and decision-making (e.g. Casas-Arce et al., 2022; Chui et al., 2018; Eichholz et al., 2023; Monteiro et al., 2022; Rohrbeck and Kum, 2018). On the other hand, forecasting is a promising case of augmenting human decision-making with algorithmic input (Blattberg and Hoch, 1990; Myers and Ramsey, 2023). Whereas traditional human forecasting uses a limited set of methods and data sources (Baets, 2021; Casas-Arce et al., 2022; Verstraete et al., 2020), AI-based algorithms allow to integrate a much broader set of heterogeneous, structured as well as unstructured data sources, thus potentially achieving more accurate and more timely forecasts that are unbiased by preferences or strategic gaming from human forecasters (Appelbaum et al., 2017; Blackburn et al., 2015; Zhang et al., 2022). Given the potential advantages, introducing algorithms in management and accounting is a 'trendy' and widely discussed topic (Bakarich and O'Brien, 2021; Enholm et al., 2022; Möller et al., 2020; Mosier and Skitka, 2018) and a persistent theme in research on management (Myers and Ramsey, 2023), management information systems (Blackburn et al., 2015) and related domains (Afsay et al., 2023; Krieger et al., 2021).

The phenomenon of persons not attaching appropriate weight to algorithmic advice in decision-making is labeled algorithm aversion (see Dietvorst et al., 2015, 2018)[1] and was found in various studies (Commerford et al., 2022; Longoni et al., 2019; Mahmud et al., 2022). However, algorithm aversion is no robust finding. It seems to be conditional on situational elements and moreover also subject to change, notably due to the spread of algorithms in many domains of private and professional life (Davenport, 2018a; Harrell, 2016; Köchling et al., 2021). Furthermore, there are instances of over-trust in inferior algorithmic output, a phenomenon coined 'algorithm appreciation' (Logg et al., 2019). Evidence also indicates that both algorithm aversion and appreciation depend on specific conditions, e.g., the subjective character of the task at hand (Castelo et al., 2019), the size of the stakes (Filiz et al., 2021), whether poor advice from the source has occurred in the past (e.g. Prahl and van Swol, 2017), or whether or not supplementary explanations for algorithmic output are provided (e.g. Zhang et al., 2022). So fundamental questions are still open, viz. how robust algorithm aversion is as a phenomenon, and, with regard to overcoming it, what the underlying behavioral mechanisms are.

We address these questions by conducting two experimental studies in which we study algorithm aversion in a realistic management setting introduced by Fildes et al. (2019): Participants receive two forecasts, one provided by a human, the second provided either by another human or an algorithm. Participants shall use them as a basis for their own forecast, which is passed on to a superior manager, a setting representing a typical situation in business planning (Mayer et al., 2023). This setting differs from the standard approach to capturing algorithm aversion,

[1] Even though Dietvorst et al. (2015) do not use algorithm in our sense of an AI-based mechanism but more a traditional understanding of providing quantitative ratings for decision-support, their paper has instigated the broad recent research stream on aversion against the use of AI-based outputs as decision aids.

where participants produce their own forecast based on "raw data" before receiving decision support, so that they at least partially have to abandon their own forecast in favor of an algorithmic one (e.g. Dietvorst et al., 2015). The standard approach puts algorithms as a source of a forecast at a disadvantage. First, it induces psychological ownership as participants have invested effort in producing their forecast (Haesebrouck, 2021; Lim and O'Connor, 1995; Pierce et al., 2001). Second, by producing a forecast from 'raw' information, participants obtain, or feel to obtain, more knowledge about the subject of the forecast. Their own forecast, for which participants know how it came about, competes with a forecast they know nothing about. Given that intransparency of algorithms is often criticized and seen as an obstacle to usage (Adadi and Berrada, 2018; Schmidt et al., 2020; Shin, 2021) this design is prone to increase algorithm aversion. Our design avoids both problems and thus allows for a differentiation between aversion due to an ownership effect and aversion concerning the algorithm. Our results indicate algorithm aversion to be much weaker than hitherto presumed, indicating that at least part of the reported aversion is a measurement effect.

In terms of behavioral mechanisms, we inquire into whether trust, often seen as a crucial antecedent of usage (Schmidt et al., 2020; Siau and Wang, 2018; Venkatesh et al., 2016), mediates the relationship between origin and usage of a forecast. We measure trust in various aspects of the forecast, including the processes of producing the forecast, but find trust to be neither systematically affected by origin nor by past performance of the source. As a second mechanism, we test, whether aversion to algorithms participants presume their superiors to have is an obstacle to usage. If this were the case, participants who believe their superiors are averse to usage of algorithms would not use an algorithm regardless of their personal preference. While there is some evidence that participants presume their superiors to be more skeptical of algorithms, this presumption does not matter for participants' usage of algorithms. As a third mechanism, we inquire whether lack of explainability, which arises from a so-called black box algorithm, affects algorithm usage but found no support for this.

Instead, we find that algorithm aversion is instigated by users tending to ignore the objective performance of a source because of its origin. While superior expertise of a human forecaster is recognized as such and appropriately used, this is not the case for algorithms. Participants do not perceive the algorithm to be better in the first place.

Our paper's first contribution is to unravel the behavioral mechanisms underlying algorithm aversion by systematically testing competing mechanisms. We find that aversion is driven by selective attention to performance and expresses itself in users acting upon their subjective beliefs about performance rather than the objective performance of the source providing advice. In both aspects, participants treat algorithms and humans differently. This mechanism was not yet covered in existing research. Our second contribution is methodological: Effects of psychological ownership may be misinterpreted as algorithm aversion and measurement approaches should take this problem into account. Thirdly, our findings have relevant practical managerial implications as they suggest that issues of responsibility and blame shifting may constitute larger obstacles to the use of algorithmic advice than lack of explainability.

Our paper is organized as follows. In section 2 we provide the theoretical background of our research with respect to measuring algorithm aversion and develop our hypotheses. In section 3 we present our research instrument. Sections 4 and 5 describe the results of the two full factorial survey experiments we conducted. Section 6 contains a qualitative validation of our results from conducting several interviews with high-ranking management accountants in firms using AI-based information technology. In section 7, we discuss our results and draw conclusions.

2 Theoretical Background and Hypotheses Development

2.1 Using Algorithmic Advice: Theoretical Considerations on Measurement Issues

Since the seminal studies of Dietvorst et al. (2015, 2018), measurement of algorithm aversion follows a more or less standardized procedure. Applied to a forecasting task, it works as follows: (1) Users are given the raw data, form a mental model of the drivers and causal relationships involved and then make their own forecast based on their model. (2) They receive an algorithm's forecast and have to decide whether to keep their own forecast or replace it with the algorithm's forecast. While details of the procedure vary with respect to the aspects motivating a specific study (see e.g. Daschner and Obermaier, 2022; Jung and Seiter, 2021; Önkal et al., 2009; Prahl and van Swol, 2017), the underlying either-or procedure always applies. Still, in the light of more general research on how decision-makers deal with advice and different sources of input to formulate a forecast (see the review by Leitner and Leopold-Wildburger, 2011), this standard measurement procedure is problematic as it may lead to over-estimation of algorithm aversion. There are several reasons for this.

First, the issue of psychological ownership (Haesebrouck, 2021; Liu et al., 2012; Pierce et al., 2001) which applies to forecasts users have derived from given data with more or less substantial effort. As a consequence, users have a stake in this forecast, because abandoning a personal output comes at the price of cognitive dissonance (Arkes and Blumer, 1985; Schultze et al., 2012). Thus, pitching a forecast produced by a user against a forecast coming from an algorithm may find aversion against giving up one's own forecast. Not because of algorithm aversion but because of a feeling of psychological ownership with regard to one's forecast. Furthermore, having decided – here about a forecast – also affects how incoming information is used

(Bronfman et al., 2015), how information from various sources is combined (Bonaccio and Dalal, 2006; Leitner and Leopold-Wildburger, 2011) and how a decision aid is evaluated (Bronner and Hoog, 1984; Chaxel et al., 2013). Employing the standard design with a forecast produced by the user will per se lower the chances that an alternative forecast, regardless of its source, is used. Even though this is not algorithm aversion it would be interpreted as such.

Second, a major objection to algorithmic advice is intransparency (Schmidt et al., 2020; Shin, 2021). With regard to this issue, the standard setting of letting users produce their own forecast also stacks the odds against using the alternative as users know exactly how their own forecast came about but know nothing about how the algorithm arrived at its forecast. Whereas users are aware of the reasons and justifications for the forecast they derived themselves, they are missing this information when receiving an algorithmic forecast, which also can induce them to rely more on their own judgment (Yaniv, 2004; Yaniv and Kleinberger, 2000). Again, this is no expression of algorithm aversion but equally applies to all forecasts, which are received without supporting elaborations.

Third, it is questionable in how far the standard setting matches the practice in firms (Fildes et al., 2019). While management accountants produce forecasts and also receive algorithmic advice, making them subject to the problems mentioned, this is not true at the level of management or top-level management accounting. Here, users' choice is not between a personally produced forecast and an alternative, but between alternatives with different performance records and different origins, like humans or algorithms.

Thus, it is unclear to what degree the standard measurement procedure captures algorithm aversion as opposed an ownership effect induced by producing a forecast or uncertainty on how a given forecast came about. In the light of these issues, testing for the robustness of algorithm aversion is required.

2.2 Hypotheses Development

While there is extant research on the antecedents of algorithm aversion, the actual mechanisms underlying the process of how an antecedent will lead to underweighting algorithmic advice are still open to discussion. This is a relevant issue inasmuch as measures addressing the problem of algorithm aversion in firms need to be counteract precisely these mechanisms. We therefore focus on the most prominent mechanisms discussed in research (Burton et al., 2020; Jussupow et al., 2020; Mahmud et al., 2022). As a framework, we use a stage model, broadly oriented at the theory of planned behavior (Ajzen, 1985) that may constitute hurdles to using algorithmic output: First, the algorithm's performance must be perceived correctly. Second, there must be trust in the algorithm. Third, there may occur obstacles to usage arising from the organizational setting in which the user is embedded.

With respect to the first stage, algorithm aversion may be caused by selective attention, i.e., users ignore the algorithm and its performance as a source of advice. Selective attention to information was found in many settings (e.g. Hales, 2007), and may be at work here, too. A typical feature of experimental research on algorithm usage and aversion is that participants are given advice from an objectively superior algorithm. Usually this is shown by high forecasting precision in the past. At the same time, participants are supposed to recognize this superiority compared to their own forecasting efforts. Rational participants should then rely more on the more informative source, as it outperforms them, and there is some evidence that they do so (Daschner and Obermaier, 2022; Lim and O'Connor, 1995). However, whether participants actually recognize the algorithm's superiority is not always ascertained. We therefore suggest to take into account how participants perceive the performance of an algorithm as algorithm aversion can express itself in the fact that they do not pay attention to the algorithm's objectively superior performance for the very reason that it is an algorithm. If this is the case, for them, there is no better alternative, or taken to the extreme, no serious alternative at all to their own forecast. If this mechanism is at work, the origin of a forecast affects its performance as perceived and thereby the usage.

Hypothesis 1a: Higher perceived past performance of a forecasting source positively affects the use of a forecast provided by this source.

Hypothesis 1b: Superior forecasting performance by an algorithm is perceived to a lesser degree than superior forecasting performance by a human expert.

With respect to the second stage, while performance is often seen as the main driver of algorithm usage it may be that users perceive the algorithm's higher performance but do not trust the source. The lack of trust then precludes usage of the algorithm's output. In extant literature, there is strong evidence that trust is seen as an antecedent of using forecasts and advice from (non-)human sources (Bayer et al., 2021; Daschner and Obermaier, 2022; Davenport, 2018a; Glikson and Woolley, 2020; Li et al., 2008). We therefore state:

Hypothesis 2a: Trust in a forecasting source positively affects its usage.

Hypothesis 2b: Participants trust algorithmic forecasts to a lesser degree than forecasts based on human expertise.

With respect to the third stage, mechanisms originating from the organizational setting may potentially drive algorithm aversion. Notably, even though users may be aware of an algorithm's superior performance and also personally trust it, they still may abstain from using it for external reasons. As in a business context, any forecasting process is embedded in a larger organizational context, such obstacles can be derived from upper echelon theory (Hambrick and Mason, 1984). Hambrick and Mason posit that organizational outcomes to a large degree have to be interpreted in the light of values and cognitive bases of a firm's top management. As a result, if users assume that the superiors themselves are algorithm averse, because they do not use algorithmic advice (Alexander et al., 2018) or if they believe that they are judged negatively if they rely algorithms, or more generally, on technology (Arkes and Blumer, 1985; Shaffer et al., 2013), this precludes the use of algorithmic advice regardless of the user's personal attitude. We therefore formulate the following two hypotheses:

Hypothesis 3a: Presumed trust of a superior in a forecasting source is positively related to its usage.

Hypothesis 3b: The origin of a forecasting source affects presumed trust, with an algorithmic source receiving less presumed trust than a human expert.

Another type of obstacle derived from the user's environment is the lack of explanation on how a specific forecast came about. Whereas a human providing advice can usually provide an explanation or justification towards superiors or other stakeholders either ex ante or ex post if needed, advanced algorithmic forecasting technologies, like, e.g., neural networks, typically cannot: They are black boxes (Giboney et al., 2015; London, 2019; Merendino et al., 2018; Vinson et al., 2018; Zhang et al., 2022). As evidence indicates that explanations, in particular elaborations on how a forecast came about, are relevant for usage (e.g. Shin, 2021), explainability should increase usage per se, and it should matter more, when black box algorithms are the source of the forecast.

Hypothesis 4a: Explainability on how a forecast came about increases its usage.

Hypothesis 4b: Explainability increases usage of forecasts by algorithmic sources more than they increase forecasts provided by human experts.

3 Method

To test our hypotheses, we conducted two factorial survey experiments (Oll et al., 2018). The first experiment aims at replicating the observation of algorithm aversion using a different measurement procedure as outlined above and also at investigating potential mechanisms underlying algorithm aversion. The second experiment specifically investigates the role of transparency in the sense of explainability for usage of algorithmic output.

Both experiments share the basic research design. Participants were asked to put themselves into the role of a firm's chief management accountant and were tasked with providing as accurately as possible a sales forecast for one of the firm's divisions for the upcoming quarter to the management with no other information than two suggestions coming from two sources. Participants were incentivized by a variable payoff, linked to the forecast/actual-deviation.

To differentiate between psychological ownership effects, arising from having to choose between a personally produced forecast and an alternative, and algorithm aversion, we compare participants' reactions to human experts and algorithms. Ownership effects would express themselves as an aversion to both, forecast from humans and algorithms. Thus, the first forecast participants received was always described as having been provided from a human staff member in charge. No further information on how this forecast came about was given. Simultaneously, participants were provided with a second forecast from another source. This forecast was also described as being produced and provided on a regular basis and also given without any further information. Participants were instructed to derive their own forecast for the upcoming quarter to report to the top management, using both input forecasts as they see fit.

With respect to the second forecast's source, we used in both experiments a 2x2 between-subjects design. Experiment 1 featured the following manipulations:

Manipulation of origin: The second forecast is either produced by an algorithm (specifically, an artificial intelligence, ALGO) or by another human expert (HUMAN).

Manipulation of performance: In the EQUAL-condition, both forecasts provided were equally accurate in the past: The sum of forecast/actual-deviations is identical, no forecast features a bias in one direction and both were right on target for the same number of quarters. In the BETTER- condition, the second forecast is substantially more accurate (the sum of forecast/actual-deviations is smaller). Given the strong evidence on the relevance of presentation formats, in particular tables vs. graphs (Paivio, 1971; Perkhofer et al., 2020), the accuracy-related information was presented in both formats, to maximize its effect on the participants (see Appendix).

Both forecasts presented to the participants diverged, but both were equally realistic given past developments. Specifically, the first forecast from the human was for 4.2% sales growth, the second forecast (human or algorithm) for 5.9%. The forecast reported by the participants constituted the experiment's dependent variable. A post-experimental questionnaire covered basic demographics but also issues of trust.

4 Experiment 1

4.1 Sample Characteristics

Participants were practitioners, management accountants and other people, who can be assumed to be familiar with the forecasting scenario used in the experiment. They were recruited via a provider of online surveys. Overall, 138 persons participated, 58% of which are male and 30% hold a university degree among which roughly a third (i.e., 9% of all participants) hold a degree in economics or business administration. About 35% of our participants work in sales and distribution functions and 19% in managerial accounting functions. Average age is 51 years, ranging from 35 to 79 years, average work experience is 27 years. A randomization check showed the demographic features to be uncorrelated with the manipulations.

4.2 Measurement Issue: True Aversion vs. Psychological Ownership

In our setting, algorithm aversion would express itself in how participants weights the two input forecasts when producing their forecast (see the definitions of Dietvorst et al., 2015; Önkal et al., 2009; Promberger and Baron, 2006, all of which are based on the weighting of advice given by humans as opposed to algorithms)(see the definitions ofDietvorst et al., 2015all of which are based on the weighting of advice given by humans as opposed to algorithms). Figure D-1 gives the means and 95% confidence intervals for forecasts obtained in the four experimental conditions.

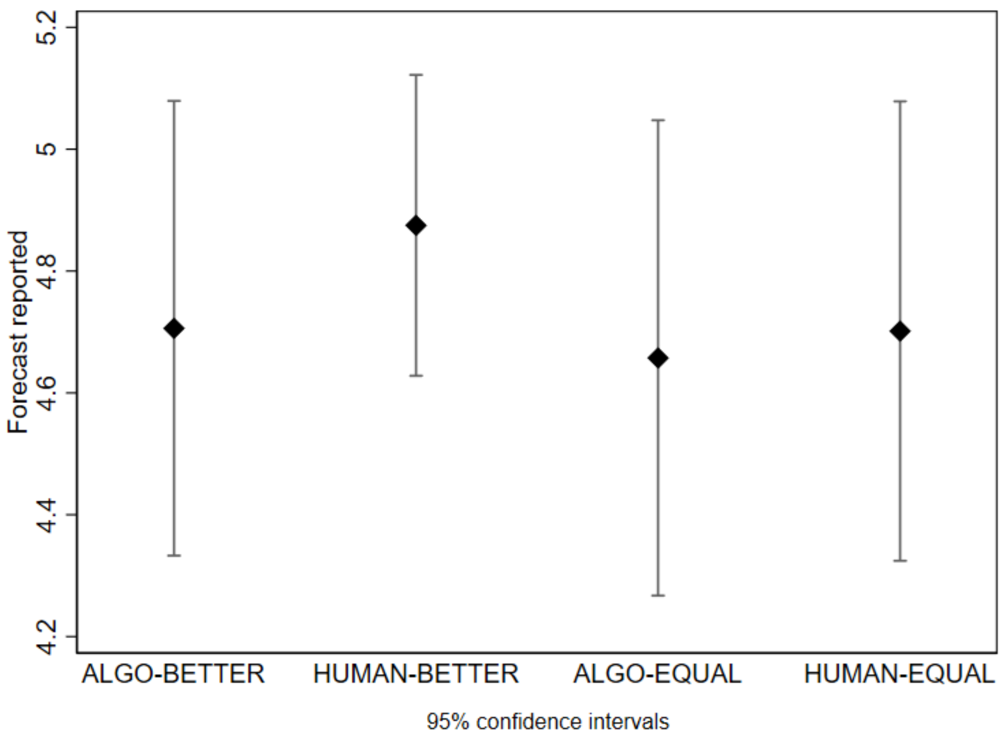

Figure D-1 Reported Forecasts by Experimental Condition

Note: The forecast from the human expert is for 4.2% sales growth, the alternative (algorithm or another human forecaster) for 5.9%. ALGO-BETTER (Mean 4.71; 95%-CI 4.34 – 5.07); HUMAN-BETTER (Mean 4.88; 95%-CI 4.64 – 5.12); ALGO-EQUAL (Mean 4.66; 95%-CI 4.28 – 5.04); HUMAN-EQUAL (Mean 4.70; 95%-CI 4.34 – 5.07).

If one source was more accurate in the past, a rational participant would report the forecast originating from the more accurate source. If, both forecasts were equally accurate in the past, a rational participant would put equal weight on both sources and report the average of both input forecasts. Aversion to a source, e.g., an algorithm, would result in discounting the forecast of this source, which results in a reported forecast shifted away from the source subject to aversion. Specifically, algorithm aversion would express itself in our experiment as follows: In the EQUAL conditions, a rational participant, weighting both forecasts equally, would report 5.05 – or 5, after rounding – which is the mid-point between the forecast of the management accountant as default source (4.2% increase) and the alternative (5.9% increase). A participant averse to using the algorithm's forecast would put in the ALGO-EQUAL condition more weight on the human forecast and report a forecast closer to 4.2%. In the BETTER condition, a rational participant would report 5.9, the forecast of the more accurate source, regardless of its nature (human or algorithm). Algorithm aversion would again lead to discounting the better forecast because it originated from an algorithm, i.e., the reported forecast is closer to 4.2%.

Figure D-1 and the underlying statistics show that the weightings of the inputs for the reported forecasts differ among experimental conditions, but not significantly, as the confidence intervals overlap. The positioning of all reported forecasts in the range defined by the two input forecasts (4.2% to 5.9%) show a slight tendency to give more weight to the 4.2%-forecast originating from the first source, as the means in all experimental conditions are below the midpoint (~5.0). Still, the alternative source is never discounted completely, as the average forecasts in all conditions differ significantly from the first source (4.2%, which is not in the confidence interval). We controlled for risk propensity but found no significant effect on the reported forecast.

As a result, the measurement procedure in our experiment, which relates more closely to business practice than the traditional approach, does not provide evidence for the existence of algorithm aversion per se. Therefore, we assume that the traditional measurement approach does not capture algorithm aversion in a narrow sense, but is rather to some degree affected by psychological ownership following from participants having to formulate their own forecast first and only then modify it after receiving (non-)algorithmic advice.

4.3 Result 1: Biased Performance Perceptions

We hypothesized that even though basically the perception of the source's performance drives usage (H1a), users pay attention and recognize superior performance only in a human expert, but ignore it in an algorithm (H1b).

Starting with the latter argument, Table 1 provides results on determinants of perceived performance of the second forecasting source relative to the default source. Perceived performance was measured as the participants' beliefs that one of the sources was superior to the other in the past measured on a 7-point Likert scale ranging from 1 (the first source, i.e., the staff member, was clearly perceived to have performed better in the past) to 7 (the second source, i.e., another human expert or an algorithm, has been perceived to be better) with the mid-point of 4 indicating belief that both sources performed equally in the past. Perceived performance was regressed on the source of the second forecast (ALGO) and whether the second forecast was actually better in the past (BETTER).

Prima facie, there is a significant effect of a forecast originating from an algorithm being perceived as performing worse (see column "All"). But this effect is due to differences in the participants' perception of performance: Participants perceive the objectively higher performance if the forecaster is human (see column "Human") but ignore it if the forecast originates from an algorithm (see column "Algorithm"), thus supporting H1b.

Table D-1 Perceived Performance of Forecasting Sources

	All	Algorithm	Human
BETTER	0.336	0.206	0.462*
ALGO	-0.365*		
constant	4.242***	3.941***	4.176***
R^2	0.039	0.006	0.040
R^2_adj	0.025	-0.009	0.026
N	138	68	70

Legend: * p<.1; ** p<.01; *** p<.001. r2 : R^2 r2_a : adjusted R^2 .

Notes: Results obtained by an OLS regression. Dependent variable: PerceivedPerformance, participant's belief regarding the past performance of the two sources, 7-point Likert scale with high values indicating the belief that the second forecast performed better in the past. BETTER: dummy variable indicating that the second forecast was objectively better in the past (reference: equal objective performance). ALGO: Dummy variable indicating that the second forecast was produced by an algorithm (reference: forecast was produced by a human).

We then test H1a by inquiring into the relevance of perceived performance for usage. To do so, we regress the participants' reported forecast on perceived performance, the objective past performance (BETTER) and the nature of the source (ALGO). As the first forecast was 4.2% sales growth and the second forecast 5.9%, positive coefficients indicate a higher weight for the forecast from the second source, characterized by its type and perceived performance.

Table D-2 Use of Alternative Forecasts

	All	Algorithm	Human
PerceivedPerformance	0.234***	0.137	0.365***
BETTER	0.033	0.020	0.005
ALGO	-0.022		
constant	3.740***	4.116***	3.177***
R^2	0.092	0.031	0.215
R^2_adj	0.072	0.000	0.192
N	137	67	70

Legend: * p<.1; ** p<.01; *** p<.001. R^2 and adjusted R^2 .

Notes: Results obtained by an OLS regression. Dependent variable: Usage measured by the forecast reported. PerceivedPerformance, participant's belief regarding the past performance of the two sources, 7-point Likert scale with high values indicating the belief that the second forecast performed better in the past. BETTER: dummy variable indicating that the second forecast was objectively better in the past (reference: equal objective performance). ALGO: Dummy variable indicating that the second forecast was produced by an algorithm (reference: forecast was produced by a human).

The regression coefficients in the first column ("All") indicates that neither the origin of the forecast per se nor the objective performance of the source matters for usage. Any algorithm aversion would show up as a negative coefficient for the dummy variable ALGO, as participants would then place more weight on the first forecast. We see no such effect. Instead, only perceptions of performance matter and result in a bias against algorithmic advice. Overall, the results in column "All" indicate that perceived performance increases usage, supporting H1a. Nevertheless, further inquiry shows that this is not always the case: As columns "Algorithm" and "Human" indicate, perceived performance matters for usage only if the forecast is provided by the human expert. For a forecast produced by an algorithm, objective superior performance translates neither into perceived performance nor into increased usage. Taken together, these findings support H1a and H1b and identify biased performance perceptions as a first relevant mechanism explaining inappropriate low weight on algorithmic advice.

4.4 Result 2: Perceptions Drive Users' Trust

A second mechanism driving algorithm aversion suggested in extant research is lack of trust in algorithms. Specifically, the origin of the source of advice – either human or algorithm – is supposed to affect users' trust in the forecast produced (H2b) and this trust is then supposed to affect usage (H2a). To test this mechanism in our experiment, we consider participants' overall trust in the source by asking whether the participant personally had higher trust in either the first or the second forecast ("Personal"). To capture procedural aspects of trust, we use the approach suggested by Bhattacherjee (2002), and survey participants' opinions on the forecasting process: Did they expect the data to be gathered correctly ("Correct")?. Did they believe that all relevant data was collected (“Complete”)? Was to their view the data underlying the forecast correctly interpreted (“Interpretation”)? All trust variables were measured by 7-point Likert scales with high values indicating that the participants believed the second forecast to be more trustworthy in this regard.

Table 3 gives the results of regressing general and procedural trust on the origin (ALGO), objective performance (BETTER) and perceived performance (PerceivedPerformance) of the second forecast. The constellation, in which the second forecast was also produced by a human serves as reference category.

Table D-3 Determinants of General and Procedural Trust

	Personal	Correct	Complete	Interpretation
PerceivedPerformance	0.710***	0.625***	0.390***	0.390***
BETTER	-0.096	0.022	0.203	0.152
ALGO	-0.001	-0.004	-0.015	-0.405*
constant	1.003**	1.215***	2.175***	2.444***
R^2	0.454	0.355	0.151	0.211
R^2_adj	0.442	0.341	0.132	0.193
N	138	138	138	138

Legend: * p<.1; ** p<.01; *** p<.001.

Notes: Results obtained by OLS regression. Dependent variables: trust variables, see text. All were measured by 7-point Likert scales with high values indicating that the participants believed the second forecast to be more trustworthy in this regard. PerceivedPerformance, participant's belief regarding the past performance of the two sources, 7-point Likert scale with high values indicating the belief that the second forecast was perceived as having performed better in the past. BETTER: dummy variable indicating that the second forecast was objectively better in the past (reference: equal objective performance). ALGO: Dummy variable indicating that the second forecast was produced by an algorithm (reference: forecast was produced by a human)

First, the results show that the origin of a forecast (ALGO) affects trust only with respect to correct interpretation of the data. Participants believe this to be less the case for an algorithm (see column "Interpretation"). Overall, algorithms do not significantly induce less trust than humans, thus, there is only limited support for hypothesis 2b.

Past performance matters for trust, but not straightforward: There is no effect of an alternative being objectively better (BETTER) on any trust variable, but only of perceived performance: What matters is the participants' belief that the second forecast is superior. The more participants perceive the second forecast as outperforming the first, the more trust they have in this source, in both, general and procedural aspects. However, whether participants perceive this to be the case depends to some degree, as we saw earlier on, on the source: Superior performance is perceived in the case of humans, but not in the case of algorithms.

Regarding the mechanism's second step, the link between trust and usage, Table D-4 reports the effects of different aspects of trust on usage, measured as the forecast reported. We ran two separate regressions, one for overall trust ("Personal"), one for the three aspects of procedural trust ("Correct", "Complete", "Interpretation"), to obtain a differentiated picture.

In terms of expectations, more trust in the alternative source should shift the reported combination of both input forecasts towards the forecast from the second source, i.e., from 5 towards 5.9. Thus, we would expect positive coefficients for the trust variables. Table D-4 indicates that, contrary to much of the existing research and our hypotheses 2a, trust is largely irrelevant for factual usage (see Panel "All"). Neither trust in general, nor procedural aspects of trust significantly affect usage. This pattern applies equally to alternative forecasts originating from humans and algorithms (see Panels "Algorithm" and "Human"). Thus, there is no evidence supporting the origin-trust-usage mechanism, as there is only a weak and highly specific link from a forecast's origin to trust and basically no link from trust to usage.

