Managerial advice-taking

with a blame avoiding intention

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Abstract

Companies and managers pay large amounts of money for costly advice and expensive consultants. Prior literature identifies two central advice-taking motives: (1) increasing decision accuracy and (2) sharing responsibility with the advisor (e.g., Bonaccio & Dalal, 2006). In contrast to previous studies, which mainly focus on factors influencing decision accuracy, this thesis analyzes whether managers use advisors to share responsibility by blaming them as scapegoats. Moreover, I analyze which factors influence managerial advice-taking with a blame avoiding intention. Specifically, I study the impact of human advisors and nonhuman advisors in the form of algorithmic decision aids on managerial blame avoiding decision-making.

The first part of the thesis focuses on discussing important findings of advice-taking literature and blame avoidance literature. I explain the importance and empirical relevance of the advice-taking motive sharing responsibility with advisors and theoretically link it to a blame avoiding strategy, which focuses on delegating difficult decisions with high blame potential to others, while demonstrating the lack of prior research on this motive. The empirical part of this thesis consists of two experiments with managers from German-speaking countries analyzing factors (i.e., managers' and advisors' characteristics) which influence managerial advice-taking with a blame avoiding intention.

Specifically, Study 1 examines whether managers increasingly utilize advice provided by potential human scapegoats (advisors' characteristics) to blame them and avoid personal blame. Additionally, the influence of managers' individual risk perceptions (managers' characteristics) on their blame avoiding decision-making is studied. Results of an online experiment with managers in an investment decision context are that potential scapegoats increase managerial advice-taking in an economic boom but

decrease it in an economic crisis due to managers' varying risk perceptions. Risk-averse managers – caused by a gain framed decision context in an economic boom – focus on avoiding personal blame by increasing advice-taking, whereas risk-seeking managers – caused by a loss framed decision context in an economic crisis – focus on avoiding financial losses and ignore potential scapegoats.

Additionally, Study 2 analyzes whether managers use nonhuman advisors in the form of algorithmic decision aids (advisors' characteristics) as scapegoats to share responsibility and avoid personal blame. In an online experiment with managers in a forecasting context, I find that managers exhibit algorithm aversion in regard to scapegoat selection by preferring to use human scapegoats compared to nonhuman scapegoats due to a perceived lack of social competence of algorithmic decision aids. However, managers also blame algorithmic decision aids and reduce their algorithm aversion when perceiving a higher level of human-likeness in the form of higher social competence of algorithmic decision aids.

Zusammenfassung

Unternehmen und hochrangige Führungskräfte geben viel Geld für kostspielige Ratschläge und teure Berater aus. Die bisherige Forschungsliteratur hat zwei zentrale Motive für die Berücksichtigung von Ratschlägen identifiziert: (1) Erhöhung der Entscheidungsqualität und (2) Verantwortungsteilung mit dem Berater (z. B. Bonaccio & Dalal, 2006). Im Gegensatz zu früheren Studien, die sich hauptsächlich auf Faktoren konzentrieren, die die Entscheidungsqualität beeinflussen, wird in dieser Arbeit analysiert, ob Führungskräfte Berater nutzen, um Verantwortung zu teilen, indem sie diese als Sündenböcke beschuldigen. Darüber hinaus analysiere ich, welche Faktoren die Ratschlagsnutzung von Führungskräften mit verantwortungsvermeidender Absicht beeinflussen. Konkret untersuche ich den Einfluss von menschlichen Beratern und nichtmenschlichen Beratern in Form von algorithmischen Entscheidungshilfen auf das Entscheidungsverhalten von Führungskräften mit verantwortungsvermeidender Absicht.

Im ersten Teil der Dissertation werden wichtige Erkenntnisse der Literatur über Ratschlagsnutzung und über Schuldvermeidung diskutiert. Ich erkläre die Bedeutung und empirische Relevanz der Verantwortungsteilung mit Beratern als Motiv für Ratschlagsnutzung und verbinde dieses theoretisch mit einer Schuldvermeidungsstrategie, die darauf abzielt, schwierige Entscheidungen mit hohem Kritikpotenzial an andere zu delegieren, und zeige gleichzeitig den Mangel an Forschung zu diesem Motiv auf. Der empirische Teil dieser Arbeit besteht aus zwei Experimenten mit Führungskräften aus dem deutschsprachigen Raum, in denen Faktoren (d. h. Eigenschaften von Führungskräften und Beratern) analysiert werden, die die Ratschlagsnutzung von Führungskräften mit verantwortungsvermeidender Absicht beeinflussen.

Konkret wird in Studie 1 untersucht, ob Führungskräfte Ratschläge potenzieller menschlicher Sündenböcke (als Eigenschaft von Beratern) verstärkt nutzen, um diese selbst zu beschuldigen und persönliche Schuldzuweisungen zu vermeiden. Darüber hinaus wird der Einfluss der individuellen Risikowahrnehmung von Führungskräften (als Eigenschaft von Führungskräften) auf ihr Entscheidungsverhalten mit verantwortungsvermeidender Absicht untersucht. Ergebnisse eines Online-Experiments mit Führungskräften im Kontext von Investitionsentscheidungen zeigen, dass potenzielle Sündenböcke die Ratschlagsnutzung von Führungskräften in einem Wirtschaftsboom erhöhen, aber in einer Wirtschaftskrise aufgrund der unterschiedlichen Risikowahrnehmung der Führungskräfte verringern. Risikoaverse Führungskräfte – verursacht durch einen gewinnorientierten Entscheidungskontext in einem Wirtschaftsboom – konzentrieren sich darauf, persönliche Schuldzuweisungen durch verstärkte Ratschlagsnutzung zu vermeiden, während risikofreudige Führungskräfte – verursacht durch einen verlustorientierten Entscheidungskontext in einer Wirtschaftskrise – sich darauf konzentrieren, finanzielle Verluste zu vermeiden und potenzielle Sündenböcke ignorieren.

Studie 2 analysiert zudem, ob Führungskräfte nichtmenschliche Berater in Form von algorithmischen Entscheidungshilfen (als Eigenschaft von Beratern) als Sündenböcke einsetzen, um Verantwortung zu teilen und persönliche Kritik zu vermeiden. In einem Online-Experiment mit Führungskräften in einem Prognosekontext stelle ich fest, dass Führungskräfte eine Aversion gegenüber algorithmischen Entscheidungshilfen in Bezug auf eine Nutzung als Sündenbock aufweisen, indem sie aufgrund der wahrgenommenen mangelnden Sozialkompetenz algorithmischer Entscheidungshilfen menschliche Sündenböcke gegenüber nichtmenschlichen Sündenböcken bevorzugen. Führungskräfte beschuldigen aber auch algorithmische Entscheidungshilfen und reduzieren ihre Aversion gegenüber nichtmenschlichen

Beratern, wenn sie eine größere Ähnlichkeit mit menschlichen Beratern in Form einer höheren sozialen Kompetenz algorithmischer Entscheidungshilfen wahrnehmen.