Table D-4 Trust as a Determinant of Usage

	All		Algorithm		Human	
	1	2	1	2	1	2
PerceivedPerformance	0.132	0.240**	0.015	0.053	0.350**	0.389***
BETTER	0.047	0.010	0.021	0.015	0.009	-0.075
ALGO	-0.021	-0.004				
Personal	0.143		0.216		0.017	
Correct		-0.092		0.054		-0.179
Complete		0.091		0.147		-0.053
Interpretation		0.042		-0.036		0.214
constant	3.596***	3.552***	3.784***	3.823***	3.174***	3.132***
R^2	0.113	0.105	0.070	0.071	0.215	0.259
R^2_adj	0.086	0.064	0.025	-0.006	0.180	0.201
N	137	137	67	67	70	70

Legend: * p<.1; ** p<.01; *** p<.001.

Notes: Results obtained by OLS regression. Dependent variable: Forecast reported. PerceivedPerformance, participant's belief regarding the past performance of the two sources, 7-point Likert scale with high values indicating the belief that the second forecast performed better in the past. BETTER: dummy variable indicating that the second forecast was objectively better in the past (reference: equal objective performance). ALGO: Dummy variable indicating that the second forecast was produced by an algorithm (reference: forecast was produced by a human). Personal: Participant's general trust in the source. Correct: Participant's trust that correct data was used to produce the forecast. Complete: Participant's trust that data gathered for the forecast was complete. Interpretation: Participant's trust that the data was interpreted correctly for formulating the forecast. All variables are 7-point Likert scales with high values indicating that the alternative source received more trust.

4.5 Result 3: Perceptions also Drive Presumed Trust of Others

A third mechanism suggested as having a potential impact on algorithm aversion is that external obstacles keep users from actually using the algorithm's output, regardless of their personal perception about what is the more accurate source.

A first obstacle may arise from the organizational context: In the experiment, as in practice, participants report a forecast to the top management. They may therefore consider how the top management as ultimate recipient of the forecast would react to a forecast produced by an algorithm. It then may be the case that even though the participant is not averse to using the algorithm, s/he still does not use it, because s/he presumes the ultimate recipient to be averse to algorithmic output and would disapprove of passing on a forecast produced by an algorithm. In this situation, algorithm aversion arises from the distrust/aversion participants presume the ultimate recipients to have. In the experimental setting chosen, just as in real life, this would be the firm's management. To evaluate this mechanism, we capture the impact of the source of a forecast on the trust the participant presumes the recipient to have, and of this 'presumed trust' on the participant's usage of forecasts.

Table D-5 Relationship between Origin, Presumed Trust and Usage

	Panel A: Origin and Presumed Trust			Panel B: Presumed Trust and Usage		
	All	Algorithm	Human	All	Algorithm	Human
BETTER	-0.046	0.117	-0.269	0.033	0.024	0.004
ALGO	-0.235			-0.023		
PerceivedPerformance	0.433***	0.289*	0.636***	0.236**	0.148	0.368***
PresumedTrust				-0.004	-0.037	-0.005
constant	2.184***	2.448***	1.404*	3.750***	4.205***	3.184***
R^2	0.170	0.081	0.280	0.092	0.033	0.215
R^2_adj	0.152	0.053	0.259	0.065	-0.013	0.179
N	138	68	70	137	67	70

Legend: * p<.10; ** p<.01; *** p<.001.

Notes: Results obtained by OLS regression. PerceivedPerformance, participant's belief regarding the past performance of the two sources, 7-point Likert scale with high values indicating the belief that the second forecast was perceived as having performed better in the past. BETTER: dummy variable indicating that the second forecast was objectively better in the past (reference: equal objective performance). ALGO: Dummy variable indicating that the second forecast was produced by an algorithm (reference: forecast was produced by a human). Panel A: Dependent variable: PresumedTrust, defined as the level of trust in a forecast the participant presumes the top management as ultimate recipient of the forecast to have. Panel B: Dependent variable is usage of the forecasts, measured as reported forecast, for explanatory variables see above. All dependent variables are 7-point-Likert scales, high values indicating that the second source received more trust.

If algorithm aversion indeed operates through this mechanism, we will find an effect of the forecast's origin on the trust participants presume the top management as recipient to have (H3b) and to find that this presumed trust affects factual usage (H3a). Table 5 indicates, at best, mixed support for this mechanism.

Panel A gives the results of regressing presumed trust on origin and perceived performance of the second forecast. While in the case of an algorithm, participants presume top management to be somewhat less trusting, the effect of ALGO not reach significant (see column "All"). Thus, participants do not systematically presume the top management to be more skeptical regarding an algorithm-based forecast than a human-made forecast. Again, algorithm aversion expresses itself more indirectly, via perceived performance: If participants personally believe a source to be more accurate (PerceivedPerformance), they tend to presume that the top management as recipient would also have more trust in this source. Perceived performance matters for presumed trust (see Panel A, column "All", but does so much more in the case of a human than in the case of an algorithm (see Panel A, columns "Algorithm", and "Human", respectively).

As for the second step of the mechanism, the relevance of presumed trust for usage, Panel B indicates that presumed trust is irrelevant for usage. In no constellation, regardless of whether all cases or the sub-samples are considered, the variable PresumedTrust exerts an effect on usage. Even if participants may presume that the ultimate recipients of a forecast are skeptical of algorithms, this presumption does not affect how the output of an algorithm is used. Thus, participants' presumption that the ultimate recipients would not accept usage of an algorithm is not the obstacle. So neither H3a, nor H3b are supported.

5 Experiment 2

5.1 Design Modifications

The second experiment evaluates whether usage of algorithms is obstructed by the black box nature of algorithms. Research design and experimental setting were adapted from the first experiment with two modifications. First, we increased the difference in forecasting accuracy between the two sources to test whether the selective attention mechanism depends on the magnitude of the performance difference. Second, we added an explanation elaborating on how the second forecast came about. The explanation was given for the algorithm as well as the second human forecaster. It illustrates the forecasting process, but beyond this does not deliver any other information relating to the content of the forecast (see Appendix). The other stimuli – information on the nature and past accuracy of the forecasting sources – were provided in the same format as in experiment 1 (see Appendix). Experiment 2 was pre-tested using students as participants, in particular with regard to the plausibility of the explanation. Dependent variable and post-experimental questionnaire were identical to experiment 1.

5.2 Sample Characteristics

Again, practitioners, management accountants or other people who can relate to the situation described in the experiment, like managers, were recruited via a provider of online studies. Overall, 204 persons participated with an average age of 45 years, ranging from 19 to 68 years. 41% of the participants were male, 38% hold a university degree with about a fifth (8% of all participants) hold a degree in economics or business administration. About 19% of our participants work in sales and distribution functions and 4% in management accounting. The average work experience of all participants is 20 years.

The findings in experiment 2 (not reported) on the relationships between origin, perceived performance, personal trust and presumed trust and usage replicate the findings from experiment 1, with the increased difference in performance resulting in an increased perception of performance. Just as in experiment 1, this matters only in the case of a human forecaster.

5.3 Result: Explanations and Usage

In terms of what an obstacle to usage might be, we argue that an elaboration on how a forecast came about increases usage (H4a) but that algorithms are more in need of an explicit explanation. Humans implicitly come with the option of getting an explanation anytime on demand, while algorithms do not (H4b). Findings on the relevance of providing an explanation for factual usage are given in Table D-6.

Table D-6 Effect of Explanation on Usage

	All	Algorithm	Human
ALGO	0.003		
PerceivedPerformance	0.152**	0.155	0.149*
EXPLANATION	0.211	0.228	0.194
constant	3.218***	3.197***	3.239***
R^2	0.047	0.041	0.053
R^2_adj	0.032	0.021	0.033
N	200	100	100

Legend: * $p<.05$; ** $p<.01$; *** $p<.001$.

Notes: Results obtained by OLS regression. Dependent variable: Forecast reported. Management accountant in charge predicted +3.4 %, the second forecast +4.9 %. PerceivedPerformance, participant's belief regarding the past performance of the two sources, 7-point Likert scale with high values indicating the belief that the second forecast was better in the past. ALGO: Dummy variable indicating that the second forecast was produced by an algorithm (reference: forecast was produced by a human). EXPLANATION: Dummy variable indicating that an explanation on how the forecast came about was presented (reference: no explanation provided).

Contrary to H4a, providing an explanation on how the forecast came about does not increase usage of the source for which the explanation is provided (see column “All”). While the coefficient obtained for EXPLANATION in the sub-sample where the second forecast was from an algorithm is slightly higher (column “Algorithm”), it is insignificant, which is also the case for situation where the second forecast originates from a human (column “Human”). Thus, there is no support for H4b, which stated that an explanation matters more for algorithms than for humans. While not reported, we also inquired whether the provision of an explanation affects perceptions of performance, but found no such effect.

6 Qualitative Validation

In order to validate our findings, we conducted four in-depth interviews with chief management accountants from large German firms on the status quo regarding the use of algorithms in forecasts and the problems they perceive in this domain.

First, the interview partners confirm the gap between the importance and potential assigned to AI: Even though algorithmic support, e.g., as predictive analytics, is used, but it does not replace human expertise which is still incorporated into forecasting.

“I don't think [AI] is particularly widespread at the moment. Some areas are perceived as pioneers, they are at the forefront, and they are making courageous progress, but I think we are still a long way from truly widespread use.” (Interview #1)

“So a complete abandonment, a really hundred percent abandonment [of human forecasting], a complete automation via AI I honestly can't imagine.” (Interview #3)

Most interestingly, the obstacles to broader usage of algorithmic forecasts are not seen in the technical domain, i.e., data availability or the performance of algorithms.

“I think there are hardly any challenges on the technical side. The technology is simply so advanced that you can say there are already suitable solutions for a large number of applications.” (Interview #1)

Instead, the obstacles to usage arise from issues of accountability or outright liability, as one of the interviewed chief management accountants confirms.

“At the end of the day, it's also a certain amount of responsibility that a person bears, and I can't imagine that this is completely delegated to a machine and then, at the end of the day, to the Management Board. So even if the AI, so to speak, the proposal of the AI, for example for a forecast, let's stick to that, is the one that is set or that is accepted. Then that would still have to be confirmed by a super-ordinate person, who at the end of the day also bears the responsibility for it.” (Interview #3)

This issue relates to the function of forecasts which oftentimes are not only used for planning purposes, but also for controlling performance (Arnold and Artz, 2019; Churchill, 1984), thus making managers responsible for meeting their forecasts.

“So, I think the liability will always remain with the human being, or liability is probably the wrong word in this context – the responsibility for a certain forecast, so I think it's inconceivable that any division manager can withdraw to a point of view - I mean the planning was done by the AI, I don't know exactly how the result comes about and therefore yes, I can't hand over any responsibility. That will always lie with the responsible persons and that is of course clear at the beginning, an acceptance problem for the planners, if they now simply see an output from such an automated forecast.” (Interview #1).

As a result, justification pressure becomes relevant which not only explains why neither trust, presumed trust or explanation drives the use of algorithms as a basis for forecasting, but also provides a tentative basis for explaining the biased performance perceptions. If higher performance in an algorithm cannot be used as a justification, it becomes irrelevant if it is not very pronounced: The worst case for users is to be forced to bear responsibility for a forecast they did neither produce nor understand.

“As the person in charge, you can't just say, or in the case of errors, "The box calculated that. I'm out of the game", or something like that. (...) The board members can't get out of liability. And they will already see that they pass on this liability downwards the hierarchy, so to speak.” (Interview #4)

In a nutshell, all interview partners see no exclusive reliance on AI-based forecasts within the accounting function, but rather a side-car approach, i.e., using algorithmic forecasts as an additional input to be combined with traditional forecasts.

“At the moment, I can well imagine that there will be a combination in the assessment between analytics, AI and a human intelligence analysis. And from such a triumvirate then at the end of the day, for example, an overall forecast or a planning is derived. Which, depending on the use

case, goes more in the direction of AI or more in the direction of analytics or more in the direction of human interpretation." (Interview #3)

7 Discussion and Conclusion

Improvements in the capabilities of algorithms have the potential to make the integration of algorithmic output into decision-making an option for increasing firms' economic success (Enholm et al., 2022; Mishra et al., 2022). However, research provides evidence of algorithm aversion and interviews with practitioners also found strong reservations against usage of algorithms (Davenport, 2018a; Dietvorst et al., 2015; Polonski, 2018). Our research question was, how strong this aversion actually is and on what mechanism it is based.

Before discussing the implications, we discuss our study's limitations. First of all, the experimental stetting is to some degree artificial. Still, given that we used practitioners with at least some experience with the situation, we can assume that they could identify with the situation. Second, the stakes – the consequence of reporting a sales forecast which turns out to be wrong – for the participants are presumably lower than they would be in real life. This, however, would imply in our view an even higher handicap for a new technology, and an even higher tendency to rely on the forecast produced by a human, in particular due to the possibilities of blame shifting in the case that problems occur. To the degree that this is the case, all experimental research underestimates algorithm aversion. Last, a one shot experiment may not be conclusive about how trust and usage develop over time and with experience, and how the need for supplementary explanations develops in the long run. Given that trust in various aspects of the algorithmic forecast varied substantially among participants, but was still irrelevant for usage, we may assume that increasing trust will not turn out to be relevant.

As it is, our findings offer new insights and call for a discussion of existing findings, also because of their implications for practice.

First, if participants are free to use and to combine human and algorithmic forecasts that are presented simultaneously, there is little evidence of algorithm aversion. Instead, the aversion reported in manifold research in the wake of Dietvorst et al. (2015) is more an aversion to abandoning the outcome of one's own forecasting efforts than aversion to algorithms. For validating our experiments, we conducted interviews with practitioners on the usage of algorithms and artificial intelligence in their firms. Their consistent answer was that currently, and for the foreseeable future, human forecasts and algorithms will operate in parallel. So in real life, for users, in particular higher up in the hierarchy, the choice will typically be between a forecast produced by humans, say the management accountant in charge, and of an algorithm. They do not have to choose between their own forecast and an alternative. Both, the theoretical arguments on psychological ownership effects and the view of practitioners imply that the situation we use is closer to practice and thus the magnitude of algorithm aversion is more limited than hitherto presumed.

Second, there is substantial support for a more indirect mechanism of aversion: Algorithm aversion operates at least in part by users not paying attention to an algorithm's superior performance. Comparing experiment 1 and 2, we find that if differences in past performance are more pronounced, this tendency is reduced. Still, to be perceived as outperforming, an algorithm has to outperform a human forecaster to a higher degree than one human forecaster has to outperform another human forecaster. This selective attention to performance is located earlier in the decision processes on usage of algorithms than trust, which strongly features in existing research (Glikson and Woolley, 2020), but which we found to be largely irrelevant.

Third, there is strong evidence that the perception of forecasting performance matters conditional on the nature of the forecasting source: Participants follow their belief about the performance in the case of a human and rely more on the source they perceive to be better, but act against their belief in the case of an algorithm by ignoring an objectively superior performance which they also perceive as superior. This mechanism is ignored in extant research that typically does not measure and use perceptions of performance.

We suggested that there are obstacles external to the user. A first obstacle, often discussed in the literature, is the black box nature of the algorithm (Schmidt et al., 2020). A second obstacle we suggested could be presumed algorithm aversion of others (Arkes and Blumer, 1985; Longoni et al., 2019; Promberger and Baron, 2006), in our case of superior managers. As it is, neither of these two obstacles turned out to be relevant: Opening up the black box by providing an explanation does not increase reliance on a source nor do algorithms profit more from an explanation than an equally intransparent human forecasters. And, while users presume their superiors to be more skeptical of algorithms, this does not affect their usage of algorithmic output.

In terms of practical implications of these findings, the organizational setting installed for integrating algorithms in decision-making should take into account that users may not pay attention to the algorithm's actual performance, in particular, when performance differences are small. To some degree, aversion operates by selective attention. Simply presuming, as most experimental research does, that users do pay attention to objective differences in performance is insufficient, as they do not. Given the central role of perceived performance, a first task for a firm interested in increasing usage of algorithms is to make users aware of algorithms' actual performance. For instance, by urging them to consider the performance of different sources in detail. Future research should address other potential obstacles, which obstruct users from following their belief about what is the better forecaster. Here, algorithms are at a disadvantage.

Concluding with regard to the robustness of algorithm aversion, we find that when the ownership effect arising from personally producing a forecast is absent, algorithm aversion is much less pronounced than in existing research where ownership effects were present. While mechanisms relying on some form of trust – general trust in algorithms, trust in the processes by which an algorithm works – are central to existing research, we find basically no support for either of them. True, the origin of a forecast is of some relevance for isolated aspects of trust, but this trust is of no relevance for usage. Providing an explanation does increase neither usage of algorithmic nor of human output, we take this as a hint to other mechanisms, like the inability of algorithms to bear responsibility for their output. Central to our findings is the relevance of the perception of performance, which is affected by the origin and of conditional relevance for usage.

E Study 4: Trust in Artificial Intelligence – the Role of Occupation and Explanations

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Abstract

The utilization of artificial intelligence (AI) varies considerably across domains. This is due to the differing technical conditions for AI application within each domain, as well as the characteristics of the individuals working within them. Among these features are personal experience with AI, situational background and occupational logics. The argument put forth is that different occupational logics, which are linked to but not identical with being trained for and active in particular occupations, account for the usage of AI-based tools in different economic and societal domains. The domains differ significantly in the necessity for justification and explanation of decisions made, the reliance on and reliability of information, and their logic of efficiency. For instance, considerations of performance and efficiency are irrelevant for lawyers, as all that matters are arguments supporting a certain position. The validity of available information is questionable. In contrast, for managers leading a firm, the information may be uncertain but not deliberately falsified, and the performance of a tool is sufficient for its acceptance. The present study operationalizes occupational logics and investigates their effect on trust and the usage of AI-based advice. Our findings indicate that occupational groups do not influence trust behavior.

1 Introduction

The utilization of artificial intelligence (AI) offers considerable advantages in a multitude of domains, particularly in the context of routine activities which constitute a significant proportion of the workload in numerous occupations. The application of AI in practice varies considerably across different domains. These differences can be attributed, in part, to technological aspects, such as the availability of data for training the AI, the appropriateness of existing algorithms for the task, and so forth. However, the differences in acceptance and usage are also due to occupational logics, which can be defined as a set of criteria for evaluating a decision or an advice as appropriate and useful. Those engaged in different occupations are socialized to evaluate decisions by certain criteria, which are shaped by their professional training and job role. For instance, for a lawyer, the economic implications of a certain judgment are irrelevant; rather, arguments and information are evaluated in terms of true or false. The efficacy of a tool in performing its designated task is of little or no consequence. A lawyer's need for justification for even trivial actions is paramount. For a manager, the rationale behind a particular action is of secondary importance, with the primary focus being on the effectiveness of the action itself. A rationale for a decision regarding a tool that is performing well is not entirely irrelevant, but secondary, particularly if the decision leads to success. Provided the decision is ultimately proven to be correct, the necessity for a justification is minimal, particularly at the upper echelons of the firm’s management. Moreover, the availability of information for decision-making varies across occupational groups. For a lawyer, information presented, even by the client, may be untrue and intentionally so. Consequently, the informational basis on which decisions are to be made is inherently insecure. For a physician, the information provided by the patient or by other physicians involved in diagnostics may be incorrect, lacking, or incomplete. However, the possibility of an intentionally false diagnostic statement is not a concern. In summary, the exploratory pre-study identified three key dimensions that define occupational logics: the need for justification, the reliability of available information, and the logic of efficiency and effectiveness. These three dimensions form typical combinations which correspond to nominal occupations, such as lawyer, physician, and manager. However, they are not fully determined by these categories. These occupational logics may influence the level of trust and usage of AI-based tools, as well as the necessity and demand for explanations and justifications of AI-based advice or decisions.

2 The Use of Artificial Intelligence in Different Occupational Groups

The advancement of digitization is consistently unveiling novel digital possibilities, which are fostering innovations in both private applications and various professional fields. One area of application or technology that is being discussed in particular in the context of digitalization is the topic of artificial intelligence. As a consequence of the intensified focus on artificial intelligence and the accelerated advancement of systems in the direction of artificial intelligence, this topic has also become more accessible to users of digital systems (Benbya et al., 2020; Mohammad et al., 2020). The proximity to the user has also prompted questions regarding the acceptance of new systems, particularly in relation to the acceptance of artificial intelligence (Hasija and Esper, 2022; Siau and Wang, 2018; Sutrop, 2019). In particular, an aversion to new technologies and algorithms, which may be termed an 'algorithm aversion' has been identified in numerous professional contexts. The reasons for this aversion and the resulting initial trust handicap are numerous and complex. These reasons include a lack of experience and limited decision-making leeway, which can influence the lack of acceptance behavior (Berger et al., 2021; Dietvorst et al., 2018, 2015; Filiz et al., 2021; Hussein, 2021; Jussupow et al., 2020). While algorithm aversion is frequently observed in the professional application framework, particularly among users with higher levels of education, a different picture emerges with lay users. In particular, those with limited experience in the field of digitization often exhibit a positive attitude towards algorithms. Algorithm appreciation in this context can be defined as a leap of faith. This implies that users have a high level of trust in new technologies, such as artificial intelligence, from the outset and have a positive or neutral attitude towards new digitization solutions (Logg et al., 2019; Logg et al., 2018a; Walter et al., 2022).

An algorithm aversion can be demonstrated in a multitude of fields of application. Additionally, there are discrepancies in the degree to which an algorithm aversion is manifested and how the respective environment affects the algorithm aversion. It remains uncertain whether cultural differences influence this aversion, given that no country-specific differences could be identified in highly developed countries, but only in comparison to less developed countries or emerging economies (Gao et al., 2020; Lennartz et al., 2021; Mahmud et al., 2022; Yamakawa et al., 2008). Nevertheless, there were discrepancies that could be attributed, to some extent, to the differences between the professional groups (Benbya et al., 2021; Glikson and Woolley, 2020; Hartner-Tiefenthaler et al., 2022; Pitardi and Marriott, 2021). The observed differences in trust behavior towards artificial intelligence can be attributed to a number of factors, including the degree of sensitivity of the information in question and the context in which a decision must be made. In particular, skepticism, which manifested itself in lower trust, was particularly evident in situations or professional environments in which an artificial intelligence or digital solution was required to make a decision regarding a sensitive topic. Furthermore, the fact that such sensitive decisions usually require a certain personal closeness between the decision-maker and the affected person also played a role. It is evident that such personal closeness, and certainly a certain degree of introductory ability, empathy and interpersonal skills that go hand in hand with it, could not be represented by an artificial intelligence (see also Langer et al., 2022; Pieters, 2011). Consequently, a trust handicap became particularly apparent in these sensitive situations. This is consistent with research findings indicating that while automation of tasks is desired and welcome, personal contact, subjective decisions and deliberations based on experience cannot yet be taken over by a machine.

Although initial research approaches already allow conclusions to be drawn about trust differences between occupational groups, the research strand is not yet mature and offers room for possible new findings and study approaches. In general, research on algorithm aversion indicates that experience can influence trust behavior (e. g. Bartneck et al., 2007; Glikson and Woolley, 2020). The experience of artificial intelligence (AI) varies considerably between professional groups. This is also related to the fact that the application fields of AI vary significantly between occupational groups. Furthermore, when looking at different occupational fields, it can be seen that the applications of AI also vary in maturity, thus influencing possible experiences with AI. It is evident that differences in the experience and application of artificial intelligence can be observed across various fields. These include business administration, medicine, law, aviation, pharmacology or chemistry (e. g. Baum et al., 2021; Contini, 2020; Kashyap, 2019). Nevertheless, these examples serve merely to illustrate the diverse potential applications of artificial intelligence, which can also demonstrate the ways in which differences can affect trust.

In the field of business administration, numerous applications of artificial intelligence pertain to process optimization. This encompasses both products and services, whereby the processing and creation of which can be expedited, enhanced in terms of accuracy, and facilitated with greater ease through the implementation of more efficacious processes. Nevertheless, in the context of processes, artificial intelligence also provides a more comprehensive perspective on digitization, concurrently fostering the advancement of digital business models and the emergence of novel digital business domains (Clark et al., 2020; Williams et al., 2020). In principle, artificial intelligence can improve automations (Agrawal et al., 2019). Furthermore, the incorporation of additional data into company decisions is facilitated by the ability to draw upon external data sources, including market and competitor information. In this regard, even satellite imagery can be evaluated by artificial intelligence, enabling the identification of geopolitical and business trends (Castro and New, 2016; Chalmers et al., 2021; Duan et al., 2019; Goldblatt et al., 2020; Shaw et al., 2021). In management accounting, the possibilities created by artificial intelligence are manifold. For example, artificial intelligence can be used to convert unstructured data, such as image files, into structured data and thus make it usable in a targeted manner. This is possible, for example, with the help of natural language processing (Langmann and Turi, 2020; Weißenberger, 2021b). Furthermore, external market data previously mentioned can be integrated with internal financial data and employed in a consolidated format for decision-making purposes. This additional external data can then, for instance, facilitate the generation of other forecasts, such as sales forecasts or cash flow forecasts, as a greater quantity of data can be included, and in some cases, more accurate decisions and forecasts can be formulated (Deipenbrock et al., 2019; Mahlendorf, 2020; Weißenberger, 2021b). Furthermore, the utilization of artificial intelligence facilitates the resolution of individual report queries and the implementation of self-service reporting. The application of AI enables the verification of data provenance, namely whether it originates from a data lake or a data warehouse, and the identification of data that is particularly pertinent to the report query. The creation of reports is enhanced through the integration of AI, enabling a more targeted approach (Weißenberger, 2021b). Also, the learning effects ensure that more precise results are displayed in the subsequent report query. This is achieved by the recognition of trends in the queries and potentially relevant comparison values by an artificial intelligence. Additionally, the improved measurement of performance enabled by artificial intelligence allows for the inclusion of more differentiated but also more performance indicators, thus enabling a more comprehensive and at the same time more precise measurement (Weißenberger, 2021b).

Artificial intelligence is also being employed in other professions, such as medicine, in various ways. In the prevention, screening, diagnostics and therapy of patients, AI applications are being introduced into the field and are demonstrating the initial innovations in the management of patients and their data. In particular, in the collection and further processing of patient data, it is possible to prepare it in a more targeted manner and, for example, to use it more comprehensively for studies and the development of new treatment methods. Furthermore, data analysis can be employed to identify potential treatment risks associated with pre-existing conditions or characteristics. In this context, artificial intelligence is utilized in imaging procedures to identify disease characteristics or as robots during operations (e. g. Hamet and Tremblay, 2017; Holzinger et al., 2019; Malik et al., 2019; Ramesh et al., 2004). The additional benefit of the new AI-based procedures appears to be a source of legitimacy for the new applications. Furthermore, it seems that the use of artificial intelligence is unethical unless it can be demonstrated to save lives. Artificial intelligence is also used in other professional fields, such as teaching, pharmacology or chemistry. The range of applications extends from digital learning programs to artificial intelligence that can suggest chemical structures in order to produce specific active ingredients and medications (Brown et al., 2020; Krishnaveni et al., 2019; Popenici and Kerr, 2017). The occupational field of pilots in aviation is also particularly interesting. It is commonly known that, in particular, aviation is characterized by a high degree of digitalization and automation. In comparison to previous occupational fields, artificial intelligence applications appear to be particularly developed in this field. In addition to the aforementioned applications, artificial intelligence is also employed in ancillary areas, such as in the context of booking systems, digital check-ins, and fleet management. The latter is particularly noteworthy, as it is used to determine rest periods and identify potential defects. Furthermore, artificial intelligence is already being extensively utilized in in-flight applications. One illustrative example is the Runway Overrun Protection System (for further details see Schirmer et al., 2018). The Runway Overrun Protection System (ROPS) was originally developed as a system to instruct pilots on the intensity of braking during landing, with the aim of preventing them from overshooting the runway. However, the system has since been enhanced by the integration of artificial intelligence (AI), enabling it to capture aircraft data and environmental data in real time and analyze it for in-flight predictions and decision support. This decision support allows pilots to select alternative flight routes in consultation with other professionals, thus avoiding potential severe weather conditions. The diverse range of professional applications of artificial intelligence (AI) illustrates the extensive potential for AI to be utilized in various fields and by a diverse range of users. Each professional field and individual professional may have their own experiences with AI and may be engaged with AI approaches at different levels of maturity. Consequently, it is uncertain whether the manner in which professionals interact with AI differs between different professional groups.

3 Hypotheses

3.1 Hypotheses

The utilization and (user) perception of artificial intelligence and the algorithms that underpin it varies considerably across different fields of work, divisions in companies as well as within the context of everyday working life (for user-perception-gap see Weißenberger et al., 2012a). The diverse applications of artificial intelligence also give rise to disparate user preferences, given that the various functional areas in which AI is employed have distinct objectives. The requisite specifications for artificial intelligence may vary accordingly (Glikson and Woolley, 2020). This can be related to both the functionalities and other features that are considered necessary and trustworthy by the user. The different requirements can also be explained by a different degree of justification. For example, the different applications in different professional groups can also lead to different responsibilities that users must face if they want to use the output of artificial intelligence without restriction and use it for decision-making purposes (see also Weitz and André). The implications for human life in medical applications are such that responsibility is very high, and therefore there is a strong need for justification, particularly in the case of errors (see also London, 2019; Longoni et al., 2019; Shaffer et al., 2013; Thakur et al., 2020). In other fields of application, such as those driven by economic considerations, it can be observed that performance and efficiency are particularly important factors in the context of artificial intelligence (Alexander et al., 2018; Emeka-Nwokeji, 2012; Mishra et al., 2022; You et al., 2022). This indicates that performance and efficiency, as opposed to accuracy, reliability and the potential for greater pressure to justify themselves among different professional groups, could also imply a different acceptance behavior and different expectations of artificial intelligence. The first hypothesis is therefore as follows:

H1: Occupation affects acceptance behavior towards artificial intelligence.

In addition to the profession and the specific professional requirements for artificial intelligence, the explanations provided can also influence the behavior of those who accept or reject the technology. Artificial intelligence is an area of advancing digitalization that is associated with a high degree of complexity and the associated uncertainty (Shin, 2021). It is evident that not all outputs, not all underlying algorithms and calculation models can be comprehended by the user. Furthermore, the scope of the application of artificial intelligence does not yet appear to be tangible for many people. It is precisely the high level of uncertainty and complexity that can increase the demand for explainable AI (Khosravi et al., 2022; Meske et al., 2022; Zhang et al., 2022). Here, explanations in particular could help to make the technology, often referred to in research as black box AI, tangible (Adadi and Berrada, 2018; Bayer et al., 2021; Rai, 2020). Explanations of how an AI works could help here, but also explanations of a specific output with which the user must continue to work. The second hypothesis states accordingly:

H2: Explanations increase usage of an output, for which the explanation is provided.

Nevertheless, the influence of explanations may also vary between professional groups, as different responsibilities and different justification pressures may determine the use of and desire for explanations. For example, in professions where performance and high efficiency benefits from artificial intelligence are important, it may be more important for AI to quickly achieve direct benefits that can be measured in monetary terms. In contrast, other professions, such as aviation, may place greater value on AI applications being rigorously tested and may require prior experience and measurements before utilizing such systems (see also Kashyap, 2019; Shmelova et al., 2019). Those engaged in frequent litigation may find it beneficial to utilize comprehensive legal documents and their summaries or judgments as a means of reinforcing their arguments (Ashley et al., 2001; Contini, 2020). Accordingly, the importance of explanations and thus the use and influence of explanations on the acceptance and use behavior of artificial intelligence may vary, so the third hypothesis is as follows:

H3: The effects of explanations differ systematically among occupational groups.

These hypotheses are critically examined in this research work and are intended to contribute to a better understanding of the acceptance behavior of different users from different professional groups and also to illustrate the role of explanations as a solution to black box AI in this context.

4 Pre-Study: Occupational Logics and AI

In order to validate our design and the setting of the study, as well as to explore and capture the different occupational logics prevalent among different occupational groups, we conducted a pre-study combining experimental settings with semi-structured interviews. In these interviews, we inquired into how occupations differ in their views of AI and their motives to use or not to use an AI-based tool.

Four occupations were selected for the study, each exhibiting a distinct combination of characteristics. These included differences in the perceived necessity for justification versus performance, as well as the extent to which AI is already integrated into their respective domains and the associated experience with AI in their occupational roles. The selected occupations included auditors, medical professionals, pilots and managers.

4.1 Setting of the Pre-Study

The experimental situation presented was designed to be equally unfamiliar for all four occupational groups, but still set to be in a professional context, i.e., they had to make a decision on behalf of their employer, not for themselves. Participants in the pre-study were put in the situation of working in an agricultural firm, which is growing different sorts of grain. Specifically, they were asked to produce a forecast of a crop yield from a newly acquired field, based on two forecasts provided to them. The first forecast was produced by a human being from the production controlling, the second forecast either by an AI or another human forecaster. The forecasts diverged and the participants had to make up their mind as to what value to forecast to the firm's management. After an initial forecasting decision, they were also given an explanation on how the second forecast (i.e., by another human or the AI) came about, and asked if and in which way they would like to change their forecast. The forecast addressed the general method in which the second forecaster / the AI produces forecast and how the specific forecast for the current year came about. Apart from the denomination of the forecaster, the forecasts were identical in both cases. After the task, we asked them for their view on the task, their trust in the AI, whether they noticed the differences in the past performance of the forecasts, whether this mattered for them, aspects of their decision-making, but also, what notions of the AI and its functioning they had and what kind of information on the AI they would like to have.

4.2 Findings of the Pre-Study

The findings shed light on the very different occupational logics occurring in exemplary domains of economics.

Auditors face a range of tasks, some of which are highly repetitive, like checking transactions, and are expecting and supporting the delegation of such tasks to automated tools. In terms of explanations, the fact that a tool works with sufficient success is sufficient for delegating such tasks. Things differ in areas, where the actual audition is concerned, and the auditor has to bear the responsibility for the decision.

Lawyers mentioned that the application of an AI in their actual core domain is still a long way off – the core of their occupation, constructing arguments, and refuting arguments of the counter- party, cannot be automated. To some degree, in the German equivalent of class action lawsuits, automated tools are / can be employed to compile letters and drafts of contracts, which are structurally similar but differ in details, which basically are to be 'filled in', like the name, the duration of an employment contract and so on. Differences between the two forecaster's performance were noticed but were of little relevance. A point mentioned explicitly was that information presented is always uncertain. Statements about facts, of the counterparty but also of the own client, may not be true.

Pilots mentioned that they rely on automated systems, auto-pilots, since decades, but still, it is important that they remain in charge and have the ability to override the system any time. Having the ultimate decision – and being responsible for it – is a central element of their professional ethos. While many things in their work are routinized, frequently, situations occur, which are unprecedented, at least for the pilot in question, and for which the autopilot has no answer. Data provided by systems, e.g., on altitude, may differ among systems, and it is not always possible to ascertain the actual situation. The stakes are immense, as failures easily end up being a question of life and death.

Overall, the preliminary study validates the various areas of application and use of new digital systems, algorithms and possibly artificial intelligence already described in the existing research literature. It is still an open question in research what influence the professional framework conditions have on the acceptance behavior and which different effects can be present here, for example, via explanations. Accordingly, the first study will focus on possible differences in acceptance behavior between occupations and examine the impact of explanations in this context.

5 Research Design

The research design of this study shall allow to identify the effects of occupational backgrounds and logics, notably the need for explanations, the relevance of considerations of performance, and the reliability of information on the trust in and factual usage of an AI-produced advice. On the side of the AI, we investigate two features, viz., its objective performance and the degree to which its general operating and specific decision-making are made transparent. While features of the AI can be experimentally manipulated, the users' occupational background is beyond manipulation and needs to be surveyed. This requires the occupational groups recruited for the study to differ in terms of e.g., their need for transparency.

5.1 Occupational Logics and Occupational Groups

Capturing occupational logics faces a dilemma: On the one hand, one can assume that the educational background required to enter a certain profession, in particular in highly regulated occupations such as medicine, airline pilots, or lawyers, require a specific education, typically obtained at a university and specific occupational training, instills a certain, relatively homogeneous professional culture in the members of a profession. On the other hand, occupational groups are not fully homogeneous, neither in the current job, which may or may not be in their original profession, nor regarding their attitudes to and experiences with AI, a feature arising during everyday activities in the course of a professional career. Thus, it is questionable whether occupational groups are homogeneous in terms of their educational background and professional standards if identified by nominal education or occupation. Thus, despite the occupational differences found in the pre-study, proxying professional logics by nominal occupation may not be an appropriate solution. Given that we are interested in how participants' need for an explanation and justification, but also their reliance on information provided in their job, affects the usage of an AI-based tool, we directly capture these features in addition to the nominal education and occupation of the participant. Given the qualitative interviews with members of different occupations we focus on capturing the following aspects of occupational logics and situations.

5.1.1. Need for Justification and Explanation

Occupations, this was a result from the qualitative pre-study, differ in the degree to which members of the occupation are required to justify their actions and decisions. Being asked to provide a justification and to elaborate arguments can be a typical and in particular unconditional requirement of a job, as in the case of lawyers. In other occupations, justifications are required only rarely and conditional. In the case of managers, justification conditional on the outcomes, and necessary only in the case of a failure. To capture the factual degree to which participants were required to be able to explain decisions in their occupation, we asked the following two questions:

How important is it in your job that you are able to give a justification for what you did?, with answers given on a 7-Point Scale, ranging from “Not at all important” to “Very important”,

and

How often are you asked by your superior to justify what you did?, with answers given on a 7-Point Scale, ranging from “Very rarely” to “Very often”.

5.1.2. Reliability of Information

Professionals act and decide based on information. This information is reliable to different degrees and is also evaluated very differently among different occupations. The sources of error, but also the chances for (un)intentional misinformation differ substantially among occupations. In some occupations, information is questionable for technical or other reasons and thus needs to be evaluated critically before using it as a basis for decisions. Examples are lawyers, who stated in the interviews that even information given by the own clients is questionable, let alone the information given by the adversary. In other professions, the validity information is unproblematic at least insofar, as all parties involved share an interest in correct information. As AI is also based on processing information, which is assumed to be true, the participant’s view on the reliability of information may also affects whether s/he believes an application of an AI to the information, which may be of questionable reliability, makes sense at all. We operationalized this dimension using the following question:

Now consider the information you use for your daily work and decision-making in your job. If you think about information you receive from other parts of your firm – what best describes your situation? Answers on a 7-Point Scale, ranging from 1, “I never have to ascertain whether an information is correct or not” to 7, “I regularly have to ascertain whether an information is correct or not”.

5.1.3. Logic of Efficiency

Occupations differ in perceptions and the role of efficiency. In health, efficiency considerations are not part of the professional standards, which often explicitly prohibit tradeoffs between health and the costs incurred for a health measure. Apart from extreme situations, physicians are not allowed to refuse a treatment with the argument that the life-years gained are too expensive and that resources would be better invested elsewhere. Managers in firms care strongly about such tradeoffs. In a legal dispute, the argument that a solution is more expensive, or resource intensive is no valid argument to favor another solution. Thus, the degree to which efficiency considerations are part of the daily routine in a job differs. The participant’s position regarding considerations of efficiency was measured by agreement to the following statement:

Consider the following statement – what is your position?

If something works fine, there is no need to know why it works, with agreement measure on a 7-Point Scale, ranging from 1, “Do not at all agree” to 7, “Do fully agree”.

5.1.4. Experience with AI in professional and private settings

Furthermore, we capture experience with AI-based tools and advice in terms of the frequency of usage and the participant’s perception of whether such tools are useful or not. Specifically, we describe typical applications of AI-based in private and professional life, like automated advice, recommendations in online shopping, and as for usage and evaluation of the usage. The four variables were the following:

Think about your job…

Do you have experience with automated advice and artificial intelligence in your job? Answers recorded on a 7-Point Scale ranging from “No, no experience” to “Yes, on a daily basis”.

If you use automated advice and artificial intelligence in your job, how useful is it for your job? Answers recorded on a 7-Point Scale ranging from “Not at all useful” to “Very useful”

Think about your private life ….

Do you have experience with automated advice and artificial intelligence in your private life?

Answers recorded on a 7-Point Scale ranging from “No, no experience” to “Yes, very much experience”.

If you use automated advice and artificial intelligence in your private life, how useful is it for you?

Answers recorded on a 7-Point Scale ranging from “Not at all useful” to “Very useful”.

Questions on the propensity to accept or to avoid risks and regarding the formal occupational education and factual occupation concluded the post experimental questionnaire.

5.2 Experimental Task

Given the multitude of occupations, we decided to choose an experimental task, which is on the one hand rather simple, on the other hand unfamiliar to participants from many occupations. We chose forecasting as a task and an agricultural setting as the application. We also emphasized the professional setting, that participants had to put themselves in the role of a management accountant in charge of producing a forecast for the firm's management. Specifically, the participants were asked to produce a forecast of the expectable harvests from a newly acquired wheat-field in tons per hectare, which is reported to the management, which needs the forecast to coordinate sales and contracts with clients. Participants were informed that the forecast should be as close as possible to the actual value, as both, overestimating and underestimating the quantity are equally problematic for the management. Participants were incentivized by the job description which emphasized the need for an exact forecast and additionally by an incentive scheme which linked a bonus to the difference between their forecast and the actual value, which was randomly computed.

5.3 Experimental Situation

The experiment was conducted as a factorial survey: Participants were introduced into a situation, presented with stimuli, their forecasts were recorded, and they completed a post experimental questionnaire covering the occupational logic and their experience with AI as describe in the preceding section.

In this professional situation, participants were told that they work in an agricultural firm and are tasked with reporting a yield forecast for a newly acquired wheat field to the management. The participant was offered a choice between two sources of forecasts. The first source was always a human being (a production manager). The second source was either another human forecaster or an AI. Both forecasts were chosen to be realistic given previous yields, but both diverged. The past performance of the two forecasts was presented together with the actual yields for different fields for several years in the past. The forecasting performance of the two sources was illustrated in form of a table but also in a graphical representation of the divergences between the forecasts and the actual yields. After presenting the information on the past performance, the two forecasts for the new wheat field were presented and participants were asked to come up with a forecast.

Contrary to most other studies on usage of AI output, which just offer an AI-based output and record the acceptance, we are closer to the situation in most occupations, where the AI-based tool is an add-on, but other, more traditional, i.e. human-made, outputs are available and used. The interviews in the run up to the study indicated that currently, and for prolonged adaptation periods, users have a choice. Moreover, most users do not produce forecasts, but receive forecasts as input. For this reason, they are not subject to ownership effects arising from having produced a forecast personally. To capture the effect of an explanation, we chose a within-design, where the participants receive a first stimulus, make a decision, receive an explanation as a second stimulus and can revise their decision.

5.4 Variables and Measurement

Variables of interests are the decisions, initial and revised, made and in particular the changes therein which result from having an explanation which increases the transparency. In a within-design design effects are at work, like anchoring and persistence, which limit the effects of the stimuli, in particular the explanation as second stimuli. The decision-process of initially arriving at a decision differs from having to revise a decision made already. Thus, both, anchoring and persistence induce a tendency to stick with a decision made. The design is thus conservative, being a setting where experimental effects, i.e., an explanation inducing a revised decision, are difficult to achieve.

5.5 Experimental Manipulations

The experimental manipulations concern the source of the second forecast and its objective past performance, which were manipulate between subjects, and the explanation, which was a within subjects' manipulation.

To capture the **effect of the origin** of an output, the alternative forecast is described as being either human-made or produced by an AI-based tool.

To capture the **effects of performance** of the source (forecasting accuracy or performance of the funds), the source was presented as either being equally or better performing in the past. In the case of higher past performance, the alternative forecast featured less deviations and also improved over time. There is no bias in that either source systematically under- or overestimates the crop yield. The performance related information was presented in form of a table and a graph.

To capture the **effect of an explanation**, the alternative forecast was after participants made their forecast, supplemented by an explanation, elaborating how the forecasting is done in general, by giving information about the data sources and the methods going into the forecast. Providing an explanation is also providing additional information on the overall situation and object of the forecast, which may affect the forecast reported by the participant. If the explanation mentions additional facts about the situation, the facts per se, and not the explanation as an elaboration of how the forecast came about, may affect the forecast reported by the participants. Based on these considerations, the explanation was formulated in a way which does not deliver any facts about the content of the forecast, i.e., does not deliver information about the expectable harvest. Participants are given the option to revise their forecast. As the explanation delivers only a procedural, but not substantive elaboration, the forecast reported should be unchanged for participants who do not feel a need for an explanation, as there is no reason to have more confidence in one or the other forecast. For participants who are in need of an explanation, providing an explanation should make the alternative forecast more relevant.

5.6 Data Collection and Sample

320 professionals from the US were recruited via MTurk in 2022, using an online survey tool. To participate, persons had to fulfill certain criteria regarding their experience with MTurk and evaluations of other principals of online studies regarding the person's effort and skill shown in their studies. Participants were informed about their role and incentivized with a potential bonus of 1 USD to produce a forecast as accurate as possible. Participants were debriefed about the aim of the experiment after concluding the experiment and their bonuses were paid, together with the show-up fee. Overall, the first study consisted of the four experimental conditions given in Table E-1 below.

Table E-1 Experimental Conditions

Group	Condition	N
1	Source: AI Performance: better	81
2	Source: AI Performance: equal	78
3	Source: Human Performance: better	80
4	Source: Human Performance: equal	81
	Total	320

In terms of quality assurance of the experiment, a randomization check indicated that there are no non-random patterns in the composition of the experimental groups based on occupations or demographics. In order to control for potential problems with the attention participants paid to the instructions, we included an attention check, in which participants were to tick an answer, regardless of their actual personal preference. All 320 participants chose the correct answer. A manipulation check, regarding the effect of objective performance differences on the perceived performance differences indicated a strong effect of the manipulation: if the alternative produced better forecasts in the past, this was perceived by the participants, see Table E-2 below.

Table E-2 Manipulation Check of Performance

Experimental Group	N	Mean	SD	
Equal Performance	159	4.11	.78	*t*-test for equality of means
Better Performance	161	5.75	1.36	t = -13.2956 (p=0.000)

Note: Dependent variable is the participant's perception which source produced more accurate forecasts in the past. Likert scale, ranging from 1 the default clerk performed better, 4, both performed equal, to 7, the alternative (human or AI), performed better.

6 Analysis

The analysis covers two aspects. First, the effect of formal occupations on occupational logics, in order to validly capture effects of occupation on decision-making, second, the usage of AI produced outputs and the role of formal occupation and occupational logics for this.

6.1 Occupations and Occupational Logics

We investigated the relevance of the formal occupation for occupational attitudes by regressing the attitudes surveyed in the post experimental survey on dummies indicating the various occupational groups (ranging from manager to lawyer). The occupational composition of the sample was as follows: 85 (26.56%) participants categorized themselves as Management, 12 (3.75%) as Lawyers, Judges, Judicial Workers, 15 (4.69%) as Accountant and Auditors, 55 (17.19%) as Computer / Mathematical Occupations, 31 (9.69%) as Life / Physical / Natural Sciences, the remaining 122 (38.13%) classified themselves as "Other". The specification here gave a highly varied group ranging from military service and crowd workers to writers and paramedics. Despite the dominance of the "other" category, the group sizes were sufficient to use dummies for group membership.

However, we did not find any systematic effects of the formal occupation on any of the occupational logics and attitudes, an indication that the links between formal education, formal job description and factual occupation are rather loose. It is no longer the case, even for a rather homogeneous group like lawyers, who received a very homogeneous education, that a formalized occupational training results in homogeneous occupational logics. Accordingly, the first hypothesis can be rejected.

6.2 Occupational Logics and Usage of AI Output

The study resulted in two dependent variables. The first represents the participants' initial forecast, after the past performance of the two sources was presented. The second the revised forecast, after the explanation on how the alternative source of advice operates, was presented.

Before analyzing the decisions, we formulate behavioral expectations in particular for rational behavior. For illustrative purposes, we use the crop yield forecasting scenario. When deciding on what crop yield forecast to report, the participant has to base his forecast on the two inputs, the forecast produced by the human production controller and the alternative, which is produced either also by a human or an AI. The participants can be presumed to mix the two available sources. The more confidence a participant has in a certain source, the more the forecast reported will reflect this source. Thus, for the situation, that both forecasts were equally accurate in the past, we expect that rational participants forecast the average of both forecasts. If a participant has an (irrational) aversion against the usage of the AI-based forecast, the reported forecast should be closer to the forecast originating from the human. However, if the participant has no algorithm aversion, the forecast reported should be an equally weighted mix of both forecasts, exactly as in the case that both forecasts originate from human beings. If the participant even in the condition where two human forecasts are available favors the first, “conventional” forecast, this deviation from the equally weighted mix is due to a conservatism. This conservatism is also at work in the AI scenario, and the mix observed in the AI-based scenario is constituted by the conservatism and by the AI aversion.

If one forecast was clearly better in the past, a rational participant should report this forecast. If the explanation makes a source more trustworthy, its weight should be increased.

Interactions between accuracy, explanation, and origin will express themselves in different magnitudes of effects of accuracy for human- vs. AI-made forecasts.

First we investigate into the effect of the source’s objective performance on usage of the source. Rational usage would imply that participants rely more on the source which performed better in the past. Panel “All Cases” of table C below indicates that there are differences in the usage of the two input forecasts which are in line with this presumption that participants rely more on the better performing source, but also indicate that the usage does not strictly follow the performance logic.

Table E-3 Effect of Performance on Usage

	Obs	Mean	SD	
All Cases				
Performance equal	159	7.08	.29	*t*-test for equality of means t=7.3359
Alternative performed better	161	6.80	.39	(p=0.000)
Alternative was Human				
Performance equal	81	7.09	.31	*t*-test for equality of means t=5.5576
Alternative performed better	80	6.78	.38	(p=0.000)
Alternative was AI				
Performance equal	78	7.07	.27	*t*-test for equality of means t=4.7835
Alternative performed better	81	6.81	.40	(p=0.000)

Note: Initial forecast as reported by the participant before the explanation. Input forecast of the default clerk is 7.5 tons, forecast of the alternative (2^{nd} human or AI) is 6.5 tons.

If the forecasting performance of the two input sources was equal in the past, participants on average report a forecast of 7.08 tons, while if the alternative source produced more accurate forecasts in the past, the average forecast was 6.8 tons, significantly closer to the forecast of the alternative source, which was 6.5 tons. We also investigated whether there is an effect in terms of performance being a more or less relevant criterion for usage depending on the nature of the alternative source, human vs. AI, but find, see the panels "Alternative was Human" and "Alternative was AI", this to be not the case.

If there are occupational differences in the relevance of performance, occupational groups and persons with different occupational attitudes should differ in how much they rely on the source which performed better in the past. In order to test this argument, we regressed the initial forecast on the formal occupation and occupational attitudes, but found no effects consistent with the expectations, neither when all cases were considered, nor when only the conditions in which the alternative was better were considered. Only for managers and persons with a positive attitude towards algorithms, effects were found, which were however opposite to the expectations, in that they relied more on the human default forecast.

In line with existing research, we argued that algorithm aversion is also due to intransparency – algorithms produce an output, but do not give an explanation for this output. If this is really the mechanism underlying algorithm aversion, providing an explanation should increase usage of the output, for which an explanation is provided. We argue specifically that occupations differ in their need for an explanation. Managers, operating under considerations of efficiency, may accept an output because it is performing better – lawyers should not, as efficiency is no criterion.

We inquired into the relevance of an explanation. If indeed providing an explanation makes the forecast which is made more transparent more relevant, the reported forecast should shift towards the second, more transparent, source after the explanation was provided. Table E-4 gives the results.

Table E-4 Effect of Explanation

All Cases	**N**	**Mean**	**SD**	*t*-test for equality of means
Forecast before Explanation	320	6.94	.37	t = 3.70 (p=0.000)
Forecast after Explanation	320	6.89	.33	
AI better				
Forecast before Explanation	81	6.81	.40	t=1.46 (p=0.1479)

Forecast after Explanation	81	6.76	.32	
AI equal				
Forecast before Explanation	78	7.07	.273	t=2.35 (p=0.0212)
Forecast after Explanation	78	7.01	.27	
Human better				
Forecast before Explanation	80	6.78	.38	t=1.87 (p=0.0649)
Forecast after Explanation	80	6.74	.29	
Human equal				
Forecast before Explanation	81	7.09	.31	t=1.96 (p=0.0538)
Forecast after Explanation	81	7.05	.34	

Note: Dependent variable is the forecast as reported by the participant before and after receiving the explanation on how the alternative source produced the forecast. Input forecast of the default clerk is 7.5 tons, forecast of the alternative source (2nd human or AI) for which the explanation is provided, is 6.5 tons.

The *t*-tests indicate that the forecasts are significantly affected by the explanation provided. Receiving an explanation shifts the forecast towards the source for which an explanation is provided. This is, taking into account the smaller number of cases in the four subsamples, true for all four experimental conditions.

Next, we are interested in whether this change is dependent on occupational logics. To capture the effects, we computed the change in the forecast from the initial to the revised forecast. Specifically, "Change" is computed as "Forecast_Initial – Forecast_Revised". Given that the input forecast of the default clerk is 7.5 tons, forecast of the alternative source (2nd human or

AI) for which the explanation is provided, is 6.5 tons, positive values of the change variable indicate that the participant puts more weight on the alternative forecast.

The first finding is that changes in the forecast as a reaction to the explanation occur only rarely: 213 of the 320 participants (67%) do not change their forecast at all. The mean of change-variable is positive (.05; 95%-CI: .02 to .07), thus, providing an explanation has some, albeit marginal, effect (ME) in the sense of making the explained forecast more relevant. Accordingly, the second hypothesis can be strengthened. In terms of occupational effects on the relevance of an explanation, regressing the change in forecast on the formal occupation of the participant and the occupational attitudes does not indicate systematic effects. Accordingly, the third hypothesis can be rejected.

7 Conclusion

The results of this study indicate that the acceptance behavior of artificial intelligence, as it relates to differences between occupational groups and the role of explanations in this context, is not influenced by the respective profession. While there was a slight tendency for explanations to have a slightly positive effect on acceptance behavior, no differences between the professions were measurable. It is uncertain whether the findings on explanations can be generalized or whether the design of explanations in particular results in changes in the observations. For example, it may be the case that the impact of explanations depends on whether they relate solely to an output, to the process of producing a result or to both. In addition, the way in which explanations are communicated could also play a role here. The effects of auditory, visual or written explanations may differ depending on the occupational group. The fact that these effects were not initially detectable allows new conclusions to be drawn about acceptance behavior. It can thus be concluded that it is not the individual professions and associated influences that generate specific changes in acceptance behavior. Rather, the reasons for acceptance or rejection of algorithms and thus also of artificial intelligence may be more general and applicable across different groups. Nevertheless, it is necessary to check whether there are other, more individual concerns that could not be mapped here using the occupational groups and differences between the test subjects. However, this study demonstrated that artificial intelligence is perceived and accepted similarly by disparate professional groups with regard to trust, credibility and utilization, with respect to acceptance or rejection. The perception between the professional groups appears to be analogous despite the respective differences in terms of responsibility, team management, the necessity for justification and other factors, which may also facilitate the influence of behavior across the professional groups and the generation of more favorable acceptance behavior. In order to facilitate acceptance behavior, it is essential that explanations are formulated in a targeted manner and designed to be understandable for the user.

8 Contribution

This study contributes to several research approaches and research directions. On the one hand, the study contributes to a broader understanding of the influence of professional backgrounds on acceptance behavior in the digital context and towards algorithms and artificial intelligence (e. g. Långstedt et al., 2023). For instance, this study indicates that the factors influencing algorithm acceptance extend beyond professional groups, suggesting the potential for more universal influences on acceptance behavior. Furthermore, this study contributes to research on the effectiveness of explanations, particularly in the context of algorithms and artificial intelligence (see also Fine Licht and Fine Licht, 2020; Giboney et al., 2015; Miller, 2019; Pieters, 2011). The study demonstrates that the design of explanations can influence acceptance behavior. Further investigation is required to ascertain the extent of this influence. The study also provides insights into existing technology acceptance models, indicating that factors other than algorithm performance can influence acceptance behavior. This study contributes to interdisciplinary research (see also Dengler and Matthes, 2018; Hartner-Tiefenthaler et al., 2022) and shows that artificial intelligence and algorithms are a subject area that needs to be considered across different disciplines and divisions. The study also indicates that communication between different disciplines is crucial, despite potential differences in the fields of application and the uses of artificial intelligence. This is evidenced by the similar acceptance behavior observed between the professional groups.

9 Limitations and Future Research

Notwithstanding the aforementioned findings on the acceptance behavior of professional groups with regard to artificial intelligence and the effectiveness of explanations in this context, this study is also subject to limitations that can also be examined and improved through future research. Primarily, it should be noted that the study was conducted digitally via Amazon Mechanical Turk with English-speaking test subjects from the USA. This implies that the geographical and cultural background may have influenced the results, necessitating further verification of the findings' transferability to other countries. Additionally, individuals who register for experiments on Amazon Mechanical Turk tend to be younger and more technologically proficient (Molyneux, 2018). Furthermore, this could also have an additional influence on the result and the findings on acceptance behavior, which may need to be validated again in a laboratory experiment. Additionally, the setting or the chosen context of the experiment, the agricultural setting, is an abstract setting, so that results would have to be validated in other contexts for further generalizability. The role of explanations can also only be examined here in a specific individual case and cannot be supplemented and verified by other representations of explanations. Furthermore, the categorization of occupational groups and the differentiation between them is limited, and further research is required to deepen this understanding. For instance, the division of management is broadly defined and should be recorded more precisely in terms of exact specialist areas, positions and the respective educational and career background in order to further subdivide the results in the future. Finally, this study provides a snapshot of acceptance behavior in relation to artificial intelligence. However, the field of artificial intelligence is developing at a particularly rapid pace. Consequently, the acceptance of AI may also change more quickly and may differ between professional groups in the future due to different fields of application. Further long-term studies will be necessary in the future in order to further investigate the influencing factors and their changes in a valid manner.

For future research, research on declarations, among other things, is still necessary in line with the aspects mentioned. For instance, explanations can be subjected to further scrutiny and elaboration based on the depth of the explanations provided, as well as the type of communication employed, the ease of access to the respective explanation, the underlying management requirements for the use of explanations, compliance regulations and other pertinent factors. Furthermore, if the occupational groups are more clearly defined in future studies and more subjects per occupational group are considered, research approaches on specific AI application fields per occupational group can examine whether the acceptance behavior (also over a period of time) is universal or dependent on professional or cultural differences or differences such as the level of education or other factors. The role of training and expectation management may also be of interest for future research approaches. This approach allows for the examination of the influences that precede contact and interaction with AI, which affect behavior and promote or diminish trust. Overall, this can contribute to the introduction of AI and initially control behavior without having to adapt and improve undesirable effects in dealing with algorithms and AI afterwards.