Contents

List of Abbreviations

AI .... *Artificial intelligence*

AT .... *AdviceTaking*

BAT .... *Blame avoidance theory*

CEO .... *Chief executive officer*

CPT .... *Cumulative prospect theory*

DDM .... *Defensive decision-making*

IPOm .... *Input-Process-Output model*

JAS .... *Judge-Advisor system*

MAPA .... *Mean absolute percentage adjustment*

MAPE .... *Mean absolute percentage error*

MTurk .... *Amazon's Mechanical Turk*

PTB .... *Passing the buck*

UTAUT .... *Unified theory of acceptance and use of technology*

WOA .... *Weight of advice*

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1 Introduction

Managers often rely on strategy consulting companies (e.g., McKinsey & Company and The Boston Consulting Group) with high external expertise to support their decision-making (Deelmann, 2006). Advice-taking literature analyzes when and why decision makers seek advice and what factors (e.g., decision makers' or advisors' attributes) influence advice utilization (i.e., the implementation of the provided advice in the final decision). In addition to human experts, there are also nonhuman advisors – algorithmic decision aids specialized in data-driven tasks (e.g., sales forecasts) – consulting managers.[1] Algorithmic decision aids are artificial tools which analyze data to predict the future and can range from simple statistical methods to complex artificial intelligence (AI). However, decisions makers generally exhibit algorithm aversion which describes their tendency to prefer and increasingly listen to human advisors than to algorithmic decision aids (e.g., Alexander, Blinder, & Zak, 2018; Burton, Stein, & Jensen, 2020; Önkal, Goodwin, Thomson, Gönül, & Pollock, 2009).

Moreover, decision makers can have different reasons for listening to (non)human advisors. Specifically, prior literature identifies two general advice-taking motives: (1) increasing decision accuracy due to the advisor's higher expertise and (2) sharing responsibility for the decision outcome with the advisor.[2] Nonetheless, current research mainly analyzes advice utilization focused on increasing decision accuracy; research on the advice-taking motive sharing responsibility is scarce (Bonaccio & Dalal, 2006; Palmeira, Spassova, & Keh, 2015).

[1] In this thesis, I use the term "algorithmic decision aids" as an operationalization for "nonhuman advisors". Therefore, I use both terms interchangeably and synonymously for the remainder of this thesis (see chapter 2.2.1 for more information).

[2] Decision makers focused on increasing decision accuracy use advisors because they want to make objectively better decisions, whereas decision makers focused on sharing responsibility listen to advisors to split the responsibility for the decision outcomes between themselves and the advisors (Bonaccio & Dalal, 2006).

Blame avoidance literature describes a similar phenomenon to the advice-taking motive sharing responsibility. This literature stream studies why individuals or managers want to avoid personal blame for a failed decision (e.g., to achieve personal goals like career promotions) and what blame avoiding strategies they can use. Similar to sharing responsibility with advisors, one possible blame avoiding strategy is the delegation of difficult decisions with high blame potential to others (e.g., advisors) and use them as scapegoats by sharing and transferring blame to them (e.g., Skarlicki, Kay, Aquino, & Fushtey, 2017; Hood, 2011; Weaver, 1986). So far, tendencies of this blame avoiding behavior are observed for politicians and public sector managers (e.g., James, Jilke, Petersen, & van de Walle, 2016), students in fictitious experimental dictator games (e.g., Bartling & Fischbacher, 2012) as well as for private sector companies (e.g., Gangloff, Connelly, & Shook, 2014) and private sector managers (e.g., Park, Kim, & Sung, 2014). Managers using advisors to avoid personal blame and not focusing on making the best possible decision for their companies can have large negative effects on corporate financial results. Despite this theoretical and empirical relevance, there is almost no research on possible factors influencing managerial advice-taking with a blame avoiding intention.

This is the basis my dissertation builds on. I connect advice-taking literature and blame avoidance literature by analyzing whether managers consciously use advisors for a blame avoiding strategy and on what factors this behavior depends on. After reviewing prior research, I identify the relevance of the following research questions:

Specifically, I am interested in whether managers utilize blamable human advisors to share responsibility (research question 1) and how their individual risk perceptions affect this behavior (research question 2).[3] Moreover, I analyze whether managers also try to share responsibility with nonhuman advisors – algorithmic decision aids – to avoid personal blame (research question 3). Finally, I study whether managers exhibit algorithm aversion when looking for blamable advisors causing managerial advice-taking with a blame avoiding intention to be stronger with human advisors than with algorithmic decision aids (research question 4).

To study these research questions, I begin with reviewing important research on managerial advice-taking and identify two general advice-taking settings – (1) advice-taking from human advisors (see chapter 2.1) and (2) advice-taking from algorithmic decision aids (see chapter 2.2). Thereafter, I analyze algorithm aversion which is the decision makers' preference of human advisors compared to algorithmic decision aids (see chapter 2.3). By discussing prior research, I demonstrate that current literature almost exclusively studies advice-taking focused on increasing decision accuracy and ignores the advice-taking motive sharing responsibility (e.g., Bonaccio & Dalal, 2006). Nonetheless, I identify relevant findings which hint at the importance of the advice-taking motive sharing responsibility across the two general advice-taking settings (e.g., Harvey & Fischer, 1997; Palmeira et al., 2015; Gönül, Önkal, & Goodwin, 2009). Then, I connect advice-taking literature with blame avoidance literature by linking the results of the advice-taking motive sharing responsibility with research on managerial blame assignment and avoidance (e.g., a blame avoiding strategy of delegating difficult decisions with high blame potential to blamable advisors) (see chapter 3). This thesis contributes to advice-taking literature and blame avoidance literature by analyzing whether and why managers blame human (e.g., external business consultants) or

[3] Managers who want to avoid personal blame have to make sure that advisors are blamable. This means that advisors need to be capable of assuming responsibility and deflecting managers' blame for a failed decision (see chapter 3.2.2 for a detailed definition of blamable advisors).

nonhuman advisors (e.g., algorithmic decision aids) to share responsibility with them and avoid personal blame. The empirical part of this thesis consists of two experimental studies – Study 1 and Study 2 (see chapters 5 and 6) – which theoretically derive and test experimental hypotheses to answer my research questions. Each study has its own motivation, research focus, and contributes differently to advice-taking literature and blame avoidance literature. Table 1 provides an overview of the research questions and my corresponding research studies.

Table 1: Overview of research questions and corresponding research studies

Research questions		Research variables
Study 1: How managers' risk perceptions affect their willingness to blame advisors as scapegoats		
Research question 1:	Do managers utilize blamable human advisors to share responsibility?	Human advisors' blame potential
Research question 2:	Do managers' individual risk perceptions influence their advice utilization of blamable human advisors to share responsibility?	Managers' risk perceptions
Study 2: Selecting (non)human scapegoats – how advisors' social competence drives managers' algorithm aversion		
Research question 3:	Do managers utilize nonhuman advice by blamable algorithmic decision aids to share responsibility?	Blame potential of algorithmic decision aids
Research question 4:	Do managers exhibit algorithm aversion when utilizing blamable advice to share responsibility?	Advisors' nature (human advisors vs. algorithmic decision aids)

Notes: This table provides a consolidated overview of my research questions and explains in which study I analyze the corresponding research variables.

Sources: Author's interpretation.

Study 1 analyzes the sharing of responsibility in the form of using a blamable human advisor as a scapegoat as the main motive of managerial advice utilization (research question 1). Furthermore, managers' risk perceptions as a possible factor influencing blame avoiding advice-taking is examined (research question 2). I conduct an online experiment with managers from German-speaking countries in an investment decision setting. I find that the presence of a potential scapegoat (i.e., blamable advisor) positively affects advice utilization in an economic boom but negatively affects it in an economic crisis due to managers' varying risk perceptions. The more risks managers perceive, the more they try to avoid personal risks by using advisors as scapegoats. Managers' risk perceptions are the main driver of scapegoating as a form of managerial blame avoiding decision-making that is also a response to a threat of justification. This study contributes to advice-taking literature and blame avoidance literature by highlighting managers' opportunistic motives behind consulting (costly) advice.

Study 2 focuses on whether managers use blamable algorithmic decision aids as scapegoats to share responsibility (research question 3) and whether managers perceive blamable advice recommended by human advisors and algorithmic decision aids differently. Specifically, I examine how the sharing of responsibility in the form of blaming the advisor as a scapegoat differs between human advisors and algorithmic decision aids (research question 4). I conduct an online experiment with managers from German-speaking countries in a forecasting setting in which they receive advice either from an algorithmic decision aid or a human expert and can adjust a preliminary recommended forecast. The results show that managers use their advisors as scapegoats by avoiding adjustments of the recommended forecast. Moreover, managers exhibit algorithm aversion and prefer to use human scapegoats due to a perceived lack of human-likeness in the form of lower social competence of algorithmic decision aids. However, a higher level of perceived human-likeness in the form of higher social competence of algorithmic decision aids increases the utilization of nonhuman scapegoats and reduces managers' algorithm aversion in regard to scapegoat selection. I contribute to advice-taking literature and blame avoidance literature by highlighting the relevance of managers' opportunistic motives when taking (non)human advice.

Finally, this thesis studies whether managers utilize advice not only to increase decision accuracy but also to avoid own responsibility and blame by instrumentalizing advisors as scapegoats. Specifically, I analyze possible managers' (i.e., risk perception) and advisors' characteristics (i.e, blame potential and nature) that influence managerial blame avoiding behavior. The remainder of this thesis is structured as follows: Chapter 2 introduces advice-taking literature and provides an overview of important studies for managerial advice-taking from human advisors and algorithmic decision aids. Then, chapter 3 discusses blame avoidance literature and links possible blame avoiding strategies to advice-taking literature. Thereafter, experimental research and common experimental designs in the advice-taking literature are explained in chapter 4. Next, chapter 5 describes Study 1 and chapter 6 presents Study 2. Finally, chapter 7 concludes my thesis.

2 Influence of advisors on managerial decision-making

2.1 Managerial advice-taking from human advisors

2.1.1 Management advisors and the Judge-Advisor system

Usually, decisions are not made by one individual person. May it be simple decisions in daily life or important decisions in a business context, decision makers tend to consciously consult advisors and utilize advice (Bonaccio & Dalal, 2006; Palmeira et al., 2015; Schultze, Mojzisch, & Schulz-Harald, 2017; van Swol, Paik, & Prahl, 2018; Yaniv & Kleinberger, 2000). There are many business consulting companies whose sole business model is to provide costly advice (Deelmann, 2006). Individuals as well as private and public sector companies spend large amounts of money to hire these advisors resulting in a consulting industry with 188 billion USD worldwide revenue in 2018 (Healey, Williams, Sullivan, & Blackmore, 2019).

Macdonald (2006) argues that managers hire external advisors to make better decisions. Furthermore, Niewiem & Richter (2006) identify three main reasons for managers hiring external advisors: (1) external expertise, (2) high amount of work, and (3) political projects for which the external advisor could be the mediator and scapegoat if necessary. An interviewed manager put it the following way:

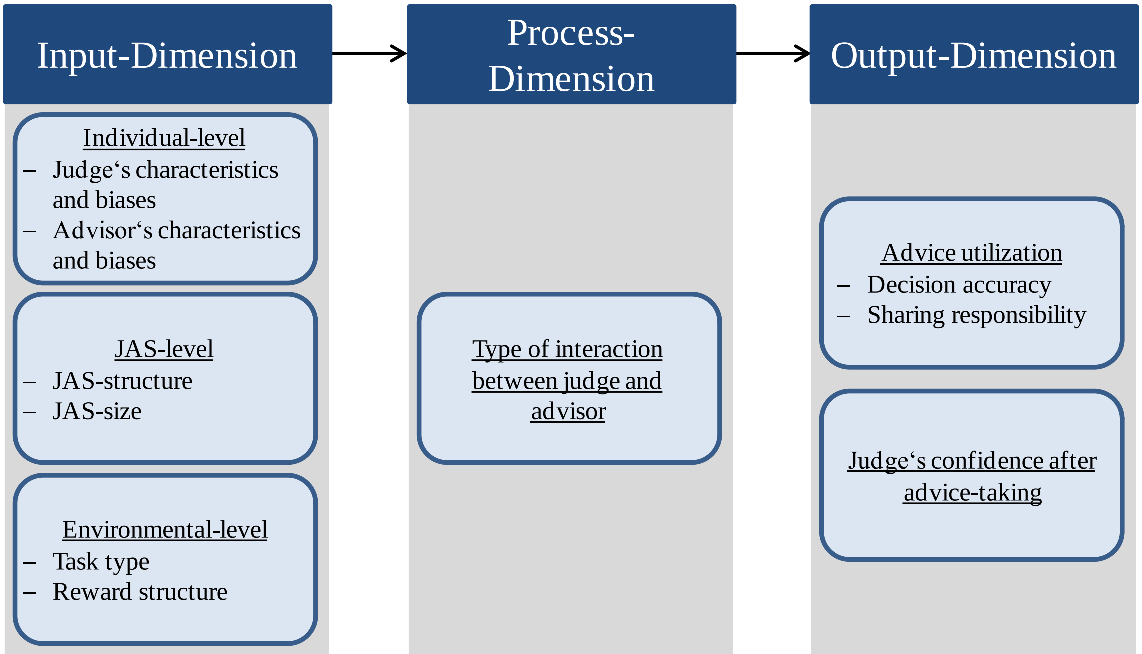
> "First, the project involved a huge amount of work and we simply did not have the capacity to do that. Second, it was important for us to get an independent perspective. Our employees would not have been able to provide the industry benchmarks. And third, bear in mind that this was a restructuring process. It was quite helpful for management to have a scapegoat for decisions that had adverse effects on our staff. We could not have done that if the project had been carried out by our own people" (Niewiem & Richter, 2006, p. 32).

Previous research on advice-taking shows that the integration of advisors' opinions, especially if they are experts, increases overall decision accuracy. Importantly, even without higher expertise, the combination of advisors' recommendations with one's own opinion does increase decision accuracy due to a decrease in randomness and a lower error term (Bonaccio & Dalal, 2006; Önkal et al., 2009; Sniezek, Schrah, & Dalal, 2004; Yaniv, 2004b; 2004a).

The advice-taking literature studies the reasons for seeking advice and how advice is utilized or discounted under different circumstances (Bonaccio & Dalal, 2006). The Judge-Advisor system (JAS) is a framework for studying decision-making in an advice-taking context. All participants in that framework can either be characterized as judges or advisors. Both parties can be individuals or groups. The individual or group (e.g., managers) making the decision is called judge. The individual or group providing recommendations is called advisor. Advisors provide advice by usually recommending what alternative or decision the judges should choose or make. However, it is the judges' decision if they want to follow the provided advice, partly accept, or completely ignore it. The JAS helps to systematically study why judges decide the way they do and tries to identify the reasons for their behavior (Bonaccio & Dalal, 2006; Dalal & Bonaccio, 2010; Hogan, 2014; Schultze et al., 2017; Sniezek & Buckley, 1995; van Swol et al., 2018). Bonaccio & Dalal (2006) propose a systematic framework to study the JAS, the Input-Process-Output model (IPOm). An overview of the IPOm for the JAS is presented in Figure 1.

The IPOm clusters all possible influencing variables on advice-taking in three main dimensions – IPOm Input-Dimension, IPOm Process-Dimension, and IPOm Output-Dimension. The IPOm Input-Dimension includes all factors affecting advice-taking before the actual advice is provided or received. The IPOm Input-Dimension itself is split in the IPOm Individual-level, IPOm JAS-level, and IPOm Environmental-level (Bonaccio & Dalal, 2006; Hogan, 2014).