F Study 5: The Effect of Framing on Trust in Artificial Intelligence: An Analysis of Acceptance Behavior

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Abstract

This study examines the effects of framing and explanations on the acceptance of artificial intelligence (AI). The aim of this study is to understand how framing can influence user and acceptance behavior before the actual application of AI and what role explanations play during the actual application process. In this experiment, 374 probands were required to make an investment decision and were given decision support from a fund manager and/or AI. All subjects received explanations during the experiment as a basis for decision-making. The results demonstrate that while explanations have no effect, framing has a significant impact on the acceptance of artificial intelligence, leading to higher acceptance and trust. The influence was so pronounced that even poor results of artificial intelligence were considered valid and trustworthy, and framing could generate an irrational algorithm appreciation. This study illustrates the role of framing as an effective means of influencing acceptance behavior, provided that the design is results-oriented and does not promote a one-sided perception of AI.

1 Introduction

The field of artificial intelligence (AI) is experiencing exponential growth in the context of digitalization. AI is being employed in an increasing number of domains that extend beyond purely economic or creative applications. Concurrently, the expansion of AI applications in these new domains necessitates their acceptance, adoption, and utilization by users. However, this is not yet the case in all areas. Consequently, research into acceptance is of great importance and should be expanded through further investigation. Two potentially significant influencing factors have not yet been sufficiently investigated: the influence of framing and the influence of explanations on user behavior and technology acceptance behavior. However, these two factors may determine behavior at two key points in the technology acceptance process. Framing can be a way of influencing users' expectations before using artificial intelligence. Furthermore, explanations can influence acceptance and user behavior during the further course of use of algorithms and artificial intelligence. Therefore, framing and explanations may provide two levers to influence behavior throughout the entire process.

In the case of other technologies and programs, for example, companies often prepare training courses that are made available to employees before they start using them. The aim is often to explain how they work in a comprehensible way to make it easier to use them afterwards. It is of particular interest to examine whether framing an artificial intelligence in advance, similar to training, not only increases understanding of the solution, but can also influence acceptance behavior by emphasizing the advantages and benefits of artificial intelligence. However, it remains questionable to what extent the framing even overcompensates for possible skepticism and prevents rational or justified critical behavior during the application process and can create a certain overtrust. At this juncture, it is beneficial to provide further clarification. This can be achieved through the provision of rational justifications and explanations regarding the technical aspects of the output and the underlying creation process. Additionally, if necessary, these explanations can serve to compensate for any one-sided framing that may have occurred prior to the application, thus preventing misguided acceptance behavior. Consequently, our research approach to this question in this study is particularly promising and demonstrates the potential role that framing and explanations can play in the context of acceptance behavior regarding artificial intelligence.

2 The Role of Setting, Explanations and Framing of Artificial Intelligence

The topic of artificial intelligence, from its initial applications to a broad range of applications, is a subject of considerable interest and debate in the field of research. This development is driven by the emergence of new points of contact with artificial intelligence in both private and professional contexts. This, in turn, raises new questions regarding the management of artificial intelligence and its potential future evolution. Conversely, users will also become more familiar with these new systems and participate in their further development. Consequently, new training foundations will also be required to further promote this development (Qasim and Kharbat, 2020). In this context, artificial intelligence is typically defined as an algorithm-based system that is capable of identifying patterns within data and generating new bases for decision-making through independent learning and interpretation (Grover et al., 2020; Haenlein and Kaplan, 2019).

In particular, the trend towards increased use of artificial intelligence is becoming increasingly evident in general business management functions in companies, such as in management accounting. In recent years, the number of applications and the search for new AI-based systems has increased significantly (Sutton et al., 2016). Counter-opinions that artificial intelligence continues to be an important component in practice and research, but that there is less focus on it than on other topics and that it is consequently less sought after and considered in research (Gray et al., 2014), could not be confirmed accordingly (Sutton et al., 2016).

Artificial intelligence (AI) is a field of study that has gained significant attention in recent years, particularly in the context of business. The potential applications of AI in the business realm are numerous and include the improvement of operational efficiency (Al Mansoori et al., 2021; Fethi and Pasiouras, 2010; Yawalkar, 2019). The incorporation of AI into a company's operations can lead to enhanced competitiveness and a reduction in errors, which in turn can facilitate long-term positioning and technological responsiveness (Agung and Darma, 2019; Borges et al., 2021; Davenport, 2018b). Nevertheless, the advantages, which are particularly evident to managers within the company, are not always duly acknowledged and endorsed by employees to the same degree (Ambati et al., 2020; Chowdhury et al., 2022; Lichtenthaler, 2019; Zhu et al., 2020). Consequently, the utilization of artificial intelligence simultaneously engenders a confrontation with risks and potential limitations, which employees at times perceive themselves to be exposed to (Cunneen et al., 2019). This confrontation is particularly visible in the professional context, as employees perceive significant risks associated with the use of artificial intelligence. These risks relate to critical issues such as the continuation of the profession and, consequently, the secure source of income (Li and Zheng, 2019). With regard to future prospects, employees express concern when using artificial intelligence (AI). On the one hand, employees perceive a need for new competencies in dealing with AI that they have not been able to cover in the past and may only be able to cover in the future with difficulty and intensive training. Furthermore, there is a concern that the specific duties and responsibilities associated with the role may undergo a significant transformation. The potential for job losses and reductions in personnel and headcount, as well as the uncertainty surrounding the future of the role itself, are additional sources of concern (Stancheva-Todorova, 2018). Such factors can serve to reinforce an aversion to algorithms, particularly in professional contexts where there is an interaction with an artificial intelligence. This can result in a lack of open and productive dealings with new systems (Mohammad et al., 2020).

The advent of artificial intelligence (AI) systems is having a profound impact on a multitude of sectors, both economically and socially (Duan et al., 2019; Dwivedi et al., 2021; Grover et al., 2020; Wamba et al., 2017). Nevertheless, there are significant differences in the fields of application of AI in professional and private contexts. In general, AI has become increasingly prevalent in private contexts and private application fields in recent years. Users install, use, and enjoy the results of new AI-based applications without much skepticism (Das et al., 2015). A frequent topic of discussion in private settings is the lack of privacy and data protection. However, these concerns do not prevent users from utilizing AI-based systems in private contexts (Cheng et al., 2020; Riddell and Fenner, 2021; Vimalkumar et al., 2021; Yang, 2021).

Applications that are used with minimal skepticism and without a significant trust handicap, such as those developed by Google, can be considered an example of this phenomenon. These applications include Google search, as well as subject-based applications such as Google Maps, Siri, and smart home devices. They are controlled via an artificial intelligence (Guo et al., 2019; Sepasgozar et al., 2020; Yang et al., 2021; Zaidan and Zaidan, 2020). The use of facial recognition, which is employed by a significant proportion of smartphone users on a regular basis, is also underpinned by the application of programmed artificial intelligence (Almeida et al., 2022). However, the fact that these fields of application deal precisely with a technology, around which a great deal of debate in the media revolves regarding many issues such as data security, is something that many users cannot initially comprehend at this level. Consequently, the aforementioned application fields demonstrate that, particularly in the private context, a trust deficit in artificial intelligence appears to be much less pronounced, and that there is a fundamentally favorable, positive and only in small subareas skeptical customer response with regard to artificial intelligence in various areas (Fan et al., 2022; Nozawa et al., 2022; Sohn et al., 2020; Zarouali et al., 2018).

In the private application field, in addition to the natural use of AI in everyday and recurring situations, it can be observed that users are less concerned with the topic of artificial intelligence as the underlying technology. One significant factor that can contribute to a lack of engagement with the technology and, concurrently, with associated risks is the dearth of references to underlying technologies, particularly in everyday applications. Although large companies are working on more references to new applications or data collection in the context of the claim of increasing transparency, these usually do not refer to the functioning of artificial intelligence. In the event that a specific technology or aspect of data protection becomes pertinent in the context of a technological application, it is most likely to be found in the lengthy terms of use. The complexity of such briefs is such that the majority of users typically do not or hardly take note of them due to information overload (Banerjee et al., 2018; Ness, 2012). Consequently, the application notes in question are not recognized in the private context and thus not applicable to the private handling of artificial intelligence. Fundamentally, the research area on excessive trust in algorithms, Algorithm Appreciation, also addresses this phenomenon in a broader context (e. g. Araujo et al., 2020; Hou and Jung, 2021; Kaufmann, 2021; You et al., 2022). For example, Logg et al. (2019) show that amateurs in particular are increasingly relying on algorithms and, by extension, on algorithm-based artificial intelligence. Given the paucity of knowledge and engagement with the topic of algorithms and artificial intelligence, particularly in the context of private applications, research on algorithm appreciation provides insight into the divergence in trust between the private and professional application contexts.

Furthermore, the aspect of framing plays a significant role in this context. In addition to usage notices, users are not informed by separate notices, such as banners, that they are interacting with an artificial intelligence in private contexts and in private domains. Instead, they are typically required to agree to the terms of use of the data (Liao and Sundar, 2021). In the context of scientific approaches, there is no framing of the application situation with an artificial intelligence. This is not because it has been explicitly dispensed with, but rather because companies often assume that users are familiar with artificial intelligence and that there are no longer any barriers to dealing with it. This is because the use of artificial intelligence, for example in the context of social media, is easily accessible and directly adaptable (Heinonen, 2011). Conversely, it can be observed that users are unaware of the presence of artificial intelligence, and thus a framing situation, even if there are minor indications of the use of artificial intelligence, does not arise due to ignorance (Lieberman, 2009).

With regard to framing, however, it becomes evident that there are clear differences in the private and professional application contexts. In the private application field, the handling of an AI does not necessarily involve concrete references to the corresponding use. In contrast, in companies, the handling of an AI is significantly more differentiated and intensive, with a greater number of references and approaches being made (Asatiani et al., 2020; Leake, 2014; Miller, 2019; Rai, 2020). In the field of professional applications, it is generally assumed that users exhibit a fundamental skepticism towards artificial intelligence (AI), which can only be reduced through further experiences with AI (Filiz et al., 2021). It is therefore assumed here that the objective is not merely to build trust and create an acceptance environment, but rather to reduce a trust handicap that has already been eliminated and thus eliminate acceptance (Glikson and Woolley, 2020; Rossi, 2018; Siau and Wang, 2018). Accordingly, it is also evident in the professional application field that existing technology acceptance models, such as the Technology Acceptance Model with its extensions (e. g. Chau, 1996; Davis, 1989; Davis et al., 1989; Surendran, 2012; Venkatesh and Davis, 2000) play a minor role, as users are assumed by the companies to have already moved into rejection behavior and previous influencing factors have already had an effect and yet have not ensured acceptance of new technologies, but have triggered a profound rejection of new artificial intelligence-based systems (Jussupow et al., 2020). Accordingly, the research of this paper also starts at the stage of possible rejection behavior and accordingly extends research approaches at a subsequent stage of possible acceptance restoration.

As previously stated, companies are also significantly engaged in the process of rebuilding trust or reducing the potential for fundamental algorithmic aversion among employees across various departments. The initiatives that are developed for employees are particularly diverse, and in comparison with private applications, they demonstrate the additional focus that companies must place on reducing an algorithmic aversion (e. g. Dietvorst et al., 2015; Jung and Seiter, 2021; Reich et al., 2022). The potential applications of algorithm aversion reduction among employees are numerous and diverse. They are based on a range of research findings that identify the underlying causes of algorithm aversion. On the one hand, companies attempt to introduce employees to new technological systems gradually, rather than immediately exposing them to a new system without assistance. Gradual introduction of employees to new systems without excessive external pressure can assist them in becoming familiar with innovations and reducing possible aversion (Ingalagi et al., 2021). Furthermore, as previously stated, the fear of potential job loss is a significant factor among employees (Jarrahi, 2018; Webster and Ivanov, 2020). This is accompanied by a changing role model, for example also in managerial accounting, which is subject to constant change due to new competencies in the context of technological trends (Greenman, 2017; Moudud-Ul-Huq, 2014; Stancheva-Todorova, 2018). In this context, managers and leaders in the company in particular demonstrate that these concerns can be addressed. Job guarantees can assist employees in reducing these concerns. Concurrently, companies provide employees with training to learn new skills, thereby enabling the acquisition of new competencies that become important, for instance, in dealing with artificial intelligence. These competencies can then be applied on the job in a target-oriented manner (Maity, 2019; Vrontis et al., 2022). The acquisition of self-assurance by employees as a result of enhanced competencies can diminish a corresponding aversion to algorithms in the professional environment. In addition to reducing career and job retention uncertainties, the reduction of AI as a black box in the organization plays an important role. For instance, some research approaches indicate that AI is an opaque and incomprehensible phenomenon for many users, particularly in a professional context (Eschenbach, 2021; Wischmeyer, 2020; Zednik, 2021). The lack of comprehensibility and follow-through of AI-based decisions can also result in an aversion to algorithms within the profession. Consequently, companies often attempt to dismantle the phenomenon of AI as a black box through comprehensive explanations, with the aim of creating greater transparency and understanding of AI (Asatiani et al., 2020). In this context, transparency is generated in the company on two levels in particular. Firstly, transparency can be created through general explanations of how an artificial intelligence (AI) works. Secondly, explanations about a concrete output of an AI can increase the comprehensibility of a certain result or the underlying decision-making of an AI, thereby reducing a result-related algorithm aversion (Felzmann et al., 2020; Felzmann et al., 2019; Fine Licht and Fine Licht, 2020; Haibe-Kains et al., 2020; Khosravi et al., 2022; Larsson and Heintz, 2020; Schmidt et al., 2020). In addition to reducing the perceived opacity of AI and the accompanying explanations for reducing it, targeted training programs are of significant importance. In addition to training to acquire new competencies, companies also use training specifically to present and make the opportunities, as well as the risks and limitations, of AI comprehensible (see also Vrontis et al., 2022). These trainings are primarily intended to foster a realistic expectation of AI (Patel et al., 2009; Ransbotham et al., 2017). Systems based on an AI can also produce errors. Research has shown that employees tend to overweight errors made by an artificial intelligence (Dietvorst et al., 2015). This should be prevented by setting realistic expectations (Dietvorst et al. 2018). In addition, companies often focus on involving employees at an early stage of implementation. For example, extra teams are put together in companies, many of which consist of interdisciplinary personnel (Bisconti et al., 2022). On the one hand, this is to ensure that different perspectives in the context of test phases guarantee the full functioning of an artificial intelligence and ensure high performance. On the other hand, the inclusion of employees from different departments also sends a signal to the rest of the workforce insofar as management signals that employees' opinions are valued. Conversely, employees also feel included, which may help to reduce any potential aversion to algorithms and even pre-empt it by emphasizing one's own importance

(Eaton, 2017; Fountaine et al., 2019; Kueper et al., 2020). In addition to this aspect, the integration of human characteristics is also of great importance. Companies are attempting to establish trust in artificial intelligence through voice controls and initial interactive exchanges (Weitz and André; Zörner et al., 2021). Nevertheless, research methodologies indicate that when humanizing systems, the dosage of human characteristics is of particular relevance. For instance, the utilization of human-like robots as the initial point of contact with an artificial intelligence may appear implausible or even intimidating (Glas et al., 2012; Nyholm et al., 2021; Yu, 2020). Consequently, the phenomenon of algorithm aversion in a professional context would not be diminished here, but rather reinforced. Furthermore, the concept of decision latitude plays a role in the context of artificial intelligence (Dietvorst et al., 2018). For instance, when implementing a new system based on algorithms, managers endeavor to ensure that employees retain a voice in the subsequent handling and processing of the results. Consequently, it is observed that aversion can be particularly triggered when employees are compelled to continue working with an artificial intelligence result (Jussupow et al., 2020; Komiak and Benbasat, 2006; Nissen and Sengupta, 2006; Palmeira and Spassova, 2015). Accordingly, decision spaces are also suitable to reduce a possible algorithm aversion here.

In the context of professional environments, there is a clear tendency to place greater emphasis on the context of application and the specific instructions required when dealing with artificial intelligence (AI). This is evidenced by the findings of numerous studies which have demonstrated the existence of an aversion to algorithms in professional setting (Castelo et al., 2019; Jussupow et al., 2020). In private use cases, however, aversion plays a minimal role, particularly in younger age groups. In addition to privacy concerns, which are not universal but rather context-specific, applications based on artificial intelligence are straightforward to use and are rarely integrated into a specific context with comprehensive application notes (Kim and Song, 2022). It is therefore of interest to consider the extent to which context can influence the level of trust placed in an artificial intelligence. During the course of research into framing situations, particularly in the context of decision-making in relation to an artificial intelligence, a complex picture emerges. On the one hand, framing can assist in the better understanding of a situation (Crow and Lawlor, 2016; Kühberger et al., 2002). Concrete cues assist in framing decisions or situations more effectively. Conversely, studies have demonstrated that over-emphasizing situations can have the opposite effect. For instance, studies have indicated that over-emphasizing the performance of an AI can be perceived as untrustworthy and may not reduce algorithm aversion, but may instead exacerbate it (Kim and Song, 2022). In the context of this study, we investigate these aspects. The aim of the study is to close a research gap that deals the effect of framing on trust behavior towards Artificial Intelligence, while also taking the effects of performance and explanations into account.

3 Hypotheses

The technical progress of recent years has demonstrated the rapid advancement of digitalization and, consequently, the development of artificial intelligence. The range of applications of artificial intelligence has expanded, and an increasing number of individuals are utilizing systems based on artificial intelligence in both their personal and professional lives (e. g. Borges et al., 2021; Duan et al., 2019; Pannu, 2015). Consequently, the issue of technology acceptance with regard to artificial intelligence has also become a matter of greater importance in research. Theories of technology acceptance demonstrate that, particularly in the case of new digital systems, acceptance by the user is not immediate; rather, a variety of factors can influence acceptance behavior (Afsay et al., 2023; Davis et al., 1989; Venkatesh et al., 2016; Venkatesh and Bala, 2008). Given that artificial intelligence is not merely another new digital system, but a particularly complex, algorithm-based technological innovation, the manner in which the outputs or advice of an AI should be accepted differs from that of a human advisor (see for example Hasija and Esper, 2022). Hypothesis 1 reads accordingly:

H1**:** Acceptance behavior differs when information is provided by an AI or a human.

Performance can play a special role in the acceptance behavior of technology or systems, particularly in a corporate and business context. Performance can enhance confidence in the efficacy, reliability, and anticipated benefits of new technologies (Alexander et al., 2018). At the same time, there is often initial skepticism about the use of new technologies or even an aversion to algorithms (Dietvorst et al., 2015), so that performance may play a special role when using artificial intelligence, especially for tasks that were previously performed by a human being. This focus on performance would then also imply that differences in performance between humans and artificial intelligence are recognized. Hypothesis 2 states accordingly:

H2**:** Performance differences between an artificial intelligence and a human are identified.

Research has shown that explanations can influence trust behavior and acceptance behavior (Shin, 2021). This is particularly pertinent in the context of artificial intelligence. Artificial intelligence is often perceived as incomprehensible and very complex and is therefore often referred to as a black box (Eschenbach, 2021). Explainable AI has therefore also become more important as a counterpoint to this development and is increasingly being addressed in research papers (e. g. Rai, 2020; Vinson et al., 2018; Wischmeyer, 2020; Zednik, 2021). The provision of explanations can facilitate transparency regarding the output of an artificial intelligence (AI) and its underlying work and computing processes. This, in turn, may enhance or at least influence trust in the AI. The third hypothesis is accordingly:

***H3*: Explanations have a positive effect on acceptance behavior.

Finally, expectations, when managed and guided, can influence the acceptance of new systems or digital technologies. These expectations can have a positive or negative influence on attitudes towards the new system or technology (Kim and Song, 2022). It is therefore of interest to examine whether framing Furthermore, the tone at the top and norm activation may also play a role in shaping expectations and acceptance behavior. Tone at the top refers to the attitudes and behavior of the senior management, which significantly impact expectations and behaviors of employees (see also Ewelt-Knauer et al., 2022; Noviyanti and Winata, 2015; Tervo et al., 2014). Norm activation, in contrast, describes the manner in which social norms and values within an organization are activated and reinforced, thereby influencing expectations and acceptance behavior (Schwartz, 1977). These factors can be pivotal in determining how changes and new requirements in the finance function are perceived and accepted. The following hypotheses are accordingly:

***H4*:** Framing a situation has a positive effect on acceptance behavior.

***H5*:** Framing makes an AI more acceptable if it performs better than an alternative.

***H6*:** Framing makes an AI more acceptable if it performs equally well as an alternative.

This research approach examines the manner in which the acceptance of a human being is perceived in comparison to that of an artificial intelligence. It also considers the role that performance and explanations play in this process and the manner in which framing can positively condition and influence the use of artificial intelligence by influencing expectations.

4 Research Design

In this study, a private application context is used in the experiment in order to investigate if there are differences in trust behavior compared to previous studies in occupational settings. Differences in trust behavior are suspected, since the private application context partly differs considerably from a professional application context. This involves both content-related and professional deviations, since artificial intelligence is already used a lot in social media, for example. In addition, however, a private application context may also represent a more fast-paced environment with faster growth of new AI solutions, which is also accessible to a broader mass. Thus, divergent experience in using an AI may also influence trust behavior in the private application context.

4.1 Need for Justification and Explanation, Reliability of Information and Logic of Efficiency

It is also questionable what role explanations and the possibility of justifying a decision play in the private application context. Here, direct justification to third parties may play less of a role than one's own understanding of the technological basis or the concrete output, perhaps in order to satisfy one's own need for security via one's own data. Efficiency also plays a role in the private context, as digital efficiency is already, it seems, expected as the foundation of any system. At the same time, the fast-moving, private digital environment provides for constantly new solutions and direct availability, which users here also always seem to expect. Nevertheless, it is questionable whether this expectation of efficiency is only linked to the rapid availability of solutions and fast outputs or is also linked to a high performance expectation depending on the area of application, which is in one specific case tested here.

4.2 Experience with and Acceptance in Private Context and Framing

The study asks about experience with automated advice and AI in private life and about the perceived usefulness of the tools. Both experience and perceived usefulness can have an influence on trust behavior, since a general rejection of new technologies due to negative experiences could be present in the case of low usefulness, and vice versa. Furthermore, it is examined whether the framing of the situation has an influence on the acceptance behavior. For this purpose, the participants of this study who belong to the framing group receive an introduction at the beginning as to why an AI was used, which performance advantages result, and which advantages can be generated here or why a human fund manager is now employed in this area and why this manager shows a particularly excellent performance.

4.3 Experimental Task and Situation

A private, accessible and understandable application was chosen for the experimental context and description of the situation to test trust behavior towards artificial intelligence. In doing so, it was important to choose an application context that is not too specific, but to which as many test subjects as possible can relate. In this case, the context chosen was one of bank communication, with the specific aim of asking the test subjects to make an investment decision. In making this decision, the subjects are asked to decide whether they would prefer to invest their money in funds managed by a fund manager or by an artificial intelligence. In addition, one group receives a framing of the situation at the beginning. Here, they get a description in more detail why the alternative fund manager, i.e. either a human or an AI, was chosen and receive hints about the particularly good performance of this alternative fund manager (human or AI). Subjects could then look graphically at the performance of the two funds from the past. Here, the returns are shown in comparison to a base rate. The deviations are also illustrated in another graphic using bar charts. Afterwards, participants could decide where in which fund they tend to invest their money in. Then, the subjects also received an explanation on how either the AI or the fund manager works in principle so that they could adjust their investment decision based on this explanation.

4.4 Experimental Manipulation

First, the **effect of origin** is a between subject manipulation in this experiment. The second fund manager varied between a human fund manager and an artificial intelligence. In addition, the **effect of performance** was manipulated in that the second fund manager (human or AI) was as good or better in managing the fund and generating returns than the first fund manager. There is no bias due to systematic deviation in one direction or systematic over- or underestimation. The deviations in the returns of the funds were presented in tabular and graphical form. Also, the **effect of an explanation** as a within-subjects manipulation was added to the experiment. After the subjects had made their initial investment decisions, they were each given an explanation from the second source (human and AI), where the explanations showed the basic decision-making process and the recommendation in the specific case, thus covering the important components of explanations - explanations of the basic functioning and a specific output. Participants could then change or maintain their decisions according to the explanation. The **effect of framing** at the beginning of the experiment is another between subject manipulation. We use framing to test whether an intentionally controlled introduction in a situation, here specifically associated with performance cues and praise for a particular solution, has an influence on acceptance behavior. Framing here, in the case of artificial intelligence, includes cues about why the AI is used, that it has been heavily tested, and that it performs well. In the case of an alternative fund manager, framing includes very similar information, namely that this fund manager works efficiently and accurately, for example, as well as independently consults an above-average amount of external market data. The framing notes are almost similar in wording and in the order of the information presented here to ensure comparability.

4.5 Data Collection and Sample

The experiment was conducted in 2022 via Amazon Mechanical Turk. For this purpose, 406 subjects were presented with a questionnaire programmed via dynamics into the various expressions. Of the 406 subjects who all completed the experiment, 32 subjects were excluded because they did not pass the Attention Check. The sample then consisted of 374 subjects. Only subjects who were from the U.S. and had an Approval Rate greater than or equal to 90% were admitted via Amazon Mechanical to ensure high response quality. Overall, the mean age of the probands was 35.84 years (standard deviation 10.98%). The youngest proband was 20 years old, the oldest proband was 67 years old. On average, the subjects bring slight experience in artificial intelligence in the private application field (mean 5.27, standard deviation 1.19), tend to find AI applications useful in a private setting (mean 5.31, standard deviation 1.25) and tend to be risk-averse (mean 8.21, standard deviation 2.06). Almost all subjects had English as their mother tongue (mean 1.01, standard deviation 0.07) and are employed mean 1.07, standard deviation 0.56). The total sample of 374 subjects is divided into 8 groups, each differing in which alternative decision basis subjects have to fund manager A (AI or another human/ fund manager B). The number of participants in the eight groups and their differences can be seen on the chart below. The groups show no significant difference between each other with respect to the respective control variables.

Table F-1 Overview of Experimental Groups

Group	Condition	n
Group 1	AI better (w framing)	31
Group 2	AI better (w/o framing)	49
Group 3	AI equal (w framing)	50
Group 4	AI equal (w/o framing)	58
Group 5	Human better (w framing)	38
Group 6	Human better (w/o framing)	51
Group 7	Human equal (w framing)	45
Group 8	Human equal (w/o framing)	52

4.6 Variables and Measurement

There are two dependent variables here, relating to the initial decision ('Investment Decision') and the reversible decision after the explanation ('Investment Decision after Explanation') as to which fund the subjects would invest the money in. The control variables are risk propensity, AI experience (mean of experience in private and professional life, only in conditions where AI was the alternative) as well as age. Employment and English as native language were not included because almost all subjects had employment and English as native language. With dummy variables the effects of the independent variables 'Origin' (AI = 1; fund manager B = 0), 'Performance' (better = 1, equal = 0) and 'Framing' (framing = 1, no framing = 0) were measured. For the influence of 'Explanation', we used a *t*-test to measure the difference between the two dependent variables.

5 Analysis

5.1 Origin, Performance and Explanations as Influencing Factors on Decisions

The following table shows the means and standard deviations as well as the correlations of the experimental variables.

Table F-2 Descriptive Statistics and Correlations

Descriptive Statistics (n = 374)

	Variable	Mean	Std. Deviation	1	2	3	4
1	Investment Decision	5,16	1,30				
2	Investment Decision after Explanation	5,22	1,22	0,591**			
3	AI Experience	5,20	1,15	0,222**	0,245**		
4	Age	35,84	10,98	0,053	-0,002	-0,059	
5	Risk Propensity	8,21	2,06	0,197**	0,198**	0,571**	-0,043

*** Correlation is significant at the 0.01 level (2-tailed).*

In addition, we performed a manipulation check to verify that subjects recognized the difference in performance as a condition. It can be seen in the following table that the subjects recognized the different conditions (better, equal) in the experiment ($p < 0.05$).

Table F-3 Manipulation Check of Performance

Mean differences of manipulation check

Experimental groups	n	Mean	SD	*t-test* for equality of means
Better performance (dummy = 1)	169	5,34	1,28	2,86**
Equal performance (dummy = 0)	205	4,95	1,38	

* $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$

We then examined the influence of origin and performance on the first independent variable ('investment decision'). We found that the origin of the forecast had no influence on the first decision of the subjects and thus no effect ($B = -0.028$, $p < 0.05$).

Accordingly, it does not matter to the subjects in the subsequent (investment) decision whether they receive support from a human or an artificial intelligence. Thus, H1 can be rejected. Furthermore, we measured the influence of the performance on the decision of the subjects and wanted to check whether and which influence the two conditions (better/equal) have on the decision of the subjects. Here we find that subjects understand the differences in the performance of the alternative source (AI or fund manager B) and take this into account in their investment decision ($B = 0.446$, $p < 0.001$). Consequently, the H2 can be confirmed.

To measure the influence of explanations, which is shown here as the difference between the first and second investment decision, we performed a *t*-test (see following table). The *t*-test shows no significant differences between the two investment decisions. Thus, there is no effect of explanations and H3 can be rejected.