Figure 1: Input-Process-Output model for the Judge-Advisor system



Notes: This figure shows the IPOm consisting of important IPOm factors describing common JAS settings with human advisors.

Sources: Author's interpretation, adapted from Hogan (2014, p. 3) and Bonaccio & Dalal (2006, p. 129).

Specifically, IPOm Individual-level factors describe judges' and advisors' individual characteristics (e.g., competence, emotion, risk propensity, self-confidence) and behavioral biases before advice-taking (Bonaccio & Dalal, 2006; Hogan, 2014).[4]

The IPOm JAS-level defines the pre- and post-advice-taking procedure (i.e., JAS-structure and JAS-size). Possible factors on JAS-structure are whether judges are allowed to form an own opinion before receiving advice and whether judges' or advisors' IPOm Individual-level factors are evaluated, recorded, and communicated before advice-taking. Specifically, advisors can communicate their own IPOm Individual-level factors (e.g., confidence) publicly or privately only to the judge and not to possible other advisors. Most studies make judges to interact and communicate with advisors by always having judges confronted with advice. However, advice-taking can also be voluntary by judges having to explicitly request and seek advice if they want decision support. In contrast to

[4] I also include behavioral biases influencing advice-taking in the IPOm Individual-level, although most biases are only caused the moment the advice is received, as the psychological reasons for the behavioral biases rest in each individual beforehand.

JAS-structure describing the advice-taking procedure, JAS-size factors set the number of participating judges and advisors (Bonaccio & Dalal, 2006; Hogan, 2014).

The IPOm Environmental-level describes the setting in which the advice-taking takes place. Common factors are task type and the judges' and advisors' reward structure (Bonaccio & Dalal, 2006; Hogan, 2014). Judges can make choice tasks (e.g., choosing among fixed alternatives) and judgment tasks (e.g., making quantitative estimation like a sales forecast) (Fischer & Harvey, 1999; Sniezek & van Swol, 2001).[5] Additionally, judges can receive financial compensation for good decisions and sometimes have to pay for costly advisors which resembles the advisors' compensation.

In contrast to the IPOm Input-Dimension focusing on general factors before the actual advice-taking, the IPOm Process-Dimension defines how the concrete advice-taking is procedurally done and how judges and advisors communicate and interact with each other (e.g., providing oral or written advice). Moreover, if there is more than one advisor, then the interaction between the advisors themselves can be observed (e.g., advisors competing for judge's advice utilization) (Bonaccio & Dalal, 2006; Hogan, 2014). The IPOm Process-Dimension exclusively focuses on the communication of the specific advice and not on whether pre-advice-taking factors (i.e., advisors' IPOm Individual-level factors) are communicated to judges (see IPOm JAS-level).

After receiving advice and judges having made their decisions, the IPOm Output-Dimension measures the effect of advice-taking (Bonaccio & Dalal, 2006; Hogan, 2014). Main output variable in the advice-taking literature is advice utilization which measures to what extent the advisors' recommendations are considered in the judges' final decisions. Literature differs between overutilization of bad advice (e.g., Schultze et al.,

[5] Investment decisions are also an important choice task for which managers regularly seek advice (e.g., Graham, Harvey, & Puri, 2015).

2017) and underutilization of good advice (e.g., Yaniv & Choshen-Hillel, 2012).[6] All described IPOm Input-Dimension and IPOm Process-Dimension factors can influence advice utilization.

Common measures for advice utilization are *weight of advice* (*WOA*) and *AdviceTaking* (AT). *WOA* measures the absolute change of the judges' pre-advice decision after receiving advice relative to the absolute distance of the advisors' recommendations and the judges' own pre-advice decision.[7] Equation 1 shows the formula for calculating *WOA* (Bonaccio & Dalal, 2006; Harvey & Fischer, 1997; Schultze et al., 2017).

Equation 1: $$WOA = \frac{|\text{Judge's decision with advice} - \text{Judge's decision without advice}|}{|\text{Advisor's recommendation} - \text{Judge's decision without advice}|}$$

AT is a non-absolute version of *WOA* in case the direction of judge's adjustment of the original decision without advice is important. Equation 2 shows the formula for calculating *AT* (Bonaccio & Dalal, 2006).

Equation 2: $$AT = \frac{\text{Judge's decision with advice} - \text{Judge's decision without advice}}{\text{Advisor's recommendation} - \text{Judge's decision without advice}}$$

Advice-taking literature proposes two main reasons for advice utilization: (1) increasing decision accuracy and (2) sharing responsibility. Judges pursuing decision accuracy try to increase the objective quality of their decisions by implementing the advisors' recommendations, whereas sharing responsibility focuses on dividing the outcome responsibility for the chosen decisions between judges and advisors (Bonaccio & Dalal, 2006; Palmeira et al., 2015; Schrah, Dalal, & Sniezek, 2006). In addition to

[6] Overutilization refers to a too high consideration of bad advice and the judges' tendency to partly utilize completely useless advice, whereas underutilization describes the judges' tendency to partly ignore good advice (Schultze et al., 2017; Yaniv & Choshen-Hillel, 2012).

[7] *WOA* is 1 for judges completely following advice, 0.5 for judges averaging their decisions and the advisors' recommendations, and 0 when ignoring advice.

advice utilization, judges' post-advice confidence of having made a qualitatively good decision is another factor in the IPOm Output-Dimension.

Finally, advice-taking research studies why, how, and when individuals integrate external recommendations in their decision-making. Specifically, prior literature clusters identified influencing factors in the IPOm framework and differs between factors before advice-taking (i.e., IPOm Input-Dimension), during advice-taking (i.e., IPOm Process-Dimension), and advice-taking results (i.e., IPOm Output-Dimension). The two main advice-taking motives are (1) increasing decision accuracy by integrating a supposedly beneficial advice and (2) sharing responsibility with the advisor for a difficult decision. The next chapter discusses general drivers affecting managerial advice-taking along the dimensions of the IPOm framework.

2.1.2 General drivers of managerial advice-taking from human advisors

I review previous literature studying advice-taking from human advisors along the IPOm framework (see Figure 1). Specifically, I group prior research by the two main motives of advice utilization as an IPOm Output-Dimension factor – (1) increasing decision accuracy (see chapter 2.1.2.1) and (2) sharing responsibility (see chapter 2.1.2.2). Moreover, I cluster important studies by their main contributions to the influence of possible IPOm Input-Dimension factors (IPOm Individual-level, IPOm JAS-level, and IPOm Environmental-level) and IPOm Process-Dimension factors on advice-taking.[8]

Current research on advice-taking is mainly based on laboratory experimental designs relying on student samples (e.g., Larson, Tindale, & Yoon, 2020; Ache, Rader, & Hütter, 2020; Hütter & Fiedler, 2019; Schultze et al., 2017). Advice-taking literature implies that advice-taking is a general psychological phenomenon which can be transferred to different settings because most identified factors are based on human

[8] The judges' post-advice confidence as an IPOm Output-Dimension factor is discussed in combination with advice utilization across both advice-taking motives (decision accuracy and sharing responsibility).

cognitive aspects. In contrast to that, Kirchler, Lindner, & Weitzel (2018) demonstrate that students and managers make different economic decisions. Nonetheless, I am confident that the general findings of the advice-taking literature can be transferred to managers because even if managers decide without advice economically different than students, behavioral biases or cognitive reasons resulting from received advice should still be general underlying factors influencing advice-taking. The scarce literature on advice-taking with manager samples confirm established advice-taking findings like the main motives for advice utilization (e.g., Niewiem & Richter, 2006; Macdonald, 2006). Therefore, I assume that the findings of the current advice-taking literature are sufficient for an overview of possible factors influencing managerial advice-taking from human advisors. In the following and in line with the JAS, managers are referred to as judges.