Table F-4 Effects of the Explanation

Mean differences in investment decisions before and after explanation

Variable	n	Mean	SD	*t-test* for equality of means
Investment decision	374	5,16	1,30	-1,042
Investment decision after explanation	374	5,22	1,22	

* $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$

5.2 Effects of Framing on Behavioral Decision Making

Of particular interest, however, is the effect of framing, which we were able to clearly demonstrate in the analysis ($B = 0.524$, $p < 0.001$).

To further investigate the effect of framing, we analyzed what effect framing has in the different groups. For this purpose, we compared groups 1 and 2, groups 3 and 4, groups 5 and, and groups 7 and 8. We found that framing had an influence in all cases, except when both fund managers were of equally good performance. Thus, H4 can only be confirmed to a limited extent, since it is only valid if the AI is better or equally good as fund manager B or if at least one human/fund manager performs better than the other fund manager.

We were able to determine a significant effect of framing in all cases in which an AI represents an alternative to the fund manager. This applies both to the case in which AI was better than fund manager A in the past and to the case in which AI was just as good as fund manager A in the past. Accordingly, hypotheses H5 and H6 can also be confirmed, since in each of the cases mentioned there is a positive influence on framing on the first dependent variable ('Investment Decision'). In addition, framing also had a significant impact when one fund manager (B) was better than the other fund manager (A). These analyzes are illustrated on the following tables.

Table F-5 Effect of Framing (Condition AI better)

	Model 1		**Model 2**	
Variables	**B**	***SE***	**B**	***SE***
Dependent Variable: Investment Decision				
Controls				
AI Experience	0,23	0,17	-0,02	0,10
Age	0,01	0,02	3,71	0,78
Risk Propensity	-0,02	0,10	0,24	0,16
Main effects				
Framing _ AI better			0,69*	0,30
R^2		0,05		0,11
ΔR^2				0,06
R^2 *Adj.*		0,01		0,05
ΔR^2 Adj.				0,04
F Change		1,195		5,076*

* $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$

Table F-6 Effect of Framing (Condition AI equally as good as Fund Manager B)

Variables	Model 1 B	Model 1 *SE*	Model 2 B	Model 2 *SE*
Dependent Variable: Investment Decision				
Controls				
AI Experience	0,17	0,12	0,15	0,12
Age	0,01	0,01	0,01	0,01
Risk Propensity	0,06	0,07	0,08	0,07
Main effects				
Framing _ AI equally as good			0,47*	0,23
R^2		0,05		0,08
ΔR^2				0,04
R^2 *Adj.*		0,02		0,05
ΔR^2 Adj.				0,03
F Change		1,657		4,07*

* $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$

Table F-7 Effect of Framing (Condition Fund Manager B better than Fund Manager A)

Variables	Model 1 B	Model 1 *SE*	Model 2 B	Model 2 *SE*
Dependent Variable: Investment Decision				
Controls				
Age	0,03*	0,01	0,03*	0,01
Risk Propensity	0,17*	0,07	0,16*	0,06
Main effects				
Framing _ Fund Manager B better			0,69**	0,23
R^2		0,11		0,20
ΔR^2				0,09
R^2 *Adj.*		0,09		0,05
ΔR^2 Adj.				-0,04
F Change		5,065**		9,321**

* $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$

Table F-8 Effect of Framing (Condition Fund Manager B equally as good as Fund Manager A)

	Model 1		Model 2	
Variables	**B**	***SE***	**B**	***SE***
Dependent Variable: Investment Decision				
Controls				
Age	0,00	0,01	-0,01	0,01
Risk Propensity	0,17**	0,06	0,16*	0,06
Main effects				
Framing _ Fund Manager B equally as good			0,36	0,28
R^2		0,08		0,09
ΔR^2				0,02
R^2 *Adj.*		0,06		0,05
ΔR^2 Adj.				-0,01
F Change		3,784*		1,596

* $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$

6 Overall Conclusion

6.1 Conclusion

This study demonstrated a significant influence of framing in different experimental situations and conditions. Thus, framing was shown to have a significant influence on the investment decision of subjects when they used artificial intelligence that performed better or equally well as the fund manager A/human. Furthermore, framing had a significant influence on the subjects' decision when the artificial intelligence performed equally well as the fund manager A. Consequently, the subjects were more inclined to trust the artificial intelligence, despite this being an irrational decision from a rational point of view and in accordance with the stated performance. Only when the second fund manager/human/fund manager B performed equally well as fund manager A did the subjects not become influenced by the framing. Consequently, no significant results were found in this instance. These results provide insight into the subjects' acceptance and trust behavior, since the acceptance of the alternative source (AI or human) is reflected in particular in the first decision in the experiment, in which the respective significant differences with respect to the effect of framing between the groups were also found. In the conditions in which either the AI or the human performed better, we were able to demonstrate that framing served as a trust or acceptance booster. The results demonstrated that trust in the alternative source was significantly higher with framing than when there was no framing. This indicates that the trust-enhancing aspect was significantly increased in these cases. Additionally, the effect observed in the groups in which the AI or fund manager B were equally as good as fund manager A was noteworthy. This revealed a clear difference in the subjects' assessment between the human and the machine. While the results of the human were apparently subjected to greater scrutiny, the artificial intelligence was apparently afforded greater trust by the framing. The framing had the consequence that, although the decision could not be justified rationally, the participants placed more confidence in the artificial intelligence than in the fund manager A. Thus, it can be assumed that framing almost triggered an overconfidence or even an overtrust/ algorithm appreciation in the artificial intelligence and at the same time replaced rational decision-making (for algorithm appreciation see also Kaufmann, 2021; Logg et al., 2019; You et al., 2022). It is often assumed in research that subjects tend to assign a trust handicap or an algorithm aversion to artificial intelligence and thus assume lower trust in the machine than in humans. However, other effects are evident here. Based on these study results, we can provide first indications that possibly prove an algorithm overtrust that can be triggered by framing. This over-trust has resulted in a lack of rationality, indicating that the initial situation of the user's trust should also be taken into account in the context of the application of framing.

6.2 Contribution

Consequently, the results of our study also permit the formulation of new implications for practice with regard to the handling and introduction of artificial intelligence. When introducing artificial intelligence, it can be particularly important to conduct a survey beforehand to assess the level of trust in the new algorithms and the new system. Surveys of this kind and mood assessments can be used to draw conclusions about how much trust there already is in the innovations and, based on our study results, what strength and intensity framing needs to have during the introduction. If, for example, it can be demonstrated in the company that, as is often assumed in research, there is a greater degree of distrust among employees towards the new technology, then framing can positively influence the acceptance of the technology. However, if it can be demonstrated that employees are neutral or even positive towards the new solution, then framing may not be useful. In this instance, framing may result in a loss of critical thinking and a shift towards a more emotional response to the technology, potentially leading to a lack of rational decision-making. This can be detrimental to the implementation of AI, as it may result in a lack of transparency and accountability. Therefore, it is crucial to consider the emotional context of the situation and to develop a suitable framing strategy. This framing could then take place, for example, in the form of a professional introduction or initial training. If necessary, individual discussions could also be held if the trust and acceptance behavior in the company is highly heterogeneous.

6.3 Limitations and Future Research

Notwithstanding the significant and interesting study results for research and practice, our study is also subject to certain limitations. For instance, the subjects were recruited via Amazon Mechanical Turk, which precluded direct observation in a laboratory setting. Consequently, factors such as the subjects' attention could only be measured to a limited extent, for example via an attention or manipulation check. Furthermore, the transferability of the setting to companies requires further investigation. As the study was conducted in a setting that is more closely related to a private situation, the results may not be fully transferable to corporate practice. Furthermore, the experiment only tested one type of framing, using a single expression. It is also possible to divide and categorize framing in further subdivisions, which would require further investigation in future studies to provide a generally valid statement on the effects of framing. Furthermore, it would be of interest for future research approaches to directly test possible use cases of framing in companies. The design of a possible opinion survey and a corresponding questionnaire could also be investigated directly in companies. Likewise, the presence and handling of overtrust should be further investigated. As a counterpart of the research strand on algorithm aversion, this research area is still underdeveloped. It would be of interest to investigate whether, for example, by new use cases such as Chat GPT, a proximity to artificial intelligence has developed that has lessened the aversion to it and led to a change in behavior, with trust advancing. It would also be of interest to investigate the conditions that would result in an overtrust. In light of the study's findings, the effect of framing in the context of overtrust could be further explored in future research, with a view to identifying potential avenues for effective management of technological innovations and artificial intelligence. It is evident that the handling of artificial intelligence and the related trust implications have not yet been fully investigated, and that further research is necessary to provide a comprehensive understanding. Furthermore, over time, the fundamental principles of trust may evolve and adapt to rapid technological advancements and the accelerated learning of employees within the enterprise. Consequently, new research in this area will continue to be a vital area of study, providing vital guidance and implications for management, employees, and the interaction between humans and artificial intelligence, especially in this fast-paced environment.

G Concluding Remarks

1 Core Results and Contribution

In summary, the five papers in this dissertation provide a comprehensive overview of the future of the finance function and management accounting as part of this function, as well as the role of trust in artificial intelligence and algorithms. As a consequence of the accelerating pace of digitization, research and companies have identified a number of key areas for further investigation. These include the topics that will be of particular relevance within the context of digitization, as well as the specialist topics and aspects that must be considered in finance and management accounting in order to ensure holistic, integrated corporate management with a strong finance function (see also Bican and Brem, 2020; Deipenbrock et al., 2019; Frankiewicz and Chamorro-Premuzic, 2020; Sebastian et al., 2020; Stavrova et al., 2021; Verhoef et al., 2021; Yasinska, 2021).

This dissertation demonstrates how digitization has transformed the finance function and management accounting. In almost all processes, an increased degree of digitization is targeted, which simultaneously ensures speed and efficiency, as well as better data linkage and thus more valid bases for decision-making. This process efficiency is of particular importance and is always a primary consideration when developing new digital solutions (see also Clark et al., 2020; Ionescu, 2020; Yasinska, 2021). This also appears to be an indicator of whether a new system will be introduced and what value is attached to it. In the first case study of this dissertation, it became particularly apparent which difficulties also arise in this process. On the one hand, digital systems – with which management accountants must increasingly work – contribute significantly to the modernization of an organization. Concurrently, data can be evaluated and processed in a more targeted, accelerated and integrated manner, thereby providing a more comprehensive overview of the company's financial situation (Yasinska, 2021). Nevertheless, the advent of digitization and process efficiency has necessitated a familiarity with new digital fundamentals and a willingness to assume a more advisory role in the sense of a business partner, as a consequence of the elimination of smaller processes. Concurrently, the introduction of completely new subject areas has become a necessity, which management accountants must also be prepared to handle. Both situations demand a willingness to learn and to devote attention to new tasks that may not have existed in this form when they entered the profession. Concurrently, companies and the finance function must facilitate the acquisition of knowledge by employees and encourage the ongoing enhancement of competencies through training, professional support within the company, for instance through centers of excellence, and an open, communicative corporate culture. It is uncertain whether this awareness is already embedded in companies, in the finance function and in management accounting, or whether digitization and familiarity with these and new issues is expected of employees as a matter of course without encouraging employees to undertake further development. Without the strong support of employees and the incorporation of new talents, digital systems will certainly not be able to achieve an autonomous digital transformation and corporate management (Frankiewicz and Chamorro-Premuzic, 2020).

Concurrently, the advent of digitization will place further demands on the finance function and management accounting. For instance, the focus on data quality will have to remain high, and data maintenance will also become more important in order to be able to supply the new digital systems with accurate data. With regard to large data volumes, external market data will also become more important in the future. The integration of this data will continue to pose a challenge. The case study presented in this dissertation revealed that some of the data in question is available in an unstructured format, which makes it more challenging to integrate into existing systems. Additionally, there is a requirement for the data to be automatically extracted and processed by the systems. This also implies that digital solutions must be capable of intelligently identifying which external market data is required to be downloaded from different sources in order to be subsequently cleansed, inserted into subsequent systems and potentially further processed. This already demonstrates that only systems operating on the basis of artificial intelligence can accomplish these complex tasks (see also Almagtome, 2021; Elliot et al., 2020; Greenman, 2017; Luo et al., 2018; Mohammad et al., 2020; Moudud-Ul-Huq, 2014; Stancheva-Todorova, 2018; Sutton et al., 2016).

The development of artificial intelligence represents a pivotal aspect of the future of the finance function and of management accounting as part of this finance function. During the course of this dissertation, it became evident that artificial intelligence, encompassing self-learning and intelligent algorithms, is not yet widely deployed in most companies. Instead, precursors of artificial intelligence, such as predictive analytics, are in use (e. g. Deipenbrock et al., 2019). Consequently, the advancement of artificial intelligence must be expedited in the future. In addition to the accessibility of training data and programming expertise, a significant obstacle will be the integration of these technologies into the financial sector. Since digital solutions are typically developed independently from the operational division in which they are ultimately deployed, this often necessitates adjustments and agreements after the fact. A direct linkage between developers and the business department can ensure efficiency and effectiveness, while also increasing the commitment of finance staff who have been involved in the development and may feel a sense of ownership. Further studies in this dissertation, primarily in the third paper on the use of artificial intelligence in accounting, demonstrated that psychological ownership can be a significant driver for acceptance and trust in algorithms, particularly with regard to new digital solutions.

Furthermore, the studies within the scope of this dissertation demonstrate that the finance function has become more complex, with numerous new topics having entered the finance function and necessitating the attention of the relevant employees. Sustainability, sustainability measurement, sustainability reporting, risk management, the handling of uncertainties and trend breaks, as well as agile controlling and supply chain controlling, are but a few examples of the considerations that accountants are obliged to address in the future (e. g. Arroyo, 2012; Bennett et al., 2013; Cokins and Căpușneanu, 2020; Maas et al., 2016; Rounaghi, 2019; Soderstrom et al., 2017; Solovida and Latan, 2017). One of the principal challenges confronting management will be to maintain an overview of employees' skills and to avoid burdening managers with new topics. As previously indicated in the context of process efficiency and digitization, training and development opportunities for employees will become increasingly important. At the same time, a certain amount of freedom is certainly also essential in order to develop and introduce new creative ideas for the company, for the finance function and for management accounting.

In light of the considerable number of new topics and professional requirements for finance employees and management accountants, it is evident that differentiated specializations within the finance function will also be of particular importance in the future. Nevertheless, it has been demonstrated that prior to transitioning to a specialization and thus becoming an expert in a particular field, a further development stage will also be of considerable importance. This dissertation demonstrated that a comprehensive understanding of the company, or in other words, a thorough comprehension of the business model, will be of particular importance at the outset of a career in the finance function and in management accounting. This implies that the operational business with its processes should be grasped. Furthermore, the success factors should also be made tangible for management accountants. Furthermore, an understanding of the business model should facilitate communication between finance employees and operational areas on a professional level, enabling them to provide optimal steering. This is because they are able to identify the levers of operational processes. Additionally, the role of the accountant as a business partner can be further strengthened in later stages, whereby they are perceived by business departments as a neutral sparring partner with comprehensive financial knowledge. The understanding of the business model, which companies and the finance function are likely to promote to a greater extent, also brings new ways of approaching the processes of the finance and accounting function itself. In the context of this dissertation, CFOs stated that their more process-oriented view will also become more important in the finance function. This includes the view that not only output KPIs should be considered and included in optimization decisions, but also that input KPIs should increasingly be used and considered as levers. Overall, there is a desire for closer integration between operational and financial KPIs. This also implies a different approach regarding EBIT, cash flow, P&L and the balance sheet. Although the finance function's strategic statements indicate an increased focus on cash, this change is more extensive than simply advocating a stronger cash view. In addition to EBIT, cash flow and CapEx, the inclusion of P&L and balance sheet analyzes will also receive greater attention. Overall, the process view should be promoted holistically and thus also contribute to value creation, as it is often postulated by companies and leaders within the finance function.

The role of management accounting is also subject to the transformation of the changing times and will be positioned in an even more differentiated way in the future. On the one hand, this dissertation shows that the linkage and integration of management accounting into the finance function will become even closer. This is also driven by stronger connected and interrelated data points between Finance and Management Accounting, as well as, for example, the operational functions that provide financial metrics to both divisions. Nevertheless, the content of management accounting is unlikely to migrate to the finance function in the future. Instead, the study results within the scope of this dissertation show that it is precisely the independence of the function within the company that is valued. Managers from operational areas perceive management accountants as a neutral sparring partner with whom they can openly discuss and execute scenarios and obtain advice. This indicates that the role of the business partner is in demand

and desired at these levels. However, other structures are emerging at lower hierarchical levels. The first study of this dissertation showed that the German term controlling is still associated with control in companies and tends to undermine recognition of the discipline. Consequently, in the future, the role of the 'business analyst' is more likely to be assumed, particularly when entering the field of management accounting, in order to circumvent any negative associations that may arise. At the same time, this role title should also more accurately reflect the new requirements, specifically the understanding of the business model. In summary, the role of the management accountant has evolved from that of a mere number presenter to that of a manager with expertise in finance, who can further differentiate his role in the company over the course of his career by specifying his responsibilities or acting in a management capacity as part of his business partner role (see also Wolf et al., 2015). It is pertinent to note that the role of the Green Controller appears to have been included in the specifications as a new role profile. In contrast, other role profiles, such as that of the Risk and Crisis Manager, appear to serve a supplementary function, in that they are intended to enhance the capabilities of existing role profiles (for role profiles see Schäffer and Brückner, 2019).

The evolution of management accounting also reveals a significant obstacle. On the one hand, the integration of more specialist topics into the management accounting and finance function necessitates the formation of more detailed specifications, which can be developed by junior staff. This implies a certain degree of outsourcing or separate consideration of subject areas. Conversely, there is a desire for greater integration and interlinking within the finance function. Furthermore, greater integration is intended to ensure that artificial intelligence, for example, is not developed separately but rather integrated into the finance function. Nevertheless, this dissertation demonstrates that this integration is often not achieved. Consequently, new digital applications are frequently presented to employees in Finance and Management Accounting in a cursory manner, with the solutions then being made available for immediate use.

Nevertheless, these new digital systems are not always utilized by employees due to a lack of trust in the systems themselves. This lack of trust or trust handicap indicates an algorithm aversion, which was also investigated in this dissertation.

The dissertation has demonstrated that the causes of algorithm aversion are numerous. A number of factors can contribute to a rejection of new algorithms, including a lack of experience, a perceived subjectivity of the decision by the algorithm, and a lack of interaction and communication possibilities (e. g. Alexander et al., 2018; Burton et al., 2020; Carey and Kacmar, 2003; Castelo et al., 2019; Goodyear et al., 2016; Lodato et al., 2011; Sutherland et al., 2016; Thayer, 2008). Furthermore, it is crucial to provide appropriate incentives, which can encompass both economic and social incentives. This approach allows for the celebration of exemplary outcomes and the commendation of exemplary employee applications (Alexander et al., 2018; Brown, 2015; Burton et al., 2020; Eastwood et al., 2012; Highhouse, 2008b; Klimoski and Jones, 2008; Kuncel, 2008; Önkal et al., 2009). Furthermore, a lack of justification mechanisms, a lack of modification and freedom of choice regarding the further processing of the algorithm output, or inadequate expectation management, which can also be interpreted in terms of a lack of framing, can result in an aversion to algorithms (e. g. Bhattacherjee and Premkumar, 2004; Burton et al., 2020; Jussupow et al., 2020). In addition, a key aspect discussed in research is the influence of explanations on acceptance behavior in relation to algorithms and artificial intelligence (Adadi and Berrada, 2018; Asatiani et al., 2020; Doran et al., 2017; Gunning et al., 2019; Khosravi et al., 2022; Zednik, 2021). This dissertation contributes to a critical examination of the aspects mentioned, with a particular focus on the influence of explanations on acceptance behavior. The studies presented herein indicate that explanations had no beneficial effect on acceptance behavior. This raises the question of the extent to which the black box problem is really decisive for trust behavior, and whether other factors may play a far greater role. For example, the framing of the situation seems to have a decisive influence on trust behavior. This dissertation demonstrates that the framing of a situation consistently affects trust behavior in a positive manner. When individuals must choose between an AI and a human as a basis for decision-making, they consistently favor the AI, even if it does not perform better objectively. In this context, the first signs of an overtrust or strongly developed algorithm appreciation appear in the context of this research (for further insight on algorithm appreciation see Logg et al., 2019) and result in irrational decision-making behavior. Such behavior could not be observed when two humans formed the basis of the decision and framing was present. Furthermore, this dissertation demonstrated that performance is not the primary driver for the decision of humans regarding an AI. Rather, effects such as psychological ownership and the adherence to previously selected results, as well as selective attention to the tasks, can influence the decision-making behavior.

In conclusion, this dissertation contributes to mapping the progress of the digital transformation in finance and management accounting and to identifying relevant aspects and influencing factors regarding trust behavior towards artificial intelligence as an essential component of future digitalization. At the same time, it was possible to contextualize the influencing factors on trust behavior presented in the research and apply them to the context of management accounting. The results presented here may also enable companies to promote digital transformation in a systematic manner. This could be achieved, for example, by addressing new areas of expertise and role profiles at an early stage and by integrating the development of artificial intelligence into the finance function. Furthermore, employee acceptance of new digital systems can be promoted by using targeted framing to create a basis of trust and understanding for algorithms and by drawing employees' attention to the application options and benefits of new systems.

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2 Future Research Implications

In light of the five studies presented in this dissertation and the corresponding research results, it is evident that further research is required to derive insights from the presented findings.

The initial paper of this dissertation, the case study on the future of the finance function, illustrates that the role profiles and areas of competence for management accounting and the finance function can be examined and expanded in a more differentiated manner in the future (for role profiles see Schäffer and Brückner, 2019). The findings indicate that, for instance, a 'Green Controller' and a 'Risk and Crisis Manager', potentially distributed across different divisions, should be examined in the context of other companies. It is particularly noteworthy to observe how the approach to trend breaks, shocks and uncertainties affects the various areas of management accounting (see also Latan et al., 2018). The interviews revealed that comprehensive risk management and expanded scenario planning with a higher degree of flexibility, as well as the increased inclusion of external market data, play a role (e. g. Adegboyegun et al., 2020). Further research is required to examine this matter in greater depth and to transfer the findings to the role profiles and areas of competence. Additionally, the results of this study indicated that a more process-oriented approach is being pursued in the finance function, which will also have an impact on the consideration of KPIs and control elements. In the future, it will be necessary to critically examine which KPIs are increasingly considered and used for strategic matters. In addition, it is to be examined whether cash orientation, which has been presented as a trend topic in research (e. g. Schäffer and Weber, 2015), has yet not been enhanced by an increased CapEx, P&L as well as balance sheet orientation. Furthermore, the case study demonstrated that the advancement of artificial intelligence should be integrated into the finance function to a greater extent in the future. This integration would facilitate professional exchange and, consequently, the targeted development of artificial intelligence at an early stage. This topic will continue to be a priority, as the development of predictive analytics towards artificial intelligence is a concern for many companies. It is anticipated that this will have a significant impact on the accounting profession, as well as competitive advantages and increased profitability (Almagtome, 2021; Araujo et al., 2020; Benbya et al., 2020; Elliot et al., 2020; Greenman, 2017; Luo et al., 2018; Mohammad et al., 2020; Moudud-Ul-Huq, 2014; Stancheva-Todorova, 2018; Sutton et al., 2016). In this context, it is necessary to examine how an integration of AI development within the finance function can be successfully advanced. Additionally, the link to trust in AI is of interest here. As the third paper of this dissertation points out, psychological ownership can also have an impact on acceptance and trust behavior and thus on decision-making behavior. It would therefore be of interest to examine the extent to which an earlier integration into the development of an artificial intelligence can eliminate trust handicaps at an early stage and facilitate realistic expectation management (see also Bhattacherjee and Premkumar, 2004; Jussupow et al., 2020).

In addition to the aforementioned points, the case study and the results and interviews of the second paper revealed a need for further research on the topic of justification and liability. As described by the interviewees involved here, legal liability represents a significant obstacle for management accountants who are reluctant to rely on artificial intelligence, as long as they are eventually personally liable for the result or further processing with the output of an artificial intelligence. This obstacle, which is presented as particularly noteworthy by practitioners, is currently receiving little attention in research. It represents an insufficiently addressed field with respect to research literature on algorithm aversion and trust in artificial intelligence (Berger et al., 2021; Burton et al., 2020; Castelo et al., 2019; Dietvorst et al., 2018, 2015; Filiz et al., 2021; Gsenger and Strle, 2021; Hou and Jung, 2021; Hussein, 2021; Jung and Seiter, 2021; Mahmud et al., 2022; Prahl and van Swol, 2017; Reich et al., 2022). It is also necessary to examine the circumstances under which systems or the creators of algorithms can be held liable in order to relieve the human decision-maker of this burden and transfer more responsibility to the system.

The justification base also contributes to the results of the pre-study of the third paper as well as to the results and further research gaps of the fourth and fifth paper. For instance, the pre-study of the fourth paper demonstrated that the various professions exhibit disparate applications of AI, with notable differences in the degree to which they require justification for their decisions. Lawyers, for instance, have indicated that the necessity for justification in their professional lives is particularly pronounced due to their interactions with clients and in court. Consequently, their skepticism about artificial intelligence is also particularly high, given that they cannot simply rely on the results of an AI. In contrast, and in opposition to this, pilots have stated that they rely on the results of an AI constantly and do not have to justify these decisions during the flight, except in special cases or in cases of damage. The differences between the occupational groups could not be mapped in this manner via Amazon Mechanical Turk. However, further interview studies should be pursued in order to depict and design a conceptual model of the role of justification and the influence on artificial intelligence between the occupational groups, as this would require a more in-depth professional exchange (for occupational effects and effects of justification see Hartner-Tiefenthaler et al., 2022; Kayande et al., 2009; Mahmud et al., 2022; Önkal et al., 2009; van Dongen and van Maanen, 2013).

Furthermore, the fifth paper highlights the necessity for further research in the field of framing, as well as the baseline situation in algorithm appreciation. In particular, the fifth study demonstrated that framing the underlying situation can influence trust behavior. However, it was also shown that this can result in irrational decisions being made, for instance, that an artificial intelligence is preferred, despite a human management accountant having provided more favorable indications in terms of better performance. It can be assumed that the decision-makers have already placed excessive trust in the artificial intelligence in the starting situation, which has been reinforced by the framing in a negative sense. Consequently, there is a need for research on how to approach framing in different initial situations of trust, namely algorithm appreciation, algorithm neutrality and algorithm aversion. This would have significant implications for companies, which would have to assess the extent of trust employees have in new systems before implementation and display. This could be done, for instance, at an introductory event. Otherwise, an introduction or framing could have the opposite effect and promote irrational behavior. In general, this also shows that research on algorithm appreciation should be expanded. It is unclear whether employees in the finance function still display an aversion to algorithms or whether this has changed considerably in recent times. Further contact with artificial intelligence may have led to an increase in trust in the performance of such systems. This might have caused an aversion to change into an appreciation behavior (Hou and Jung, 2021; Kaufmann, 2021; Logg et al., 2019; You et al., 2022), which would have profound consequences for the measures that companies are currently advised to take to introduce new technologies - assuming that employees tend to have an aversion to new systems and algorithms.

Overall, it is evident that research on trust in artificial intelligence is still a broad and dynamic field, in line with the rapidity of digital change. Further research is required to drive digital transformation in management accounting forward in a focused manner and to ensure employee acceptance and the desired process efficiency in equal measure.

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I Appendix

Appendix A Study 1 – Future of Finance (Interview Questions for Semi-Structured Interviews)

Questions for Key Informant #1 CFO Corporate Controlling Global Business Services

- Wie würden Sie den Verlauf der Digitalisierung bei Ihnen im Verlauf der vergangenen 5 – 10 Jahre beschreiben? Welche Veränderungen waren möglicherweise Treiber der internen Digitalisierung?
- Welche Lösungen oder Aspekte im Rahmen der Digitalisierung halten Sie – gerade auch im Bereich Controlling und Finance – kurz-, mittel- und langfristig für besonders relevant?
- Welche Aspekte fallen bei Ihnen unter den „Finance going digital“ Plan und warum?
- Welche Rollen haben Big Data und größere Datenmengen bei Ihnen eingenommen?
- Werden zusätzlich zu internen Daten auch externe (Markt-)Daten bei Ihnen verwendet, aufbereitet und in Entscheidungen mit einbezogen?
- Welche Rolle spielen Echtzeitdaten aktuell bei Ihnen und wie schätzen Sie die künftige Entwicklung ein?
- Welche Innovationen sehen Sie künftig beim Thema Datenverarbeitung?

- Welche Hürden sehen Sie künftig beim Thema großer Daten und Datenverarbeitung?
- Welchen Stellenwert haben die automatisierte Datenverarbeitung und Self-Service Anwendungen bei Ihnen eingenommen? Welche Hürden haben sich hier in der Vergangenheit ergeben und wie schätzen Sie die künftige Entwicklung ein?
- Welchen Stellenwert ordnen Sie aktuell und künftig Business Process Outsourcing, als Auslagerung von Support-Prozessen die eine geringere Rolle spielen, zu?
- Welchen Stellenwert ordnen Sie aktuell und künftig digitalen Service als neue Funktion im Rahmen von Finance zu?
- Welche digitalen Anwendungen haben bei Ihnen den Aspekt der Kommunikation und des Austauschs verändert und wie schätzen Sie hier die künftige Entwicklung ein?
- Welche Rolle spielt künstliche Intelligenz bei Ihnen in aktuellen Lösungen und welche Bedeutung schreiben Sie der KI für die Finance Funktion künftig zu?
- Wie hat und wie wird sich Ihrer Meinung nach die Rolle des CFOs durch die Digitalisierung bei Ihnen verändern?
- Inwiefern kommen durch verstärkte Digitalisierungslösungen neue Kompetenzfelder für Controller und die Finance Funktion hinzu? Welche neuen Kenntnisse müssen hier erworben werden?
- Inwiefern wurde die Digitalisierung durch den Umgang mit Unsicherheiten und Krisen, denen sich Unternehmen ja verstärkt in der vergangenen Zeit ausgesetzt fühlten, gehemmt oder nicht? Welche Rolle ordnen Sie - im Rahmen der Entwicklung der Digitalisierung – Unsicherheiten und Krisen zu?