2.1.2.1 Factors influencing managerial advice-taking focused on decision accuracy

Judges (e.g., managers) frequently seek advice and consult human advisors to make better decisions (Bonaccio & Dalal, 2006; Sniezek et al., 2004; Yaniv, 2004b; 2004a). So far, advice-taking research has identified several IPOm Input-Dimension (IPOm Individual-level, IPOm JAS-level, and IPOm Environmental-level) and IPOm Process-Dimension factors influencing advice utilization focused on increasing decision accuracy as an IPOm Output-Dimension factor.

Prior studies explain the importance of IPOm Individual-level factors on advice utilization and differ between judges' and advisors' individual characteristics as well as general behavioral biases. Especially, judges' characteristics like emotions influence advice-taking. Gino, Brooks, & Schweitzer (2012) find that anxious judges with low self-confidence seek more advice and cannot differ between good and bad advice. Moreover, Gino & Schweitzer (2008) argue that incidental emotions that have nothing to do with the decision task, distort advice-taking. Grateful judges utilize advice more compared judges feeling anger. Moreover, the judges' feelings of power have an impact on advice utilization. Van Swol, Prahl, MacGeorge, & Branch (2019) demonstrate that judges with perceived high power utilize imposed advice less than weak judges. Powerful judges generally discount advice more than less powerful ones (Tost, Gino, & Larrick, 2012).

In addition to the judges' characteristics, prior research identifies several advisors' characteristics which influence advisors' advice-giving and judges' advice utilization. Schaerer, Tost, Huang, Gino, & Larrick (2018) find that advisors who want to have own power tend to give more advice, whereas Feng & Magen (2016) stress that the advisors' relationship closeness to judges is the main driver affecting unsolicited advice-giving. Advisors who feel more closely connected to judges are more inclined to provide unsolicited advice. However, in most research studies advisors have no opportunity to provide unsolicited advice but advice is usually explicitly requested by judges (e.g., Bonaccio & Dalal, 2006). Several studies argue that advisors' characteristics affect how judges perceive advice and find increased advice utilization when the advisors are experts and have more knowledge than the judges (Harvey & Fischer, 1997; Sniezek et al., 2004; Yaniv & Kleinberger, 2000). Moreover, judges are more inclined to trust and listen to self-confident advisors than low-confident advisors and also have a higher post-advice confidence of having made the right decision (Price & Stone, 2004; Sniezek & Buckley, 1995; Sniezek & van Swol, 2001). Bonaccio & Dalal (2010) find that judges increasingly trust advisors who they believe to be competent and have aligned personal interests. However, van Swol (2009) also shows that persuading advisors who pursue personal opportunistic goals are more influential than advisors who are aligned with the judges' interests. Persuading advisors inflate confidence and thereby strongly influence judges even when judges are primed to be suspicious but are still unable to detect advisors' personal motives.

Apart from individual characteristics, the judges' perception of advice quality and advice utilization is influenced by many behavioral biases. An egocentric bias causes judges to systematically overestimate their own opinion and underestimate beneficial advice (Yaniv & Kleinberger, 2000). This bias is stronger, the more competent the judge is and can be reduced by imagining what other decision makers would do in this situation (Yaniv, 2004b; Yaniv & Choshen-Hillel, 2012). In contrast to overestimating one's own opinion, Schultze et al. (2017) analyze that bad advice is overutilized due to an anchoring effect. Judges tend to utilize advice with a minimal weight of 20%-30% independent of the advisors' expertise because they do not want to completely reject bad advice (Bonaccio & Dalal, 2006; Harvey & Fischer, 1997). Hütter & Fiedler (2019) show that even arbitrary, random anchors influence advice-taking. However, the advice distance to the judges' own decision also impacts advice utilization. Advice deviating by a large or very small margin are less utilized than moderately deviating advice (Schultze, Rakotoarisoa, & Schulz-Hardt, 2015; Yaniv, 2004b; Yaniv & Milyavsky, 2007). Moreover, judges tend to choose binary between their decision and advice although averaging is mostly beneficial (Soll & Larrick, 2009). Nonetheless, Bednarik & Schultze (2015) demonstrate that weighting advice is superior to choosing binary or averaging when judges can estimate advisors' competence correctly. Furthermore, the way how advice is formulated and framed influences the weighting of advice in the form of advice utilization. Jang & Feng (2018) argue that gain-framed advice (e.g., doing this will help you) causes more positive reactions and judges think it is helpful and tend to utilize it more than loss-framed advice (e.g., if you do not do this, then something bad will happen).

While these IPOm Individual-Level factors have an impact on advice-taking, IPOm JAS-Level factors (e.g., JAS-structure and the number of judges or advisors involved in the decision) also affect judges focused on decision accuracy. Specifically, Sniezek & Buckley (1995) argue that JAS-structure influences advice-taking. Judges make better decisions and are more confident if they make own decisions before listening to advice (Independent Judge) than receiving advice simultaneously with information on the decision task (Cued Judge) or even completely relying on advisors without receiving information on the decision task (Dependent Judge). Moreover, JAS-structure can also distort established behavioral biases (e.g., egocentric bias). Larson et al. (2020) find that a group of judges making a single decision collectively show higher egocentric bias when they reach consensus before receiving advice and lower egocentric bias without pre-advice consensus than individual judges. In addition to JAS-structure, JAS-size – the number of judges and advisors – has an impact on advice-taking. Several studies find that judges have a higher post-advice confidence, the more independent advisors recommend the same decision (Budescu & Rantilla, 2000; Budescu, Rantilla, Yu, & Karelitz, 2003). Moreover, van Swol, MacGeorge, & Prahl (2017) argue that judges perceive different advice quality depending on whether they want to listen to advice or not. Advice which is sought by judges or unsolicitedly provided by advisors is perceived to be better than advice which judges explicitly declined to listen to but advisors provide it anyway. However, Brooks, Gino, & Schweitzer (2015) demonstrate that judges are hesitant to seek advice because they fear to appear incompetent. But, in contrast to that fear, judges seeking advice for difficult tasks are perceived to be more competent. Moreover, Hütter & Ache (2016) argue that judges seek more advice and consult additional advisors if the first advice is distant from their own opinion.

Finally, IPOm Environmental-level factors like task type and reward structure impact advice-taking. Soll & Klayman (2004) analyze different task types and find that judges exhibit higher post-advice confidence when making judgmental decisions compared to choice tasks. Moreover, judges especially seek advice with increasing task complexity but only after conducting most of the information acquisition for the task by themselves (Schrah et al., 2006). Similarly, Gino & Moore (2007) argue that judges overweight advice in difficult decision tasks and underweight it in easy decision tasks. Interestingly, Ache et al. (2020) find that judges utilize advisors‘ recommendations more than advisors would like for difficult tasks and less than advisors would like for easy tasks. Judges’ excessive involuntary advice utilization for difficult tasks reduces advisors’ willingness to provide future advice. However, not only the task type influences advice utilization but also the cost of advice. Judges utilize costly advice more than free advice due to sunk costs fallacy (Gino, 2008). In line with this, Sniezek et al. (2004) argue that paying for expert advice before receiving the actual advice increases advice utilization compared to paying afterwards for it.