- Inwiefern würden Sie sagen kann bei Ihnen zwischen Controlling und Finance unterschieden werden? Gleichen sich diese Bereiche inhaltlich künftig an – im Sinne von einer größer gefassten Finance Funktion - oder würden Sie sagen besteht künftig eine klare Trennung zwischen Finance und Controlling?
- Was sind Ihrer Meinung nach die wesentlichen Treiber für künftige Digitalisierung in Ihrem Unternehmen?
- Was sind Ihrer Meinung nach die künftigen Schwerpunkte für digitale Lösungen in der Finance Funktion in Ihrem Unternehmen?

Questions for Key Informant #2 Head of Global Controlling Finance Functions

- Wie wird das Thema Geschäftsmodellverständnis bei Ihnen für die Finance Funktion künftig definiert und gestaltet werden?
- Wie hat sich die Wichtigkeit des Geschäftsmodellverständnisses in den vergangenen Jahren verändert?
- Welchen Stellenwert wird das Geschäftsmodellverständnis für die Finance Funktion generell kurz-, mittel- und langfristig einnehmen und warum?
- Welche inhaltlichen Aspekte des Geschäftsmodells werden für die Finance Funktion bzw. für das Controlling künftig den höchsten Stellenwert einnehmen und warum?
- In der Literatur werden derzeit für das Controlling verschiedene Kompetenzfelder definiert. So fallen darunter Finanzen und Controlling (klassischem Wissen zu Kennzahlen, Prozesse), Management (Projektmanagement/ agile Methode, Change-Management), Kommunikation (Storytelling, Leadership,

Präsentationsfähigkeit), Technologie und Analyze (IT, Datensysteme und Datenanalyse, Datensicherheit und Datenschutz) und persönliche Fähigkeiten (Problemlösungsfähigkeit, analytisches Denken, Durchhaltevermögen und Offenheit). Würden Sie sagen, dass diese Kompetenzfelder so künftig auch für das Controlling bzw. die Finance Funktion bestehen?

- Im Rahmen von in der Literatur definierten Kompetenzfeldern wird das Geschäftsmodellverständnis ebenfalls genannt und beispielsweise insoweit beschrieben, als dass das Kerngeschäft sowie die Erfolgsfaktoren verstanden werden müssen und auch strategisches Denken zur Entwicklung des Geschäftsmodells von Controllern gefordert ist. Stimmen Sie dem noch zu oder wird sich dieses Kompetenzfeld Ihrer Meinung nach verändern/ erweitern?
- Inwiefern würden Sie sagen ist das Thema Nachhaltigkeitscontrolling/ Green Controlling auch ein Zukunftsthemen im Rahmen der Finanzfunktion? Kann hieraus gegebenenfalls ein neues Kompetenzfeld entstehen?
- Inwiefern wird künftig ebenfalls ein Augenmerkt auf den Controller als Risk Manager/ Krisenmanager vor dem Hintergrund globaler Unsicherheiten und Veränderung liegen? Kann auch hier in neues Kompetenzfeld entstehen?
- Sehen Sie weitere Kompetenzfelder, die für das Controlling/ die Finanzfunktion künftig wichtig werden?
- Neben den bereits genannten Kompetenzfeldern gibt es auch in der Forschung definierte Rollenbilder. Würden Sie sagen, dass die folgenden Rollenbilder so künftig auch noch für das Controlling und die Finanzfunktion relevant sind?
    - Service Expert für operative Controlling Prozesse

  - Functional Lead für methodische und fachliche Expertise und die Kommunikation von Controlling Strategien
  - Change Agent der Veränderungsprozesse treibt
  - Scorekeeper, der Routineaufgaben in operativen Controlling-Prozessen übernimmt
  - Guardian, der die Ziele und die Zielerreichen sowie die Einhaltung von Richtlinien überwacht
  - Business Partners für die strategische Unterstützung des Managements
  - Data Engineer, der die Datenqualität sicherstellt und neue digitale Lösungen implementiert
  - Data Scientist, der Analyze von Big Data durchführt und neue digitale Lösungen entwickelt
  - Decision Scientist, der sicherstellt, dass datenbezogen relevante Fragen gestellt und die Ergebnisse von Analysen in Initiativen überführt werden
- Darüber hinaus könnten zwei weitere Rollenbilder relevant werden. Wie schätzen Sie das Vorhandensein und die Wichtigkeit der folgenden Rollenbilder für die künftige Entwicklung von Finance und Controlling ein?
  - Green Controller als 1) Green Business Partner, der im Rahmen finanzieller Analysen gemeinsam mit dem Management über Nachhaltigkeitsstrategien entscheidet 2) Green Budget Manager, der investitions- und Ökologiebudgets bestimmt und verwaltet 3) Green Performance Auditor, der im Rahmen von Green Compliance, Green Audit und Carbon Accounting die Einhaltung von Standards überwacht und KPIs mit entwickelt

  - Risk & Crisis Manager als 1) ICS Agent zur Festlegung neuer Kontrollen, Überwachung der Durchführung, Einleiten von Maßnahmen bei ungenügenden Kontrollen 2) Compliance Guardian zur Einhaltung gesetzlicher Rahmenbedingungen und als interne Kontrolle der Umsetzung von Maßnahmen 3) Uncertainty Steward zur Erstellung von Risk Maps, Einordnung von Risiken, Ableitung von neuen Strategien zur Risikominimierung und -vermeidung 4) Supply Chain Guardian (kosteneffiziente) Absicherung der Lieferketten, Szenarioanalysen
- Welche Rollen würden Sie sagen spielen für folgenden Themen für die Zukunft der Finanzfunktion und für das Controlling?
  - Supply Chain Controlling
  - Akquise neuer (Finance und Controlling) Talente sowie Weiterbildung und Talentförderung
  - Zunehmende Cash Orientierung
  - Agiles Controlling
- Inwiefern würden Sie sagen werden Controlling und Finance künftig getrennt oder zusammen betrachtet? Kann man künftig eine klare Abgrenzung schaffen oder wird Controlling mehr als ein Teil der größer gefassten Finanzfunktion betrachtet werden?

Questions for Key Informant #3 CFO Real Estate

- Was sind für Sie die wichtigsten Aspekte und Treiber im Rahmen der Zukunft der Finanzfunktion und des Controllings?

- Was sind die wesentlichen Aspekte für die Zukunft der Finanzfunktion und welche Rolle spielt dabei das Thema „Keep the House clean“?
- Welche Aspekte fallen bei Ihnen unter „Keep the House clean“ und warum?
- Controller und Manager sind in der Vergangenheit immer mehr Unsicherheiten und globalen Krisen ausgesetzt gewesen, deren Implikationen sie auch in das Unternehmen übersetzen und in die Strategien integrieren mussten. Könnte ein Kompetenzfeld „Krisen- und Risikomanagement“ Ihrer Meinung nach wichtig werden und auch neue interne Kontrollsysteme sowie Risikoanalyse und Ableitung neuer Strategien umfassen?
- Würden Sie sagen, dass sich aus dem Kompetenzfeld „Krisen- und Risikomanagement“ auch ein neues Rollenprofil für Mitarbeiter aus den Finanzfunktionen ableiten lässt, beispielsweise mit dem „Controller“ oder Finanzmanager als Risk & Crisis Manager?
- Kann man künftig eine klare Abgrenzung schaffen oder wird Controlling mehr als ein Teil der größer gefassten Finanzfunktion betrachtet werden?

Questions for Key Informant #4 CFO Procurement and Legal

- Was sind die wesentlichen Aspekte für die Zukunft der Finanzfunktion bei Ihrem Unternehmen und welche Rolle spielt dabei das Thema „Best Finance Team“?
- Welche Aspekte fallen bei Ihnen unter „Best Finance Team“ und warum?
- Wie würden Sie die Zukunft der Talentakquise bei Ihnen beschreiben? Was sind Aspekte, die besonders wichtig werden?

- Anknüpfend daran, wie würden Sie die Zukunft und die inhaltlichen Pläne der Talentförderung und Weiterentwicklung von Mitarbeiterinnen und Mitarbeitern bei Ihnen beschreiben?
- Welche Eigenschaften werden Ihrer Meinung nach bei künftigen Mitarbeiterinnen und Mitarbeitern in Controlling und in den Finance Funktionen besonders wichtig werden?
- Kann man künftig eine klare Abgrenzung schaffen oder wird Controlling mehr als ein Teil der größer gefassten Finanzfunktion betrachtet werden?

Questions for Key Informant #5 CFO Mobility

- Was sind für Sie die wichtigsten Aspekte und Treiber im Rahmen der Zukunft der Finanzfunktion und des Controllings?
- Was sind die wesentlichen Aspekte für die Zukunft der Finanzfunktion und welche Rolle spielt dabei das Thema „Cash is king“?
- Welche `Priorität hat das Thema „Cash is king“ bei Ihnen?
- Wird das Thema der Cash-Orientierung bei Ihnen in Ihren Augen stärker priorisiert, als bei anderen vergleichbaren Unternehmen?
- Warum ist das Thema des Cash-Managements generell bei Ihnen wichtiger geworden?
- Welche Themen für die Finanzfunktion sehen Sie künftig als besonders wichtig an und welche Hürden sehen Sie künftig bei diesen Themen, die Unternehmen nehmen müssen?

- Welche gänzlichen neuen Themen kommen Ihrer Ansicht nach künftig auf die Finanzfunktion zu bzw. müssen von dieser beachtet werden?
- Welche Priorität ordnen Sie dem Thema der Digitalisierung zu?
- In Bezug auf Künstliche Intelligenz: Welche Rolle spielen Ihrer Meinung nach Verständlichkeit und damit Reduzierung der KI als Black Box und die Klärung von Haftungsfragen beim Umgang mit Outputs einer KI?
- Welche Priorität ordnen Sie der Nachhaltigkeit zu und welche Rolle spielt hier auch die Messbarkeit von Daten?
- Welche Priorität ordnen Sie dem Thema des Risikomanagements zu und denken Sie, dass Risiken künftig besser antizipiert werden können?
- Welche Rollenprofile werden, neben der klassische Business Partner Rolle, Ihrer Meinung nach künftig für Mitarbeiterinnen und Mitarbeiter in der Finance Funktion wichtiger und warum?

Questions for Key Informant #6 CFO IT Services

- Was sind die wesentlichen Aspekte für die Zukunft der Finanzfunktion bei Ihrem Unternehmen und welche Rolle spielt dabei das Thema „Sustainability“?
- Ist das Thema der Nachhaltigkeit ein Aspekt, der auch Auswirkungen auf das Selbstverständnis der Finanzfunktion und die Unternehmenskultur bei Ihnen hat?
- Welche Aspekte fallen bei Ihnen unter den definierten „Sustainability Expert“ Schwerpunkt und warum?
- Welche Eigenschaften muss ein „Sustainability Expert“ mitbringen und warum?
- Welche Aufgaben fallen unter diesen Rollenprofil bei Ihnen?

- Was sind die zentralen Hürden im Rahmen der Integration von Nachhaltigkeitswerten in Reporting und Steuerung?
- Welche Rolle spielen Datenqualität und Echtzeitdaten im Rahmen von Nachhaltigkeits-Reporting?
- Ist die Zuordnung von Verantwortlichkeiten eine Schwierigkeit, die im Rahmen der Messung von Nachhaltigkeit und auch der Steuerung von Nachhaltigkeit Ihrer Meinung nach in Ihrem Unternehmen vorliegt?
- Woran orientieren Sie sich bei der Integration von Nachhaltigkeitsmessungen und Nachhaltigkeitssteuerung? Welche Rolle spielen Vergleiche mit Wettbewerbern und gesetzliche Vorgaben hierbei?
- Was sind Ihrer Ansicht nach weitere Themenfelder oder Hürden, denen sich die Finance Funktion in Bezug auf Nachhaltigkeit und ESG künftig stellen müssen?

Questions for Key Informant #7 CFO Global Finance

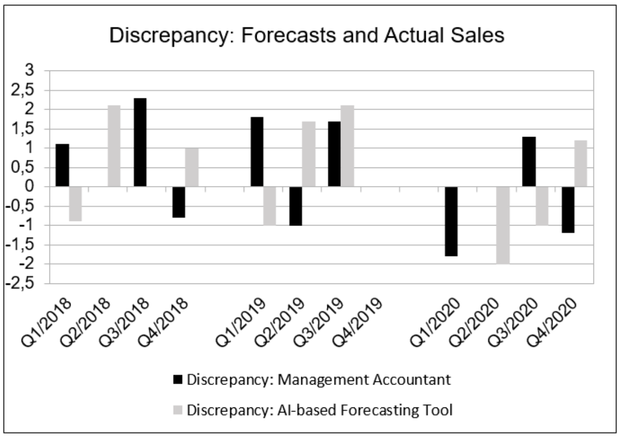
- Welche Themen spielen Ihrer Ansicht nach für die Zukunft der Finanzfunktion eine besonders Rolle?
- Welche neuen Themen oder Spezialthemen kommen Ihrer Ansicht nach künftig auf die Finanzfunktion zu?
- Welches Leitbild oder welche Mission ist für Sie besonders wichtig, um die Finance Funktion zu steuern?
- Welche Rolle spielt eine verstärkte Prozesssicht bei Ihnen für die Finance Funktion?

- Ist Ihrer Meinung durch eine ganzheitlichere Betrachtung von KPIs und Prozessen auch der Austausch mit den operativen Funktionen wichtiger geworden?
- Welche Implikationen haben diese Entwicklungen auch für das Aufgabenprofil des Controllers und wie man sich fachlich für die Rolle aufstellen muss?
- Welche Rolle spielen Kommunikationsfähigkeiten und Storytelling für (künftige) Controller?
- Welchen Stellenwert nimmt Ihrer Ansicht nach die Digitalisierung in der Finance Funktion ein und welche Rolle spielt hier die Künstliche Intelligenz?
- Kommt Künstliche Intelligenz bei Ihnen derzeit schon zum Einsatz und wenn ja, welche Anwendungsfälle wurden hier gewählt?
- Welche Schwerpunkte im Rahmen der Digitalisierung sollen innerhalb der Finance Funktion künftig gelegt werden?
- Wie hat sich die Rolle des CFOs bislang entwickelt und verändert?
- Wie würden Sie die künftige Entwicklung der CFO-Rolle einschätzen?
- Welche (neuen) fachlichen Themen werden für CFOs künftig besonders wichtig werden?
- Wie leisten CFOs einen Beitrag dazu, dass Nachwuchscontroller auf künftige Themen und Herausforderungen und gut vorbereitet sind?

Appendix B Study 3 – Experiment 1

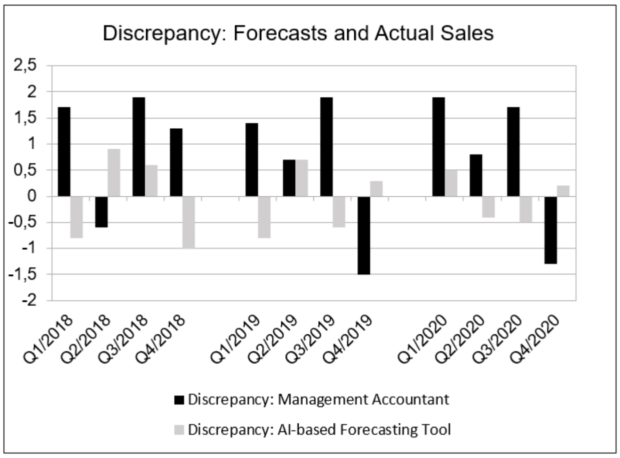
Information on Forecast Accuracy

Panel A: Equal Accuracy



	Forecast of Management Accountant	AI-based Forecasting Tool	*Actual*
Q1/2018	6,2	4,2	5,1
Q2/2018	3,9	6	3,9
Q3/2018	-0,2	-2,5	-2,5
Q4/2018	5,6	7,4	6,4
Q1/2019	7,5	4,7	5,7
Q2/2019	3,2	5,9	4,2
Q3/2019	-1,8	-1,4	-3,5
Q4/2019	5,8	5,8	5,8
Q1/2020	2,9	4,7	4,7
Q2/2020	4,1	2,1	4,1
Q3/2020	-2	-4,3	-3,3
Q4/2020	5,2	7,6	6,4*

Panel B: Higher Accuracy



	Forecast of Management Accountant	AI-based Forecasting Tool	*Actual*
Q1/2018	6,8	4,3	5,1
Q2/2018	3,3	4,8	3,9
Q3/2018	-0,6	-1,9	-2,5
Q4/2018	7,7	5,4	6,4
Q1/2019	7,1	4,9	5,7
Q2/2019	4,9	4,9	4,2
Q3/2019	-1,6	-4,1	-3,5
Q4/2019	4,3	6,1	5,8
Q1/2020	6,6	5,2	4,7
Q2/2020	4,9	3,7	4,1
Q3/2020	-1,6	-3,8	-3,3
Q4/2020	5,1	6,6	6,4*

Note: This part of the appendix is also part of the submitted research paper.

Appendix C Study 3 – Experiment 2

Supplementary Explanation for the Second Forecast

Explanation (AI, Human)

The [Artificial intelligence (AI)-based forecasting tool / management accountant B] uses a large amount of current and past-related data from the company, but also e.g. from social media. [It / He] determines patterns in this data and uses this as a basis to forecast the development of sales. For the forecast of the second quarter of 2021, [the AI-tool / management accountant B] gives a seasonal trend pattern as the reasons for [its/his] forecast, in which the sales development decreases slightly from the first to the second quarter, the third quarter is typically very weak, but the fourth quarter is again very strong. In addition to this seasonal pattern, [the AI-tool / management accountant B] determined a base turnover and adjusted it with the seasonal pattern found.

Note: This part of the appendix is also part of the submitted research paper.

Appendix D Study 3 – Experimental Design

Note: The experimental design of experiment 1 and experiment 2 from study 3 have the same structure. Only the forecast values differ (see Appendix B) and Experiment 1 had no additional explanation for the second forecast (see Appendix C). Accordingly, the following Appendix D refers to the second experiment of the third study; changes in the first experiment are shown in Appendix B.

Version 1: AI Better

Note: Description of the situation is the same for all versions

Situationsbeschreibung

Stellen Sie sich vor, Ihnen wurde vor kurzem die Leitung des Controllings für den Geschäftsbereich Tobix des Konsumgüterunternehmens Bento AG übertragen. Eine Ihrer wichtigsten Aufgaben ist es, der Ihnen vorgesetzten Geschäftsleitung der Bento AG eine Prognose der Umsatzentwicklung für den Geschäftsbereich Tobix für das kommende Quartal zu melden.

Für die Geschäftsleitung der Bento AG ist die erwartete Umsatzentwicklung eine sehr wichtige Information für die Steuerung des Gesamtunternehmens. Es ist daher absolut entscheidend, dass die von Ihnen berichtete Prognose der Umsatzentwicklung im Geschäftsbereich Tobix möglichst nahe an der tatsächlichen Umsatzentwicklung liegt. Die

Geschäftsleitung erwartet von Ihnen als Prognose den Wert, den Sie für den realistischsten bzw. wahrscheinlichsten halten.

Sie wissen, dass sich der Geschäftsbereich Tobix seit März 2020 äußerst robust gegen Auswirkungen der Corona Krise erwiesen hat, die für die Umsatzentwicklung keine Rolle gespielt hat.

In Ihrer Funktion als Leitung des Controllings im Geschäftsbereich Tobix ist für Ihre Performanceevaluation nur relevant, wie zutreffend Ihre Prognosen sind. Sie erhalten einen Bonus, der umso höher ausfällt, je besser die von Ihnen an die Geschäftsleitung der Bento AG übermittelte Prognose der tatsächlichen Umsatzentwicklung im Geschäftsbereich Tobix entspricht. Ein Unterschätzen der Umsatzentwicklung ist hierbei ebenso problematisch wie ein Überschätzen.

- Bei einer Abweichung zwischen Ihrer gemeldeten Prognose und der tatsächlichen Umsatzentwicklung von mehr als 3 Prozentpunkten erhalten Sie keinen Bonus.
- Bei einer Abweichung von 2 bis maximal 3 Prozentpunkten erhalten Sie einen Bonus in Höhe von 50 mingle-Punkten.
- Bei einer Abweichung von 1 bis unter 2 Prozentpunkten erhalten Sie einen Bonus in Höhe von 100 mingle-Punkten.
- Bei einer Abweichung von unter einem Prozentpunkt erhalten Sie einen Bonus in Höhe von 200 mingle-Punkten.

Ihre Aufgabe

Der zuständige Sachbearbeiter im Controlling hat für Sie eine Prognose für die Umsatzentwicklung im nächsten Quartal mit traditionellen Prognoseinstrumenten erstellt. Daneben erhalten Sie eine zweite Prognose durch ein im Controlling parallel entwickeltes

Prognoseinstrument, das Methoden Künstlicher Intelligenz (KI) einsetzt. Mit diesem KI-Instrument wurden bereits in den letzten drei Jahren parallel Prognosen erstellt. In Ihrer Funktion erhalten Sie beide Prognosen. Sie sind jedoch frei, wie Sie die Prognosen verwenden.

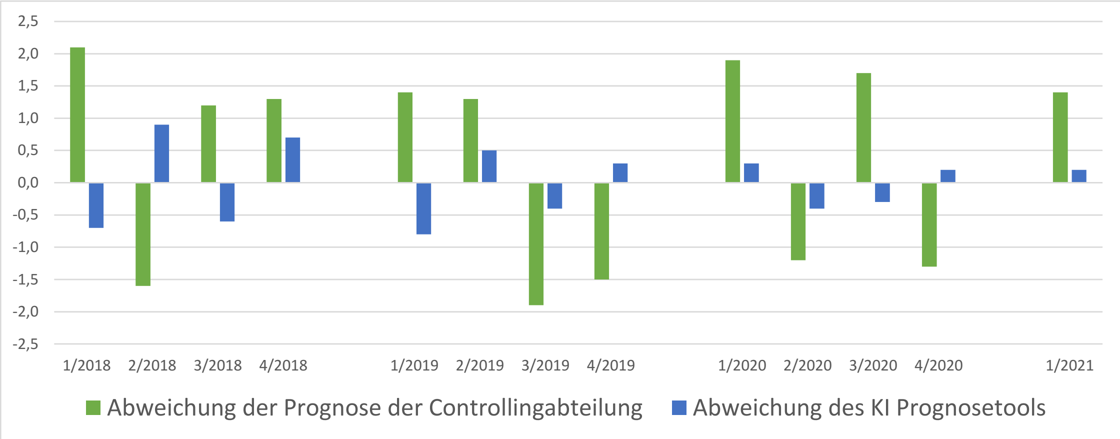
Damit Sie sich einen Eindruck über die Qualität der Prognosen aus der Controllingabteilung und dem auf Künstlicher Intelligenz basierenden Prognoseinstrument verschaffen können, liegen Ihnen die beiden Prognosen der Umsatzentwicklung für den Geschäftsbereich Tobix für die letzten drei Jahre sowie für das erste Quartal in 2021 zusammen mit der jeweils tatsächlich eingetretenen Umsatzentwicklung vor.

Prognosen der Controllingabteilung und Prognose des KI Prognosetools

Quartal/Jahr	Prognose der Controllingabteilung	KI-basiertes Prognosetool	Ist
1/2018	7,5	4,7	5,4
2/2018	2,3	4,8	3,9
3/2018	-1,3	-3,1	-2,5
4/2018	7,7	7,1	6,4
1/2019	6,5	4,3	5,1
2/2019	6,2	5,4	4,9
3/2019	-5,4	-3,9	-3,5
4/2019	4,3	6,1	5,8
1/2020	7,2	5,6	5,3
2/2020	2,2	3,0	3,4
3/2020	-1,6	-3,6	-3,3
4/2020	5,1	6,6	6,4
1/2021	6,6	5,4	5,2

Hinweis: Die Umsatzentwicklung für das 1. Quartal 2021 ist eine Hochrechnung

Abweichungen beider Prognosen zum Ist-Wert. Je geringer die Abweichungen, desto besser die Prognose, **je kleiner ein Balken, desto besser ist die Vorhersage**.



Für das 2. Quartal 2021 schätzt die Controllingabteilung das Umsatzwachstum für Ihren Geschäftsbereich auf +3.4 %.

Das auf Künstlicher Intelligenz (KI) basierende Prognoseinstrument schätzt das Umsatzwachstum für Ihren Geschäftsbereich auf +4.9 %.

Version 2: AI Better (see V1) with Explanation

Das KI-basierte Prognose Tool gibt für seine Prognose die folgende Begründung:

Die künstliche Intelligenz (KI) verwendet eine große Menge an aktuellen und vergangenheitsbezogenen Daten aus dem Unternehmen, aber auch z.B. den sozialen Medien. Sie ermittelt in diesen Daten Muster und prognostiziert auf dieser Basis die Umsatzentwicklung. Für die Prognose des zweiten Quartals 2021 gibt die KI als Gründe für ihre Prognose ein saisonales Trendmuster an, bei dem die Umsatzentwicklung vom ersten zum zweiten Quartal hin etwas absinkt, das dritte Quartal typischerweise sehr schwach ist, das vierte

Quartal jedoch wieder sehr stark. Neben diesem saisonalen Muster hat die KI einen Sockelumsatz ermittelt und diesen mit dem gefundenen saisonalen Muster angepasst.

Version 3: AI Equal

Ihre Aufgabe

Der zuständige Sachbearbeiter im Controlling hat für Sie eine Prognose für die Umsatzentwicklung im nächsten Quartal mit traditionellen Prognoseinstrumenten erstellt. Daneben erhalten Sie eine zweite Prognose durch ein im Controlling parallel entwickeltes Prognoseinstrument, das Methoden Künstlicher Intelligenz (KI) einsetzt. Mit diesem KI-Instrument wurden bereits in den letzten drei Jahren parallel Prognosen erstellt. In Ihrer Funktion erhalten Sie beide Prognosen. Sie sind jedoch frei, wie Sie die Prognosen verwenden.

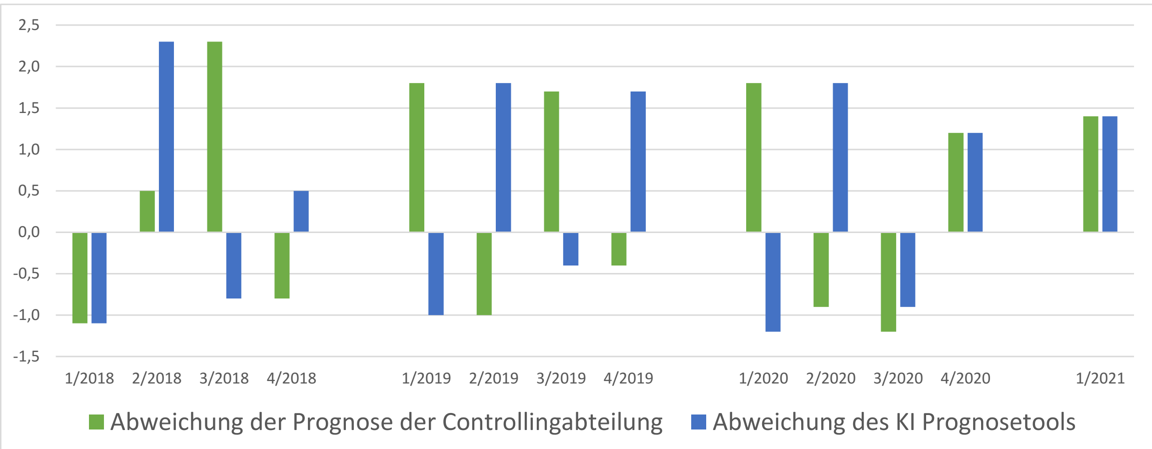
Damit Sie sich einen Eindruck über die Qualität der Prognosen aus der Controllingabteilung und dem auf Künstlicher Intelligenz basierenden Prognoseinstrument verschaffen können, liegen Ihnen die beiden Prognosen der Umsatzentwicklung für den Geschäftsbereich Tobix für die letzten drei Jahre zusammen sowie für das erste Quartal in 2021 mit der jeweils tatsächlich eingetretenen Umsatzentwicklung vor.

Prognosen der Controllingabteilung und Prognose des KI Prognosetools

Quartal/Jahr	Prognose der Controllingabteilung	KI-basiertes Prognosetool	Ist
1/2018	4,3	4,3	5,4
2/2018	4,4	6,2	3,9
3/2018	-0,2	-3,3	-2,5
4/2018	5,6	6,9	6,4
1/2019	6,9	4,1	5,1
2/2019	3,9	6,7	4,9
3/2019	-1,8	-3,9	-3,5
4/2019	5,4	7,5	5,8
1/2020	7,1	4,1	5,3
2/2020	2,5	5,2	3,4
3/2020	-4,5	-4,2	-3,3
4/2020	7,6	7,6	6,4
1/2021	6,6	6,6	5,2

Hinweis: Die Umsatzentwicklung für das 1. Quartal 2021 ist eine Hochrechnung

Abweichungen beider Prognosen zum Ist-Wert. Je geringer die Abweichungen, desto besser die Prognose, **je kleiner ein Balken, desto besser ist die Vorhersage**.



Für das 2. Quartal 2021 schätzt die Controllingabteilung das Umsatzwachstum für Ihren Geschäftsbereich auf +3.4 %.

Das auf Künstlicher Intelligenz (KI) basierende Prognoseinstrument schätzt das Umsatzwachstum für Ihren Geschäftsbereich auf +4.9 %.

Version 4: AI Equal (see V3) with Explanation

Das KI-basierte Prognose Tool gibt für seine Prognose die folgende Begründung:
Die künstliche Intelligenz (KI) verwendet eine große Menge an aktuellen und vergangenheitsbezogenen Daten aus dem Unternehmen, aber auch z.B. den sozialen Medien. Sie ermittelt in diesen Daten Muster und prognostiziert auf dieser Basis die Umsatzentwicklung. Für die Prognose des zweiten Quartals 2021 gibt die KI als Gründe für ihre Prognose ein saisonales Trendmuster an, bei dem die Umsatzentwicklung vom ersten zum zweiten Quartal hin etwas absinkt, das dritte Quartal typischerweise sehr schwach ist, das vierte Quartal jedoch wieder sehr stark. Neben diesem saisonalen Muster hat die KI einen Sockelumsatz ermittelt und diesen mit dem gefundenen saisonalen Muster angepasst.

Version 5: Management Accountant Better

Ihre Aufgabe

Der zuständige Sachbearbeiter A im Controlling hat für Sie eine Prognose für die Umsatzentwicklung im nächsten Quartal mit traditionellen Prognoseinstrumenten erstellt. Daneben erhalten Sie eine zweite Prognose durch einen zweiten Sachbearbeiter B im Controlling. Beide Sachbearbeiter haben bereits in den letzten drei Jahren parallel

Prognosen erstellt. In Ihrer Funktion erhalten Sie beide Prognosen. Sie sind jedoch frei, wie Sie die Prognosen verwenden.

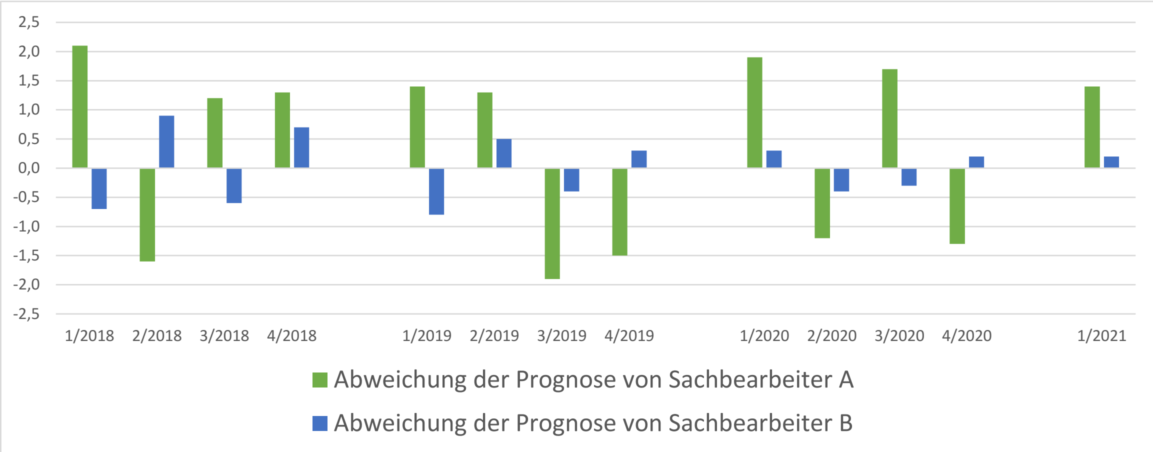
Damit Sie sich einen Eindruck über die Qualität der Prognosen der beiden Sachbearbeiter verschaffen können, liegen Ihnen die beiden Prognosen der Umsatzentwicklung für den Geschäftsbereich Tobix für die letzten drei Jahre zusammen sowie für das erste Quartal in 2021 mit der jeweils tatsächlich eingetretenen Umsatzentwicklung vor.

Prognosen von Sachbearbeiter A und Sachbearbeiter B

Quartal/Jahr	Prognose von Sachbearbeiter A	Prognose von Sachbearbeiter B	Ist
1/2018	7,5	4,7	5,4
2/2018	2,3	4,8	3,9
3/2018	-1,3	-3,1	-2,5
4/2018	7,7	7,1	6,4
1/2019	6,5	4,3	5,1
2/2019	6,2	5,4	4,9
3/2019	-5,4	-3,9	-3,5
4/2019	4,3	6,1	5,8
1/2020	7,2	5,6	5,3
2/2020	2,2	3,0	3,4
3/2020	-1,6	-3,6	-3,3
4/2020	5,1	6,6	6,4
1/2021	6,6	5,4	5,2

Hinweis: Die Umsatzentwicklung für das 1. Quartal 2021 ist eine Hochrechnung

Abweichungen beider Prognosen zum Ist-Wert. Je geringer die Abweichungen, desto besser die Prognose, **je kleiner ein Balken, desto besser ist die Vorhersage**.



Für das 2. Quartal 2021 schätzt Sachbearbeiter A das Umsatzwachstum für Ihren Geschäftsbereich auf +3.4 %.

Der Sachbearbeiter B schätzt das Umsatzwachstum für Ihren Geschäftsbereich auf +4.9 %.

Version 6: Management Accountant Better (see V5) with Explanation

Sachbearbeiter B gibt für seine Prognose die folgende Begründung:

Sachbearbeiter B verwendet eine große Menge an aktuellen und vergangenheitsbezogenen Daten aus dem Unternehmen, aber auch z.B. den sozialen Medien. Er ermittelt in diesen Daten Muster und prognostiziert auf dieser Basis die Umsatzentwicklung. Für die Prognose des zweiten Quartals 2021 gibt Sachbearbeiter B als Gründe für seine Prognose ein saisonales Trendmuster an, bei dem die Umsatzentwicklung vom ersten zum zweiten Quartal hin etwas absinkt, das dritte Quartal typischerweise sehr schwach ist, das vierte Quartal jedoch wieder sehr stark. Neben diesem saisonalen Muster hat Sachbearbeiter B einen Sockelumsatz ermittelt und diesen mit dem gefundenen saisonalen Muster angepasst.

Version 7: Management Accountant Equal

Ihre Aufgabe

Der zuständige Sachbearbeiter A im Controlling hat für Sie eine Prognose für die Umsatzentwicklung im nächsten Quartal mit traditionellen Prognoseinstrumenten erstellt. Daneben erhalten Sie eine zweite Prognose durch einen zweiten Sachbearbeiter B im Controlling. Beide Sachbearbeiter haben bereits in den letzten drei Jahren parallel Prognosen erstellt. In Ihrer Funktion erhalten Sie beide Prognosen. Sie sind jedoch frei, wie Sie die Prognosen verwenden.

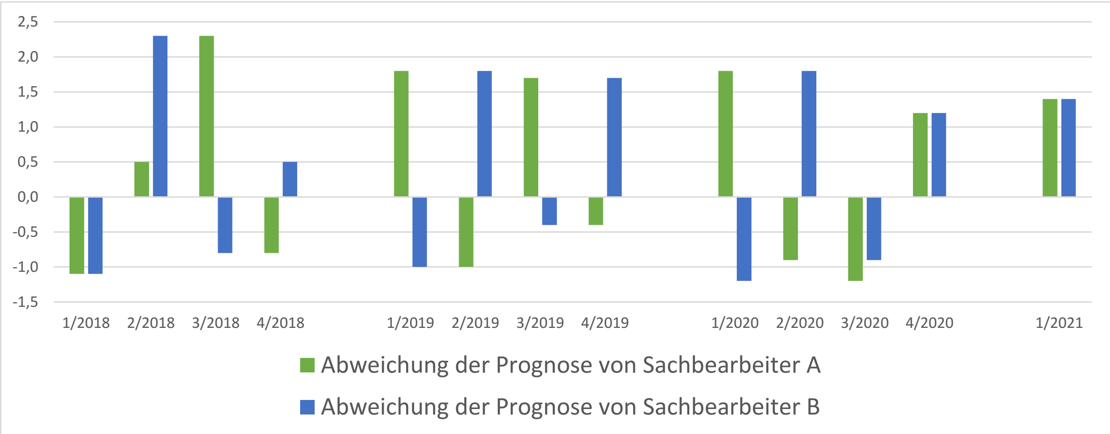
Damit Sie sich einen Eindruck über die Qualität der Prognosen der beiden Sachbearbeiter verschaffen können, liegen Ihnen die beiden Prognosen der Umsatzentwicklung für den Geschäftsbereich Tobix für die letzten drei Jahre zusammen sowie für das erste Quartal in 2021 mit der jeweils tatsächlich eingetretenen Umsatzentwicklung vor.

Prognosen von Sachbearbeiter A und Sachbearbeiter B

Quartal/Jahr	Prognose von Sachbearbeiter A	Prognose von Sachbearbeiter B	Ist
1/2018	4,3	4,3	5,4
2/2018	4,4	6,2	3,9
3/2018	-0,2	-3,3	-2,5
4/2018	5,6	6,9	6,4
1/2019	6,9	4,1	5,1
2/2019	3,9	6,7	4,9
3/2019	-1,8	-3,9	-3,5
4/2019	5,4	7,5	5,8
1/2020	7,1	4,1	5,3
2/2020	2,5	5,2	3,4
3/2020	-4,5	-4,2	-3,3
4/2020	7,6	7,6	6,4
1/2021	6,6	6,6	5,2

Hinweis: Die Umsatzentwicklung für das 1. Quartal 2021 ist eine Hochrechnung

Abweichungen beider Prognosen zum Ist-Wert. Je geringer die Abweichungen, desto besser die Prognose, **je kleiner ein Balken, desto besser ist die Vorhersage**.



Für das 2. Quartal 2021 schätzt Sachbearbeiter A das Umsatzwachstum für Ihren Geschäftsbereich auf +3.4 %.

Der Sachbearbeiter B schätzt das Umsatzwachstum für Ihren Geschäftsbereich auf +4.9 %.

Version 8: Management Accountant Equal (see V7) with Explanation

Sachbearbeiter B gibt für seine Prognose die folgende Begründung:

Sachbearbeiter B verwendet eine große Menge an aktuellen und vergangenheitsbezogenen Daten aus dem Unternehmen, aber auch z.B. den sozialen Medien. Er ermittelt in diesen Daten Muster und prognostiziert auf dieser Basis die Umsatzentwicklung. Für die Prognose des zweiten Quartals 2021 gibt Sachbearbeiter B als Gründe für seine Prognose ein saisonales Trendmuster an, bei dem die Umsatzentwicklung vom ersten zum zweiten

Quartal hin etwas absinkt, das dritte Quartal typischerweise sehr schwach ist, das vierte Quartal jedoch wieder sehr stark. Neben diesem saisonalen Muster hat Sachbearbeiter B einen Sockelumsatz ermittelt und diesen mit dem gefundenen saisonalen Muster angepasst.

Version 9: AI

Ihre Aufgabe

Der zuständige Sachbearbeiter im Controlling hat für Sie eine Prognose für die Umsatzentwicklung im nächsten Quartal mit traditionellen Prognoseinstrumenten erstellt. Daneben erhalten Sie eine zweite Prognose durch ein im Controlling parallel entwickeltes Prognoseinstrument, das Methoden Künstlicher Intelligenz (KI) einsetzt. Mit diesem KI-Instrument wurden bereits in den letzten drei Jahren parallel Prognosen erstellt. In Ihrer Funktion erhalten Sie beide Prognosen. Sie sind jedoch frei, wie Sie die Prognosen verwenden.

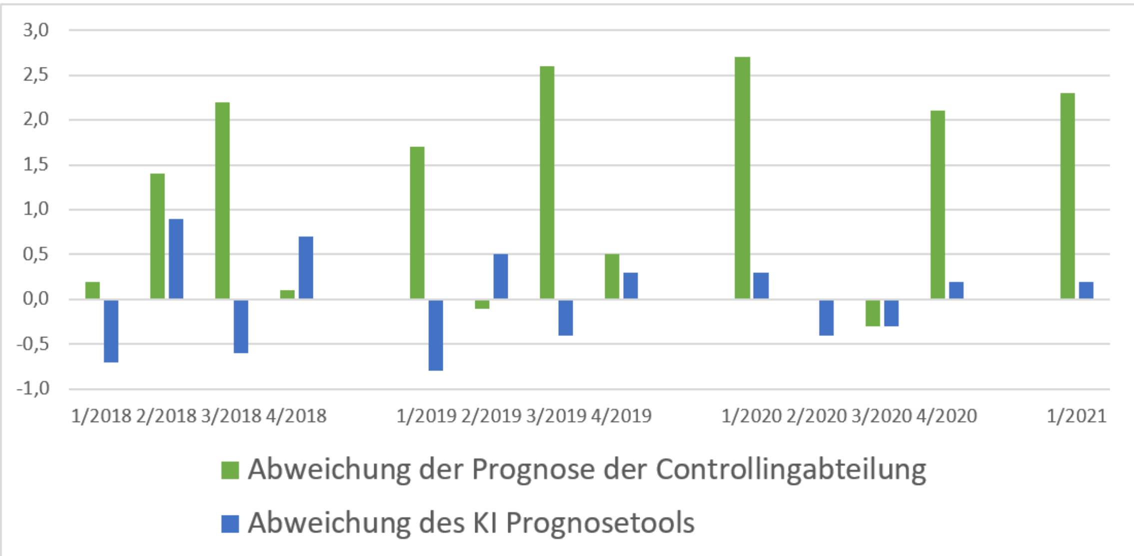
Damit Sie sich einen Eindruck über die Qualität der Prognosen aus der Controllingabteilung und dem auf Künstlicher Intelligenz basierenden Prognoseinstrument verschaffen können, liegen Ihnen die beiden Prognosen der Umsatzentwicklung für den Geschäftsbereich Tobix für die letzten drei Jahre sowie für das erste Quartal in 2021 zusammen mit der jeweils tatsächlich eingetretenen Umsatzentwicklung vor.

Prognosen der Controllingabteilung und Prognose des KI Prognosetools

Quartal/Jahr	Prognose der Controllingabteilung	KI-basiertes Prognosetool	Ist
1/2018	5,6	4,7	5,4
2/2018	5,3	4,8	3,9
3/2018	-0,3	-3,1	-2,5
4/2018	6,5	7,1	6,4
1/2019	6,8	4,3	5,1
2/2019	4,8	5,4	4,9
3/2019	-0,9	-3,9	-3,5
4/2019	6,3	6,1	5,8
1/2020	8,0	5,6	5,3
2/2020	3,4	3,0	3,4
3/2020	-3,6	-3,6	-3,3
4/2020	8,5	6,6	6,4
1/2021	7,5	5,4	5,2

Hinweis: Die Umsatzentwicklung für das 1. Quartal 2021 ist eine Hochrechnung

Abweichungen beider Prognosen zum Ist-Wert. Je geringer die Abweichungen, desto besser die Prognose, **je kleiner ein Balken, desto besser ist die Vorhersage**.



Für das 2. Quartal 2021 schätzt die Controllingabteilung das Umsatzwachstum für Ihren Geschäftsbereich auf +4.9 %.

Das auf Künstlicher Intelligenz (KI) basierende Prognoseinstrument schätzt das Umsatzwachstum für Ihren Geschäftsbereich auf +3.4 %.

Version 10: Management Accountant Better (Reverse)

Ihre Aufgabe

Der zuständige Sachbearbeiter A im Controlling hat für Sie eine Prognose für die Umsatzentwicklung im nächsten Quartal mit traditionellen Prognoseinstrumenten erstellt. Daneben erhalten Sie eine zweite Prognose durch einen zweiten Sachbearbeiter B im Controlling. Beide Sachbearbeiter haben bereits in den letzten drei Jahren parallel Prognosen erstellt. In Ihrer Funktion erhalten Sie beide Prognosen. Sie sind jedoch frei, wie Sie die Prognosen verwenden.

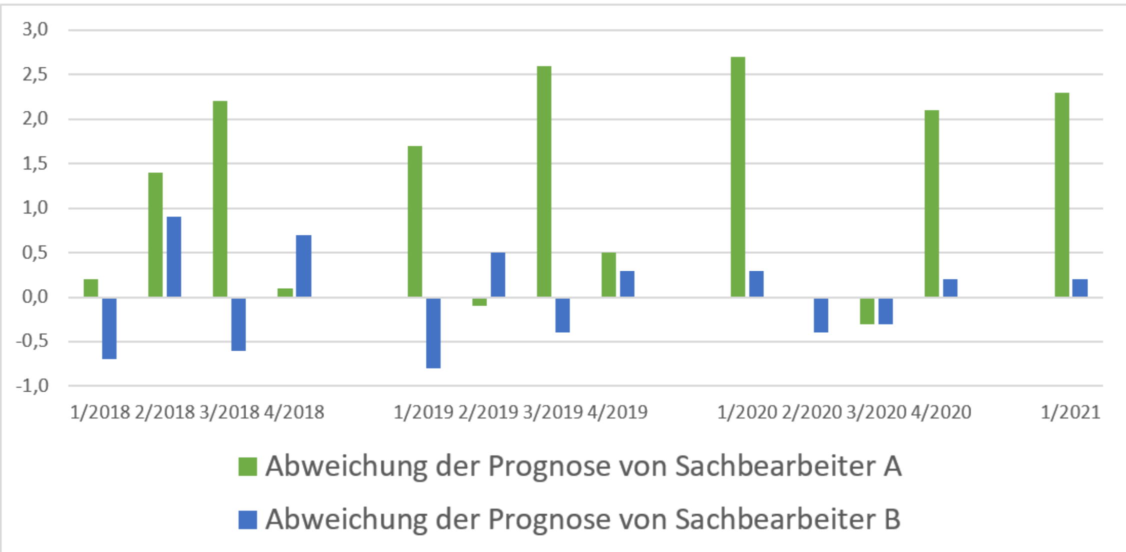
Damit Sie sich einen Eindruck über die Qualität der Prognosen der beiden Sachbearbeiter verschaffen können, liegen Ihnen die beiden Prognosen der Umsatzentwicklung für den Geschäftsbereich Tobix für die letzten drei Jahre zusammen sowie für das erste Quartal in 2021 mit der jeweils tatsächlich eingetretenen Umsatzentwicklung vor.

Prognosen von Sachbearbeiter A und Sachbearbeiter B

Quartal/Jahr	Prognose von Sachbearbeiter A	Prognose von Sachbearbeiter B	Ist
1/2018	5,6	4,7	5,4
2/2018	5,3	4,8	3,9
3/2018	-0,3	-3,1	-2,5
4/2018	6,5	7,1	6,4
1/2019	6,8	4,3	5,1
2/2019	4,8	5,4	4,9
3/2019	-0,9	-3,9	-3,5
4/2019	6,3	6,1	5,8
1/2020	8,0	5,6	5,3
2/2020	3,4	3,0	3,4
3/2020	-3,6	-3,6	-3,3
4/2020	8,5	6,6	6,4
1/2021	7,5	5,4	5,2

Hinweis: Die Umsatzentwicklung für das 1. Quartal 2021 ist eine Hochrechnung

Abweichungen beider Prognosen zum Ist-Wert. Je geringer die Abweichungen, desto besser die Prognose, **je kleiner ein Balken, desto besser ist die Vorhersage**.



Für das 2. Quartal 2021 schätzt Sachbearbeiter A das Umsatzwachstum für Ihren Geschäftsbereich auf +4.9 %.

Der Sachbearbeiter B schätzt das Umsatzwachstum für Ihren Geschäftsbereich auf +3.4 %.

Version 11: No Alternative

Ihre Aufgabe

Der zuständige Sachbearbeiter im Controlling hat für Sie eine Prognose für die Umsatzentwicklung im nächsten Quartal mit traditionellen Prognoseinstrumenten erstellt. Sie sind jedoch frei, wie Sie die Prognosen verwenden.

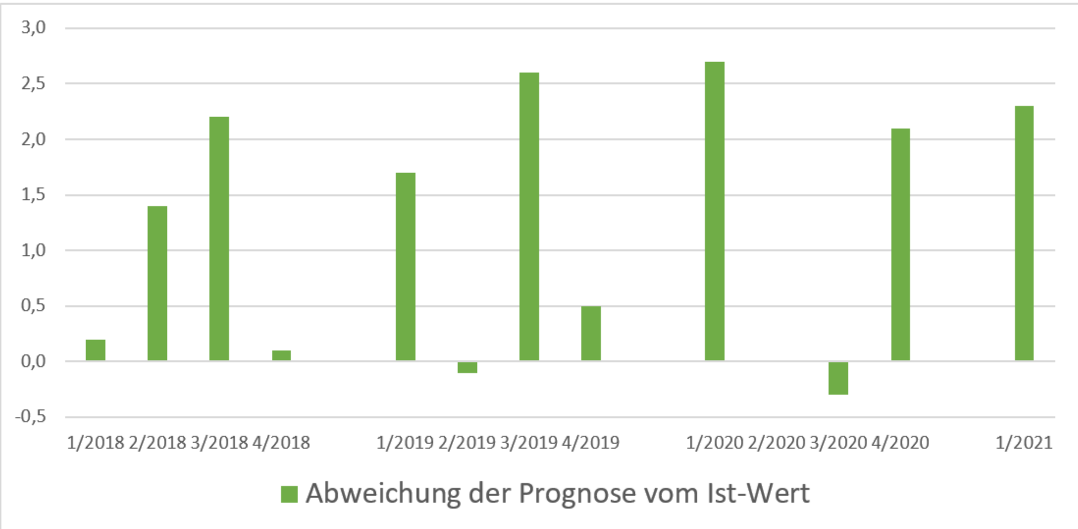
Damit Sie sich einen Eindruck über die Qualität der Prognosen des Sachbearbeiters verschaffen können, liegen Ihnen die Prognosen der Umsatzentwicklung für den Geschäftsbereich Tobix für die letzten drei Jahre zusammen sowie für das erste Quartal in 2021 mit der jeweils tatsächlich eingetretenen Umsatzentwicklung vor.

Prognosen des Sachbearbeiters

Quartal/Jahr	Prognose des Sachbearbeiters	Ist
1/2018	5,6	5,4
2/2018	5,3	3,9
3/2018	-0,3	-2,5
4/2018	6,5	6,4
1/2019	6,8	5,1
2/2019	4,8	4,9
3/2019	-0,9	-3,5
4/2019	6,3	5,8
1/2020	8,0	5,3
2/2020	3,4	3,4
3/2020	-3,6	-3,3
4/2020	8,5	6,4
1/2021	7,5	5,2

Hinweis: Die Umsatzentwicklung für das 1. Quartal 2021 ist eine Hochrechnung

Abweichungen der Prognosen zum Ist-Wert. Je geringer die Abweichungen, desto besser die Prognose, **je kleiner ein Balken, desto besser ist die Vorhersage**.



Für das 2. Quartal 2021 schätzt der Sachbearbeiter das Umsatzwachstum für Ihren Geschäftsbereich auf +4.9 %.

Appendix E Study 4 – Experimental Design

Version 1: Clerk A and B are equally as good

Note: Description of the situation is the same for every version

Situation description in the agricultural sector

You work in a company called Plantion Corporation, which is active in the agricultural sector. Your function is at the interface between management and production controlling. One of your core tasks is the preparation of yield forecasts.

Your company owns various acreages for cereals. Recently, your company has acquired new arable land for further wheat cultivation, on which wheat has now been sown for the first time. You are asked by your supervisor to determine the wheat yield (in tons per hectare) to be expected in the coming year on the newly acquired arable land.

In your function, the only relevant factor for your performance evaluation is how accurate your forecasts are, so that you can appropriately coordinate your tasks in downstream or upstream areas of agriculture, such as the food industry, and properly structure contracts with your business partners. You will receive a bonus, which will be higher the better the yield quantity forecast you submit to the management of Plantion Corporation corresponds to the actual yield quantity. Underestimating the yield quantity is just as problematic as overestimating it.

In order to be able to make a precise forecast of the yield of the new wheat field D for the year 2022, you firstly obtain the forecast that the responsible clerk A from production controlling makes for the area in question.

/* Human

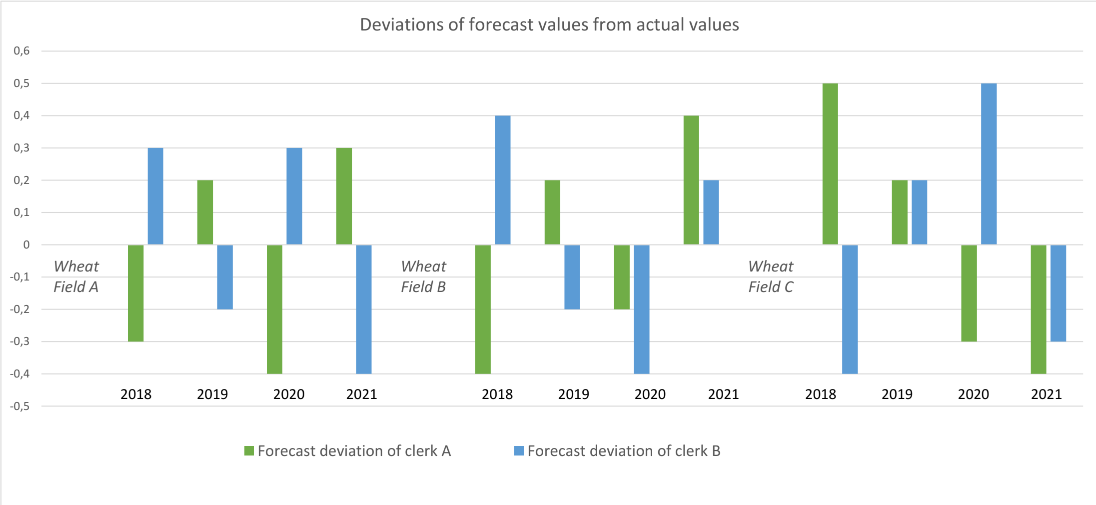
On the other hand, the production controllers also send you the forecast of a second clerk B, who creates a forecast in parallel to the production department. Currently, the two forecasts, i.e. the forecast of production controlling (clerk A) and the forecast of clerk B, run in parallel in your company.

Your Forecasting Decision

It is your task to report a forecast of the yield of the new wheat field D for the year 2022 to the management.

In order to assess the quality of the forecasts of the controlling department itself (clerk A) and clerk B, you have the following information on the past accuracy of the two forecasters:

		Forecast of clerk A	Forecast of clerk B	Actual value
Year	*Field*			
2018	A	7,5	8,1	7,8
2019	A	7,6	7,2	7,4
2020	A	6,6	7,3	7,0
2021	A	7,5	6,8	7,2
2018	B	7,2	8,0	7,6
2019	B	7,5	7,1	7,3
2020	B	7,0	6,8	7,2
2021	B	7,9	7,7	7,5
2018	C	8,0	7,1	7,5
2019	C	6,7	6,7	6,5
2020	C	6,2	7,0	6,5
2021	C	7,1	7,2	7,5



Notes

The graph shows the deviations of both forecasts from the actual value. The smaller the deviations, the better the forecast, i.e. the smaller a bar, the better the forecast. If there is no bar (directly next to the respective different colored bar), there is no deviation of the forecast from the actual value.

/* Manipulation

Based on past data, you find that the yield quantity forecasts of clerk B **was equally as good** in the past.

Current projections for the new wheat field D in 2022 are as follows:

Production controlling/ Clerk A estimates a yield of **7.5 tons** per hectare.

Clerk B estimates a yield of **6.5 tons** per hectare.

Version 2: Clerk B performs better

In order to be able to make a precise forecast of the yield of the new wheat field D for the year 2022, you firstly obtain the forecast that the responsible clerk A from production controlling makes for the area in question.

/* Human

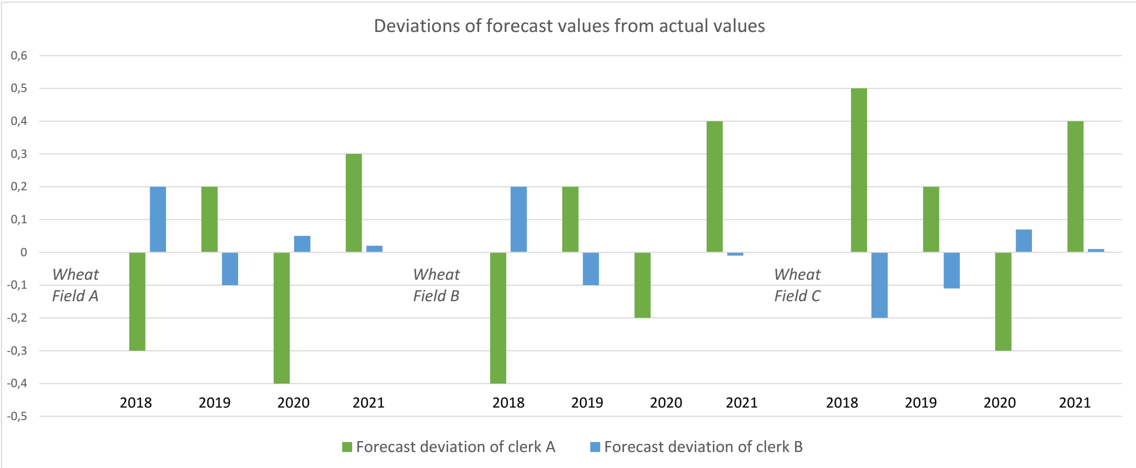
On the other hand, the production controllers also send you the forecast of a second clerk B, who creates a forecast in parallel to the production department. Currently, the two forecasts, i.e. the forecast of production controlling (clerk A) and the forecast of clerk B, run in parallel in your company.