After discussing potential IPOm Input-Dimension factors influencing judges focused on increasing decision accuracy, possible IPOm Process-Dimension factors describing the interaction between judges and advisors are elaborated. While most research on advice-taking assumes that advisors provide recommendations for an alternative (positive-advice), Dalal & Bonaccio (2010) argue that judges want to feel autonomous. Therefore, judges generally prefer advice which does not limit their perceived decision autonomy. This can be advice against an alternative (negative-advice) or even better providing new information on unknown decisions alternatives (additional-advice). Specifically, van Swol & Ludutsky (2007) show that judges utilize advice more if it contains unknown information. Moreover, providing supposedly very detailed advice (i.e., overprecision) and expressing high levels of confidence, enables advisors to beat possible competing advisors for the judges’ advice utilization (Radzevick & Moore, 2011).

Finally, prior advice-taking literature has identified a broad range of possible IPOm factors influencing advice utilization. Specifically, several IPOm Input-Dimension factors affect advice-taking before the actual advice is provided. On an IPOm Individual-level, there are many different judges’ and advisors’ characteristics (e.g., emotions) as well as behavioral biases (e.g., egocentric bias) impacting advice utilization (Bonaccio & Dalal, 2006; Gino et al., 2012; Yaniv & Kleinberger, 2000). Moreover, IPOm JAS-level factors describing the advice-taking procedure (e.g., making own decisions before advice-taking) as well as IPOm Environmental-level factors like task difficulty and reward structure (e.g., having to pay for advice) influence whether and to what degree judges integrate recommendations in their decision-making (Gino, 2008; Gino & Moore, 2007; Sniezek & Buckley, 1995). While these are all factors focusing on circumstances before the actual advice-taking, prior research also identifies IPOm Process-Dimension factors like type of advice (e.g., additional-advice) that influence advice utilization by providing advice in a different way (Dalal & Bonaccio, 2010).

Nonetheless, the discussed studies in this chapter predominantly implicitly assume that judges always want to make good decisions and concentrate on identifying factors which distort advice-taking focused on increasing decision accuracy (e.g., Bonaccio & Dalal, 2006). In contrast to that, the next chapter discusses IPOm factors influencing advice utilization focused on sharing responsibility.

2.1.2.2 Factors influencing managerial advice-taking focused on sharing responsibility

Research studies discussed in the previous chapter mainly identify factors influencing advice utilization due to judges' perceived and expected change in decision accuracy if advice is utilized (e.g., advisors' competence or confidence). In contrast to that motive, judges can also utilize advice to share responsibility with the advisor for the decision outcome, not caring whether decision accuracy is positively or negatively affected (Bonaccio & Dalal, 2006; Hogan, 2014). Overall, there are only very few studies which analyze advice utilization focused on sharing responsibility as an IPOm Output-Dimension factor.

On an IPOm Individual-level, Harvey & Fischer (1997) show that experienced judges utilize advice stronger than usually with very important decisions associated with risk. „[T]hey appeared to be sharing responsibility when risk associated with error was high" (Harvey & Fischer, 1997, p. 117). This finding is interesting because one would generally assume that novices with less expertise would try to avoid own mistakes by taking more advice than experienced judges. High competent judges avoiding own responsibility for risky decisions is especially remarkable because they usually exhibit a greater egocentric bias and tend to underweight advice in normal circumstances (Yaniv, 2004b; Yaniv & Choshen-Hillel, 2012). This indicates that in some situations experienced judges do not focus on increasing decision accuracy – explaining the lack of egocentric bias – but exclusively on avoiding own responsibility for risky decisions. Specifically, judges should only be able to avoid responsibility and blame advisors for bad decision outcomes when the advisors can assume responsibility and are held accountable for bad advice by individuals or institutions evaluating judges' decision accuracy. In this thesis, I refer to advisors with these specific attributes as "blamable advisors" because judges can blame the advisors and their recommendations when having to justify low decision accuracy (see chapter 3.2.2 for a more detailed explanation).

In contrast to Harvey & Fischer (1997), Palmeira et al. (2015) find that judges attribute positive decision outcomes to advisors and negative decision outcomes to themselves due to a hindsight bias. In retrospect, advisors look very competent predicting a successful decision outcome while judges blame themselves for listening to supposedly incompetent advisors in case of a failed decision outcome.

Concerning potential factors of the IPOm JAS-level, IPOm Environmental-level, and IPOm Process-Dimension, there is no advice-taking research predominantly focusing on sharing responsibility as the main motive of advice utilization. There are only some general advice-taking studies which hint a possible connection. Gino & Moore (2007) find that judges overweight advice in difficult decisions and underweight it in easy circumstances. Moreover, Gino et al. (2012) find increased advice seeking and utilization when judges are anxious. However, Gino et al. (2012) attribute this to a decrease in judges' self-confidence and not to a fear of being responsible for a risky decision. It is speculative, but both studies could theoretically support the findings of Harvey & Fischer (1997) and indicate that fearful judges attribute utility to advisors by sharing responsibility with them for risky and difficult decisions independent of their effect on decision accuracy.

Cumulative prospect theory (CPT) is usually used to explain different decision-making behavior (e.g., advice-taking for investment decisions) in regard to varying risk perceptions depending on monetary decision framing (e.g., Kahnemann & Tversky, 1979; Tversky & Kahneman, 1992; Fennema & Wakker, 1997). According to CPT, judges are loss-averse and try to avoid losing existing resources. Specifically, monetary problem framing induces higher individual risk perceptions in a positive frame (e.g., performing above target level and gaining something) due to judges' desire to preserve the positive state and lower individual risk perceptions in a negative frame (e.g., performing below target level and losing something) due to the judges' desire to regain something lost. Moreover, decision makers prefer a safe and secure achievement of their target level to a risky overachievement. However, they also prefer a risky chance of achieving their target level to a sure target missing. These risk preferences cause decision makers to be risk-seeking in negative monetary framed situations (e.g., loss situations) and to be risk-averse in positive framed situations (e.g., gain situations) (Bromiley, 1991; Sitkin & Weingart, 1995; Tversky & Kahneman, 1992). Prior research has found empirical evidence supporting this decision-making behavior in a managerial context.[9]

[9] Companies are risk-seeking when performing below target level and risk-averse when performing above their target level (Chen, 2008; Miller & Chen, 2004).

Overall, there is scarce research on advice-taking focused on sharing responsibility as an IPOm Output-Dimension factor. Nonetheless, current findings indicate that experienced anxious judges prefer to share responsibility for difficult decisions tasks rather than maximizing decision accuracy (Gino et al., 2012; Gino & Moore, 2007; Harvey & Fischer, 1997). The next chapter identifies the research gap on managerial advice-taking from human advisors.

2.1.2.3 Identified research gap on managerial advice-taking from human advisors

Current advice-taking literature mainly focuses on possible factors, mostly psychological effects, influencing judges' perceptions of a change in decision accuracy (see chapter 2.1.2.1). So far, research exclusively studying sharing responsibility as the main motive of advice utilization is scarce and does not systematically analyze potential factors along the IPOm framework (see chapter 2.1.2.2). Table 2 presents a consolidated overview of important advice-taking studies along the IPOm framework.