Your Forecasting Decision

It is your task to report a forecast of the yield of the new wheat field D for the year 2022 to the management.

In order to assess the quality of the forecasts of the controlling department itself (clerk A) and clerk B, you have the following information on the past accuracy of the two forecasters:

		Forecast of clerk A	Forecast of clerk B	Actual value
Year	*Field*			
2018	A	7,5	8,0	7,8
2019	A	7,6	7,3	7,4
2020	A	6,6	7,1	7,0
2021	A	7,5	7,2	7,2
2018	B	7,2	7,8	7,6
2019	B	7,5	7,2	7,3
2020	B	7,0	7,2	7,2
2021	B	7,9	7,5	7,5
2018	C	8,0	7,3	7,5
2019	C	6,7	6,4	6,5
2020	C	6,2	6,6	6,5
2021	C	7,9	7,5	7,5



Notes

The graph shows the deviations of both forecasts from the actual value. The smaller the deviations, the better the forecast, i.e. the smaller a bar, the better the forecast. If there is no bar (directly next to the respective different colored bar), there is no deviation of the forecast from the actual value.

/* Manipulation

Based on past data, you find that the yield quantity forecasts of clerk B **was significantly better** in the past.

Current projections for the new wheat field D in 2022 are as follows:

Production controlling/ Clerk A estimates a yield of **7.5 tons** per hectare.

Clerk B estimates a yield of **6.5 tons** per hectare.

Version 3: Artificial Intelligence performs better

In order to be able to make a precise forecast of the yield of the new wheat field D for the year 2022, you firstly obtain the forecast that the responsible clerk A from production controlling makes for the area in question.

/* AI

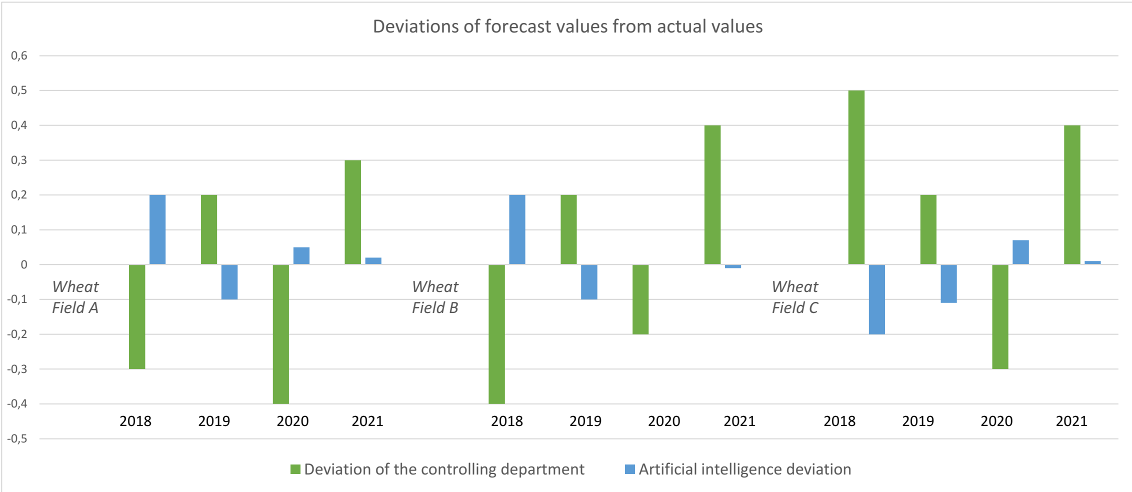
On the other hand, the production controllers also send you the forecast of an artificial intelligence (AI), which was developed in the department for forecasting purposes and has already been tested in the past years. Currently, the two forecasts, i.e. the production controlling forecast and the AI forecast, are running in parallel in your company.

Your Forecasting Decision

It is your task to report a forecast of the yield of the new wheat field D for the year 2022 to the management.

In order to assess the quality of the forecasts of the controlling department itself and the artificial intelligence, you have the following information on the past accuracy:

		Forecast of the controlling department	Forecast of the artificial intelligence	Actual Value
Year	*Field*			
2018	A	7,5	8,0	7,8
2019	A	7,6	7,3	7,4
2020	A	6,6	7,1	7,0
2021	A	7,5	7,2	7,2
2018	B	7,2	7,8	7,6
2019	B	7,5	7,2	7,3
2020	B	7,0	7,2	7,2
2021	B	7,9	7,5	7,5
2018	C	8,0	7,3	7,5
2019	C	6,7	6,4	6,5
2020	C	6,2	6,6	6,5
2021	C	7,9	7,5	7,5



Notes

The graph shows the deviations of both forecasts from the actual value. The smaller the deviations, the better the forecast, i.e. the smaller a bar, the better the forecast. If there is no bar (directly next to the respective different colored bar), there is no deviation of the forecast from the actual value.

/* Manipulation

Based on past data, you find that the yield quantity forecasts of the AI **was significantly better** in the past.

Current projections for the new wheat field D in 2022 are as follows:

Production controlling estimates a yield of **7.5 tons** per hectare.

The artificial intelligence (AI)-based forecasting tool estimates a yield of **6.5 tons** per hectare.

Version 4: Artificial Intelligence performs equally as good

In order to be able to make a precise forecast of the yield of the new wheat field D for the year 2022, you firstly obtain the forecast that the responsible clerk A from production controlling makes for the area in question.

/* AI

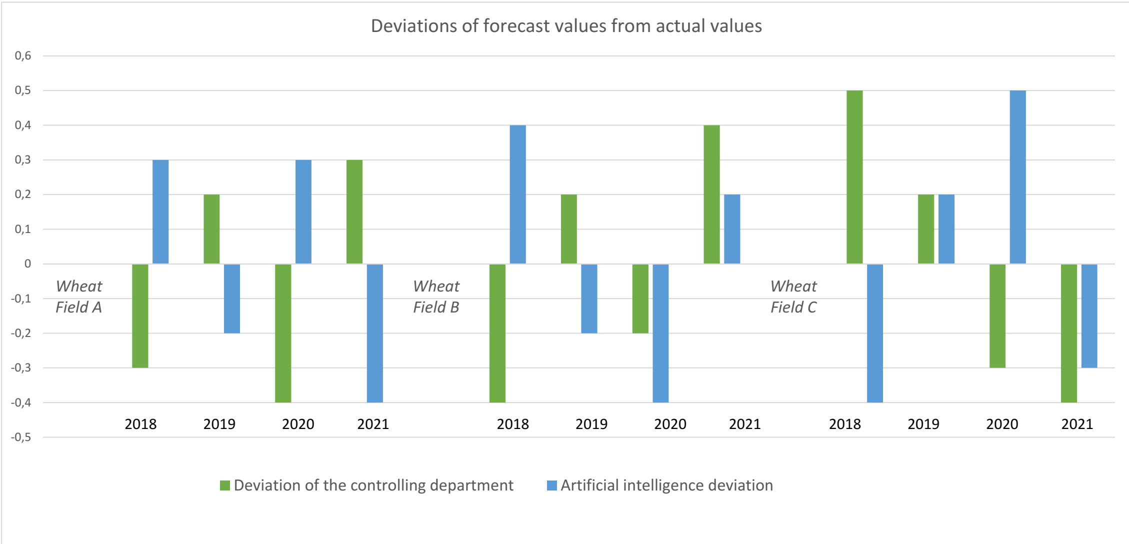
On the other hand, the production controllers also send you the forecast of an artificial intelligence (AI), which was developed in the department for forecasting purposes and has already been tested in the past years. Currently, the two forecasts, i.e. the production controlling forecast and the AI forecast, are running in parallel in your company.

Your Forecasting Decision

It is your task to report a forecast of the yield of the new wheat field D for the year 2022 to the management.

In order to assess the quality of the forecasts of the controlling department itself and the artificial intelligence, you have the following information on the past accuracy:

		Forecast of the controlling department	Forecast of the artificial intelligence	Actual Value
Year	*Field*			
2018	A	7,5	8,1	7,8
2019	A	7,6	7,2	7,4
2020	A	6,6	7,3	7,0
2021	A	7,5	6,8	7,2
2018	B	7,2	8,0	7,6
2019	B	7,5	7,1	7,3
2020	B	7,0	6,8	7,2
2021	B	7,9	7,7	7,5
2018	C	8,0	7,1	7,5
2019	C	6,7	6,7	6,5
2020	C	6,2	7,0	6,5
2021	C	7,1	7,2	7,5



Notes

The graph shows the deviations of both forecasts from the actual value. The smaller the deviations, the better the forecast, i.e. the smaller a bar, the better the forecast. If there is no bar (directly next to the respective different colored bar), there is no deviation of the forecast from the actual value.

/* Manipulation

Based on past data, you find that the yield quantity forecasts of the AI **was equally as good** in the past.

Current projections for the new wheat field D in 2022 are as follows:

Production controlling estimates a yield of **7.5 tons** per hectare.

The artificial intelligence (AI)-based forecasting tool estimates a yield of **6.5 tons** per hectare.

Appendix F Study 5 – Experimental Design

Version 1 and 2: AI performs better (V1 Framing, V2 No Framing)

Note: Description of the situation is the same for every version

Your Situation: Choosing Investments

You are considering various investment opportunities. It is important to you that you achieve an adequate return on your capital investment. In order to invest your capital even better in 2022, you talk to your bank, UBP Investment Bank, to find out about investment opportunities.

In terms of investment options, you are particularly interested in actively managed mutual funds, which seem to you to be a safe investment option both in the short and long term. You are aware that your money is invested in a selection of stocks and that you can expect a possible return at the end of the year. Nevertheless, you are unsure how, for example, market-related price fluctuations or yield risks have to be taken into account when choosing the best investment fund for your money. However, your bank will be happy to help you with this.

The bank offers you two actively managed fund models.

On the one hand, you have an experienced fund manager A from the bank at your side who manages a fund ("ValuePlus").

/* AI

On the other hand, you can choose a fund managed by an Artificial Intelligence (AI) developed internally by the bank ("CapitalStar").

/*FRAMING

Before you make an investment decision, the bank informs you why Artificial Intelligence is now being used in the bank. According to the bank, the Artificial Intelligence ensures much greater efficiency and accuracy of targeting. At the same time, the Artificial Intelligence can arguably incorporate much more global market data than humans into its decision-making and thus better validate investment recommendations. In addition, the Artificial Intelligence is highly tested in the banking and investment sector and shows an extraordinary performance in comparable companies and thus achieves the best possible results for bank customers.

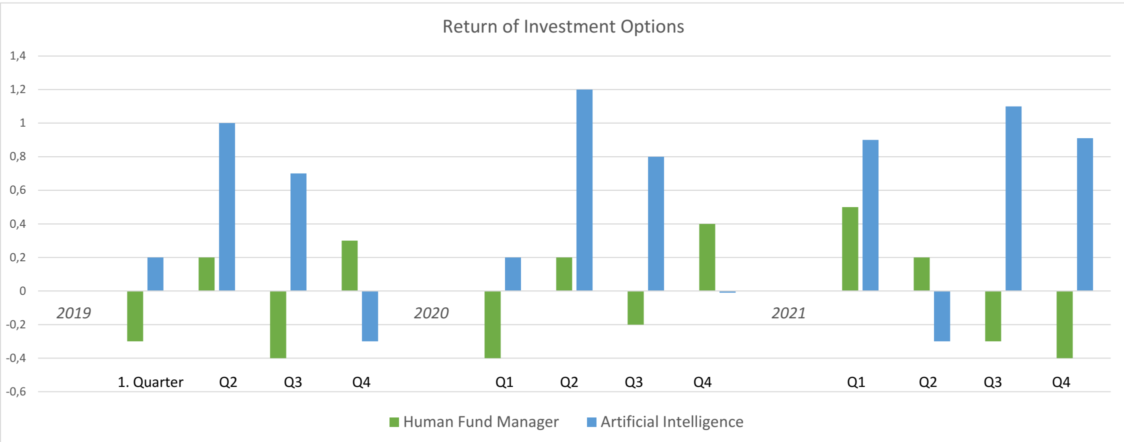
Your Investment Decision

Your task now is to identify the best possible investment option for you.

In order to provide you with comprehensive information on the success of the two offerings, the bank first provides you with some data on the past performance of both funds. First, you will get an overview of the returns of the funds that the Fund Manager A as well as the Artificial Intelligence (AI) have each generated in the past.

/* Manipulation Performance

Year	Quarter	Human Fund Manager	Artificial Intelligence	Base Rate
2019	1	0,9	1,4	1,2
2019	2	0,9	1,7	0,7
2019	3	-2,7	-1,6	-2,3
2019	4	4,6	4,0	4,3
2020	1	0,8	1,4	1,2
2020	2	-14,8	-13,8	-15,0
2020	3	2,8	3,8	3,0
2020	4	18,4	18,0	18,0
2021	1	8,0	8,4	7,5
2021	2	5,6	5,1	5,4
2021	3	2,2	3,6	2,5
2021	4	2,6	3,9	3,0



Notes

The table shows the absolute quarterly performance of the funds, the chart the relative performance of the two funds relative to the overall market

Now that you have sifted through the data, you need to decide: How do you want to invest your money?

Note: This is followed by further questions in the questionnaire.

/* Explanation AI

About how Artificial Intelligence works in principle, the following explanation is available:

Artificial Intelligence was initially programmed based on known factors relevant to stock returns. For its investment decisions, it uses a large amount of current and past data in which it recognizes patterns for successful price developments. However, the AI continuously develops itself and its process on the basis of this data, but is subject to regular internal quality control by the bank.

The data used by the AI are, on the one hand, basic data such as macroeconomic developments, the competitiveness of the companies in the fund, the financial situation of the companies in the fund and past returns with the respective payout date. On the other hand, all relevant key figures such as "Ownership Risk", "Ownership Uncertainty" or "Valuation Uncertainty" are included in the analysis.

Regarding the current composition of the fund, the Artificial Intelligence makes the following statements:

Specifically for the current selection of the most important companies in the fund "CapitalStar", the Artificial Intelligence states that the most important factors for its decision was the competitiveness of the companies. Artificial Intelligence assumes that the companies it selects for the "CapitalStar" fund are so strongly positioned that they will displace competing companies over a long period of time, while generating very high returns.

Now that you have sifted through the data, you need to decide: How do you want to invest your money?

Note: This is followed by further questions in the questionnaire.

Version 3 & 4: Artificial Intelligence is equally as good (V3 Framing, V4 No Framing)

The bank offers two actively managed fund models for you and your investment.

On the one hand, you have an experienced fund manager A from the bank at your side who manages a fund ("ValuePlus").

/* AI

On the other hand, you can choose a fund managed by an artificial intelligence developed internally by the bank "(CapitalStar").

/*FRAMING

Before you make an investment decision, the bank informs you why Artificial Intelligence is now being used in the bank. According to the bank, the Artificial Intelligence ensures much greater efficiency and accuracy of targeting. At the same time, the Artificial Intelligence can arguably incorporate much more global market data than humans into its decision-making and thus better validate investment recommendations. In addition, the Artificial Intelligence is highly tested in the banking and investment sector and shows an extraordinary performance in comparable companies and thus achieves the best possible results for bank customers.

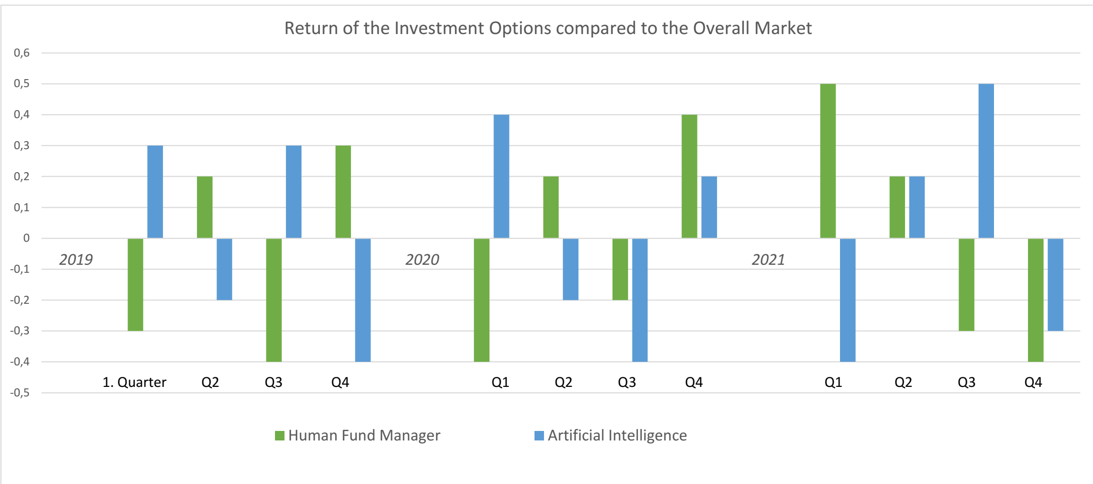
Your Investment Decision

Your task now is to identify the best possible investment option for you.

In order to provide you with comprehensive information on the success of the two offerings, the bank first provides you with some data on the past performance of both funds. First, you will get an overview of the returns of the funds that the fund manager A as well as the AI have each generated in the past.

/* Manipulation

		Human Fund Manager	Artificial Intelligence	Base Rate
Year	*Quarter*			
2019	1	0,9	1,5	1,2
2019	2	0,9	0,5	0,7
2019	3	-2,7	-2,0	-2,3
2019	4	4,6	3,9	4,3
2020	1	0,8	1,6	1,2
2020	2	-14,8	-15,2	-15,0
2020	3	2,8	2,6	3,0
2020	4	18,4	18,2	18,0
2021	1	8,0	7,1	7,5
2021	2	5,6	5,6	5,4
2021	3	2,2	3,0	2,5
2021	4	2,6	2,7	3,0



Notes

The table shows the absolute quarterly performance of the funds, the chart the relative performance of the two funds relative to the overall market

Now that you have sifted through the data, you need to decide: How do you want to invest your money?

Note: This is followed by further questions in the questionnaire.

/* Explanation AI

About how Artificial Intelligence works in principle, the following explanation is available:

Artificial Intelligence was initially programmed based on known factors relevant to stock returns. For its investment decisions, it uses a large amount of current and past data in which it recognizes patterns for successful price developments. However, the AI continuously develops itself and its process on the basis of this data, but is subject to regular internal quality control by the bank.

The data used by the AI are, on the one hand, basic data such as macroeconomic developments, the competitiveness of the companies in the fund, the financial situation of the companies in the fund and past returns with the respective payout date. On the other hand, all relevant key figures such as "Ownership Risk", "Ownership Uncertainty" or "Valuation Uncertainty" are included in the analysis.

Regarding the current composition of the fund, the Artificial Intelligence makes the following statements:

Specifically for the current selection of the most important companies in the fund "CapitalStar", the Artificial Intelligence states that the most important factors for its decision was the competitiveness of the companies. Artificial Intelligence assumes that the companies it selects for the "CapitalStar" fund are so strongly positioned that they will displace competing companies over a long period of time, while generating very high returns.

Now that you have sifted through the data, you need to decide: How do you want to invest your money?

Note: This is followed by further questions in the questionnaire.

Version 5 & 6: Fund manager better (V5 Framing, V6 No Framing)

The bank offers two actively managed fund models for you and your investment.

On the one hand, you have an experienced fund manager A from the bank at your side who manages a fund ("ValuePlus").

/* Human

On the other hand, you can choose a fund managed by a fund manager B "(CapitalStar").

/* Framing

Before you begin with the investment decision, the bank informs you why, in addition to the experienced fund manager A, fund manager B is now also working for the bank. Fund

Manager B was recruited for the bank's investment division because he seems to work very efficiently and precisely. At the same time, he independently obtains an above-average amount of global market data in order to better validate his investment recommendation. In addition, he had many years of experience as a fund manager and probably showed an extraordinary performance and achieved the best possible results for previous customers.

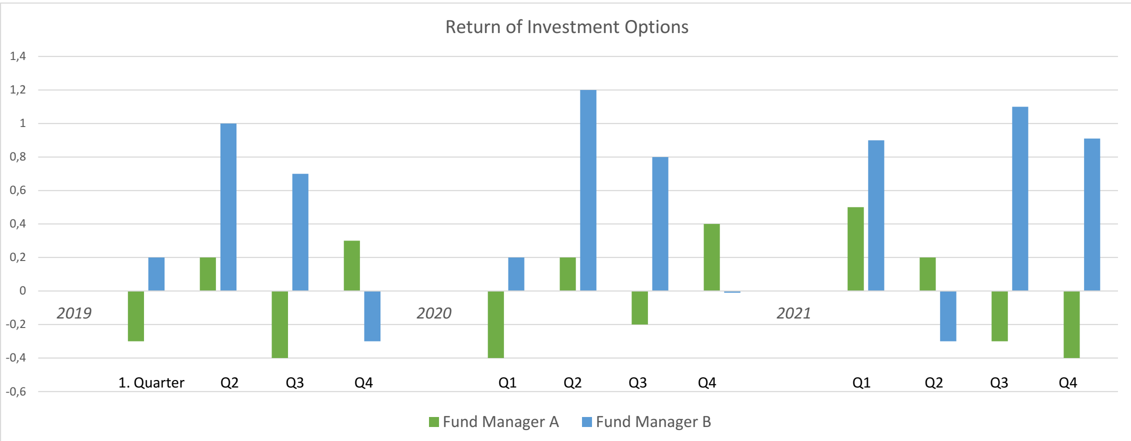
Your Investment Decision

Your task now is to identify the best possible investment option for you.

In order to provide you with comprehensive information on the success of the two offerings, the bank first provides you with some data on the past performance of both funds. First, you will get an overview of the **returns of the funds** that the fund manager A as well as fund manager B have each generated in the past.

/* Manipulation

Year	Quarter	Fund Manager A	Fund Manager B	Base Rate
2019	1	0,9	1,4	1,2
2019	2	0,9	1,7	0,7
2019	3	-2,7	-1,6	-2,3
2019	4	4,6	4,0	4,3
2020	1	0,8	1,4	1,2
2020	2	-14,8	-13,8	-15,0
2020	3	2,8	3,8	3,0
2020	4	18,4	18,0	18,0
2021	1	8,0	8,4	7,5
2021	2	5,6	5,1	5,4
2021	3	2,2	3,6	2,5
2021	4	2,6	3,9	3,0



Notes

The table shows the absolute quarterly performance of the funds, the chart the relative performance of the two funds relative to the overall market.

Now that you have sifted through the data, you need to decide: How do you want to invest your money?

Note: This is followed by further questions in the questionnaire.

/* Explanation human

About how fund manager B manages the fund "Capital Star", the following explanation is available:

Fund Manager B based his decisions on known factors relevant to stock returns. For his investment decisions he uses a large amount of current and past data in which he recognizes patterns for successful price developments. Fund Manager B, however, continuously develops himself and his procedures independently on the basis of this data, but is subject to regular internal quality control by the bank.

The data used by fund manager B are, on the one hand, basic data such as macroeconomic development, competitive capabilities of the companies in the fund, the financial situation of the companies in the fund and past returns with the respective payout date. On the other hand, all relevant key figures such as "Ownership Risk", "Ownership Uncertainty" or "Valuation Uncertainty" are included in the analysis.

Regarding the current composition of the fund, fund manager B makes the following statements:

Specifically for the current selection of the most important companies in the "CapitalStar" fund, fund manager B states that the most important factors for his decision were the competitiveness of the companies. Fund Manager B believes that the companies he selects for the "CapitalStar" fund are so strongly positioned that they will displace competing companies over a long period of time while generating very high returns.

Now that you have sifted through the data, you need to decide: How do you want to invest your money?

Note: This is followed by further questions in the questionnaire.

Version 7 & 8: Fund managers are equally as good (V7 Framing, V8 No Framing)

The bank offers two actively managed fund models for you and your investment.

On the one hand, you have an experienced fund manager A from the bank at your side who manages a fund ("ValuePlus").

/* Human

On the other hand, you can choose a fund managed by a fund manager B "(CapitalStar").

/* Framing

Before you begin with the investment decision, the bank informs you why, in addition to the experienced fund manager A, fund manager B is now also working for the bank. Fund Manager B was recruited for the bank's investment division because he seems to work very efficiently and precisely. At the same time, he independently obtains an above-average amount of global market data in order to better validate his investment recommendation. In addition, he had many years of experience as a fund manager and probably showed an extraordinary performance and achieved the best possible results for previous customers.

Your Investment Decision

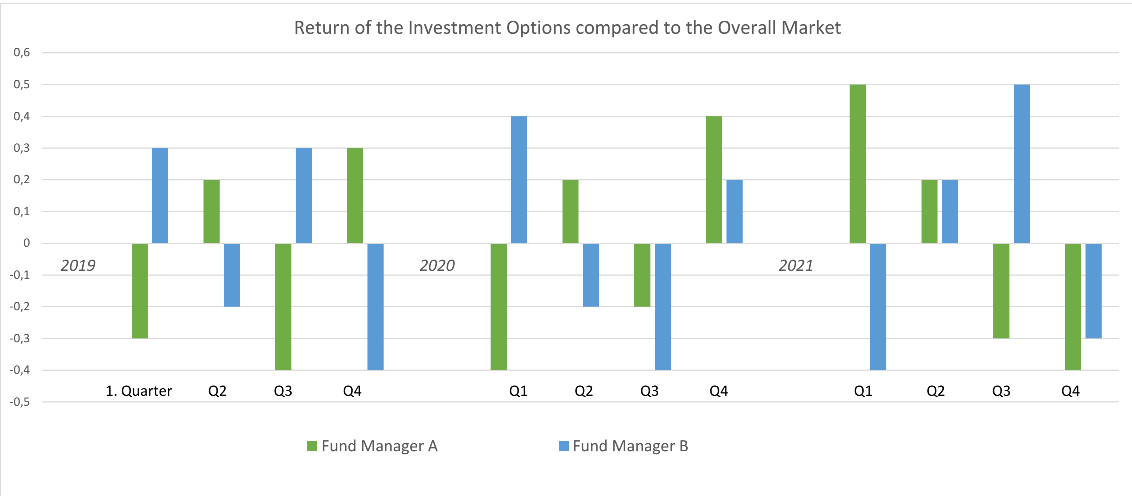
Your task now is to identify the best possible investment option for you.

In order to provide you with comprehensive information on the success of the two offerings, the bank first provides you with some data on the past performance of both funds.

First, you will get an overview of the **returns of the funds** that the fund manager A as well as fund manager B have each generated in the past.

/* Manipulation

		Fund Manager A	Fund Manager B	Base Rate
Year	*Quarter*			
2019	1	0,9	1,5	1,2
2019	2	0,9	0,5	0,7
2019	3	-2,7	-2,0	-2,3
2019	4	4,6	3,9	4,3
2020	1	0,8	1,6	1,2
2020	2	-14,8	-15,2	-15,0
2020	3	2,8	2,6	3,0
2020	4	18,4	18,2	18,0
2021	1	8,0	7,1	7,5
2021	2	5,6	5,6	5,4
2021	3	2,2	3,0	2,5
2021	4	2,6	2,7	3,0



Notes

The table shows the absolute quarterly performance of the funds, the chart the relative performance of the two funds relative to the overall market.

Now that you have sifted through the data, you need to decide: How do you want to invest your money?

Note: This is followed by further questions in the questionnaire.

/* Explanation human

About how fund manager B manages the fund "Capital Star", the following explanation is available:

Fund Manager B based his decisions on known factors relevant to stock returns. For his investment decisions he uses a large amount of current and past data in which he recognizes patterns for successful price developments. Fund Manager B, however, continuously develops himself and his procedures independently on the basis of this data, but is subject to regular internal quality control by the bank.

The data used by fund manager B are, on the one hand, basic data such as macroeconomic development, competitive capabilities of the companies in the fund, the financial situation of the companies in the fund and past returns with the respective payout date. On the other hand, all relevant key figures such as "Ownership Risk", "Ownership Uncertainty" or "Valuation Uncertainty" are included in the analysis.

Regarding the current composition of the fund, fund manager B makes the following statements:

Specifically for the current selection of the most important companies in the "CapitalStar" fund, fund manager B states that the most important factors for his decision were the competitiveness of the companies. Fund Manager B believes that the companies he selects for the "CapitalStar" fund are so strongly positioned that they will displace competing companies over a long period of time while generating very high returns.

Now that you have sifted through the data, you need to decide: How do you want to invest your money?

Note: This is followed by further questions in the questionnaire.

J Affidavit

Ich, Frau Sonja Gabriele Prinz, versichere an Eides statt, dass die vorliegende Dissertation von mir selbstständig und ohne unzulässige fremde Hilfe unter Beachtung der „Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Heinrich-Heine-Universität Düsseldorf“ erstellt worden ist.

Düsseldorf, 07.11.2024

Sonja Gabriele Prinz