Most of our knowledge about the advice-taking motive sharing responsibility is from additional results of research studies focused on decision accuracy. However, there are some promising speculative suggestions on possible IPOm Individual-level factors like judges' risk perceptions in combination with CPT (e.g., Harvey & Fischer, 1997), judges' anxiousness and self-confidence (e.g., Gino et al., 2012), and even IPOm Environmental-level factors like task complexity (e.g., Gino & Moore, 2007) regarding increased sharing of responsibility. Moreover, several researchers call for a systematic analysis of other advice-taking motives than increasing decision accuracy:

> „A strength of the [..] literature on advice taking has been its focus on informational motives. It is also a limitation. Motives for seeking and using advice clearly extend beyond the solely informational. The time is ripe to reconnect with the social influence literature and reintroduce normative motives into this paradigm" (Rader, Larrick, & Soll, 2017, p. 11).

> „Several motives may influence decision-makers' receptivity to interpersonal assistance from an advisor. However, motives other than maximizing decision accuracy have not been studied systematically" (Dalal & Bonaccio, 2010, p. 12).

> "Yet, there has been no research on how decision-makers allocate responsibility between themselves and their advisor" (Palmeira et al., 2015, p. 14).
>
> "[P]eople add a component to their advice-taking that represents a sharing of responsibility for the judgment when risk associated with error is high. [...] [T]his [...] is plausible but speculative. To test it, it would be useful to employ monetary pay-offs and to combine them with a means of making the responsibility of advisors explicit" (Harvey & Fischer, 1997, p. 131).

Even manager practitioners hint that they sometimes use blamable advisors because they want to share responsibility (Niewiem & Richter, 2006): "It was quite helpful for management to have a scapegoat for decisions" (p. 32). Managers making decisions and utilizing advice not focused on increasing decision accuracy but on sharing and avoiding own responsibility can have large negative effects on companies. Moreover, in line with CPT, decision makers' risk perceptions drive individual risk-taking (Bromiley, 1991; Sitkin & Weingart, 1995; Tversky & Kahneman, 1992). Therefore, building on Harvey & Fischer's (1997) idea, I propose that managers' risk perceptions influence their perceived need to share responsibility with advisors. Consequently, I study the following research questions:

Research question 1: Do managers utilize blamable human advisors to share responsibility?

Research question 2: Do managers' individual risk perceptions influence their advice utilization of blamable human advisors to share responsibility?

These research questions contribute to advice-taking literature by studying advice utilization focused on sharing responsibility as an IPOm Output-Dimension factor as well as analyzing advisors' blame potential and managers' individual risk perceptions as IPOm Individual-level factors influencing advice-taking. Moreover and in contrast to prior advice-taking literature (see chapter 2.1.2), I do not use student samples but test my research questions with real-world manager practitioners.

Table 2: Overview of important research studies on advice-taking

IPOm factors by Bonaccio & Dalal (2006)	Study	Main findings
Advice utilization focused on decision accuracy		
Individual-level	Gino et al. (2012)	Anxious judges seek more advice and are less confident.
	van Swol et al. (2019); Tost et al. (2012)	Powerful judges utilize advice less than weak judges.
	Harvey & Fischer (1997); Sniezek et al. (2004)	Judges utilize advice from experts more than from novices.
	Price & Stone (2004); Sniezek & van Swol (2001)	Judges listen more to confident advisors.
	Van Swol (2009); Bonaccio & Dalal (2010)	Judges want to utilize advice more from advisors with positive intentions, but are unable to recognize persuasive advisors who inflate confidence for higher advice utilization.
	Bednarik & Schultze (2015); Soll & Larrick (2009)	Judges tend to utilize a choosing strategy although weighting would have been beneficial when advisors' competence is correctly evaluated.
	Yaniv & Choshen-Hillel (2012); Yaniv & Kleinberger (2000); Yaniv (2004b)	Judges overestimate their own opinion and underutilize advice (egocentric bias); imagining making a decision for someone else decreases the egocentric bias.
	Schultze et al. (2017); Hütter & Fiedler (2019)	Judges overutilize arbitrary bad advice due to an anchoring bias.
	Schultze et al. (2015); Yaniv & Milyavsky (2007),	Judges utilize advice more if advice is closer to their own opinion and makes them more confident.
JAS-level	Brooks et al. (2015)	Judges who seek advice appear to be more competent.
	Larson et al. (2020)	If pre-advice consensus is reached, a group of judges shows higher egocentric bias than individual judges.
	Hütter & Ache (2016)	Judges seek more advice if the first given advice is distant to their own opinion.
	van Swol et al. (2017)	Judges perceive higher advice quality and utilize advice more if advice-giving is requested.
Environmental-level	Gino & Moore (2007); Schrah et al. (2006)	Judges seek advice and overweight it with difficult tasks and underweight it with easy tasks.
	Ache et al. (2020)	Judges rely for difficult tasks more on advice than preferred by advisors which reduces their willingness to provide future advice.
	Gino (2008), Sniezek et al. (2004)	Judges utilize costly advice more than free advice.
Process-Dimension	Dalal & Bonaccio (2010); van Swol & Ludutsky (2007)	Judges prefer advice with additional information to positive- or negative-recommendations.
	Radzevick & Moore (2011)	Competing advisors use overconfidence to convince judges to take their advice.
Advice utilization focused on sharing responsibility		
Individual-level	Harvey & Fischer (1997)	Judges seem to share responsibility in high-risk decisions.
	Palmeira et al. (2015)	Judges attribute responsibility for success to advisors and failures to themselves due to a hindsight-bias.

Notes: Only selected studies discussed in chapter 2.1.2 are shown. All studies are allocated to the dimensions of the IPOm framework depending on their main contribution. Only, Harvey & Fischer (1997) is included twice due to their important additional finding of judges' potential motive of sharing responsibility.

Source: Author.

2.2 Managerial advice-taking from algorithmic decision aids

2.2.1 Algorithmic decision aids and their fields of application

"Algorithms are everywhere: from self-driving cars and self-flying airplanes, to search engines and online stores recommending what you should buy next" (Alexander et al., 2018, p. 279). In many different contexts people receive solicited or unsolicited advice by artificial nonhuman advisors. These decisions aided by algorithms can range from diagnosing and selecting medical treatments (e.g., Grove, Zald, Lebow, Snitz, & Nelson, 2000; Esmaeilzadeh, Sambasivan, Kumar, & Nezakati, 2015), to predicting students' academic success (e.g., Dietvorst, Simmons, & Massey, 2015; Xing, Guo, Petakovic, & Goggins, 2015), to detecting movement in war zones in a military context (e.g., Parasuraman, Cosenzo, & Visser, 2009), to managing investment portfolios (e.g., Xidonas, Mavrotas, Zopounidis, & Psarras, 2011) as well as making financial forecasts in a business context (e.g., Leitner & Leopold-Wildburger, 2011; Lawrence, Goodwin, O'Connor, & Önkal, 2006).

The main reason for the widespread adoption of algorithmic decision aids is increased decision accuracy in its specialized field of application because algorithms do not make human-like mistakes (e.g., individual behavioral biases or errors due to a lack of concentration) (Alexander et al., 2018; Lowens, 2020). However, due to this wide range of different fields of application, there is no general definition of algorithmic decision aids and different literature streams use a somewhat similar but slightly different wording for the same thing – nonhuman decision support: algorithms, decision support systems, forecasting support systems, automation, AI, prediction models, computers, robots, or statistical methods (e.g., Burton et al., 2020). Cormen, Leiserson, Rivest, & Stein (2002) define an algorithm as follows:

> "[A]n ***algorithm*** is any well-defined computational procedure that takes some value, or set of values, as ***input*** and produces some value, or set of values, as ***output***. An algorithm is thus a sequence of computational steps that transform the input into the output" (p. 10).

This general definition of an algorithm describes the discussed phenomenon of algorithms aiding human judges in decisions tasks fittingly. Prior research studying the influence of algorithms on human decision-making have in common that an artificial machine or software analyzes data, tries to predict the future by identifying patterns, and recommends a decision or behavior to human judges who have to comprehend and integrate this advice in their own decision-making. In line with Burton et al. (2020), I cluster all dimensions and forms of nonhuman technical and artificial decision support which analyzes data to predict the future and helps increasing decision accuracy independent of its technical sophistication ranging from simple statistical methods to complex AI under the term "algorithmic decision aid".[10] Using algorithmic decision aids is comparable to using human advisors and is becoming more and more common:

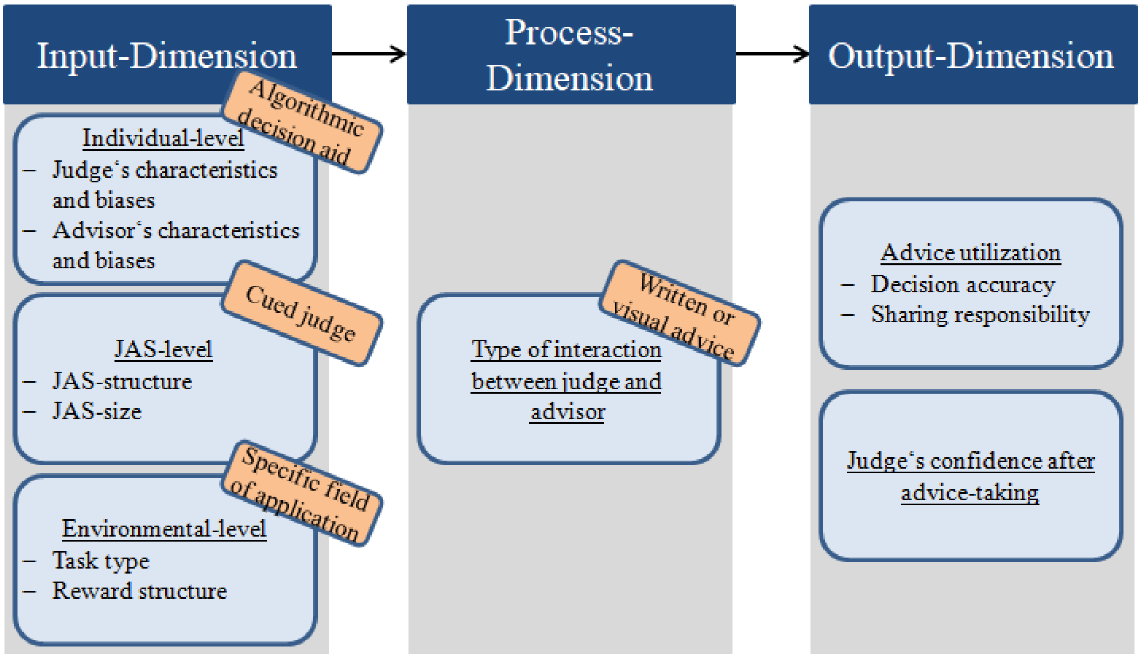
> "When most people think about advice, they likely imagine an interpersonal situation with two (or more) humans exchanging information. However, it is becoming increasingly common in both personal and professional life to seek advice from automation" (Van Swol et al., 2018, p. 32).

Transferring the different dimensions of the IPOm framework from chapter 2.1.1 to algorithmic decision aids, I find no major differences (see Figure 2). Similar to advice-taking from human advisors, judges (e.g., managers) (IPOm Individual-level) are receiving advice (IPOm JAS-level and IPOm Process-Dimension), make decisions in different environmental settings (IPOm Environmental-level), and pursue different goals like increasing decision accuracy (IPOm Output-Dimension). Moreover, judges are affected by behavioral biases when receiving advice (IPOm Individual-level). Advice-taking from algorithmic decision aids is just a special variation of each IPOm factor. The advisor is an algorithmic decision aid (IPOm Individual-level) which usually provides advice first before judges can make own decisions (i.e., cued judge) (IPOm JAS-level), is used in a very specific task type context (IPOm Environmental-level), and probably

[10] Specifically, I introduce the term „algorithmic decision aids" as an operationalization for "nonhuman advisors" and use both terms interchangeably.

predominantly communicates advice writtenly or visually (IPOm Process-Dimension). In the end, judges just have to decide to what extent they want to utilize advice by algorithmic decision aids.

Figure 2: Input-Process-Output model for algorithmic decision aids



Notes: This figure shows the IPOm framework and the specialization of each IPOm factor for algorithmic decision aids compared to common JAS settings with human advisors.

Sources: Author's interpretation, adapted from Hogan (2014, p. 3) and Bonaccio & Dalal (2006, p. 129).

Finally, the increasing integration of algorithmic decision aids in human decision-making leads to a new form and type of advisors: algorithmic decision aids (Sutherland, Harteveld, & Young, 2016). Similar to human advisors, the influence of algorithmic decision aids on its advice utilization can be described by the IPOm framework. Specifically, algorithmic decision aids just represent a specialization of each IPOm factor. The next chapter discusses the use of algorithmic decision aids in managerial forecasting settings in business contexts, which I consider as a specialization of general advice-taking literature.

2.2.2 Algorithmic decision aids in managerial forecasting settings

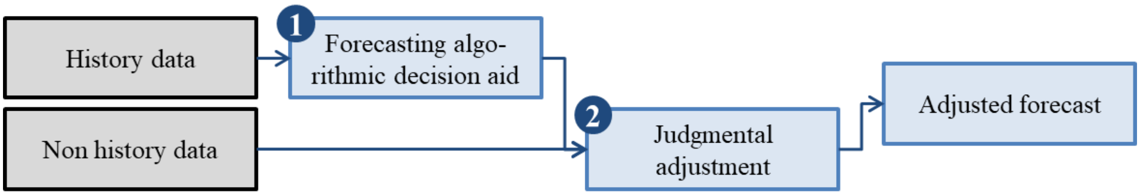
2.2.2.1 Importance and procedure of managerial forecasting

Making accurate demand or sales forecasts is a central task for managers because companies can better identify sales opportunities, minimize operational costs by reducing inventories, optimize product distribution channels, increase customer satisfaction, and maximize corporate profits (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009; Moon, Mentzer, & Smith, 2003; Salehzadeh, Tabaeeian, & Esteki, 2020). Managers and humans in general struggle to aggregate, comprehend, and integrate many different pieces of information from a variety of sources to a single decision. However, managers using algorithmic decision aids have higher decision accuracy in forecasting tasks (Blattberg & Hoch, 1990; Dietvorst et al., 2015; Lim & O'Connor, 1996a). Therefore, not human advisors but algorithmic decisions aids are usually used to support managers making forecasting decisions (Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011).

Algorithmic decision aids are especially relevant for industries in which forecasting is more complex (e.g., clothing industry) (Thomassey, 2010; Trapero, Pedregal, Fildes, & Kourentzes, 2013). Thomassey (2010) argues that textile companies work in a very competitive environment with volatile demand and have to consider strong seasonality, time criticality as well as produce a wide range of customizable products with short product life cycles on almost no historical data.

Research on advice-taking in forecasting settings describes how to create practical algorithmic decisions aids for improved supply chain planning including sales, demand, and inventory forecasts but also corporate earnings forecasts (Fildes, Nikolopoulos, Crone, & Syntetos, 2008; Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011; Syntetos, Kholidasari, & Naim, 2016; Syntetos, Nikolopoulos, & Boylan, 2010; Trapero et al., 2013). Specifically, literature provides industry specific recommendations to practitioners for building forecasting algorithmic decision aids (e.g., forecasting algorithmic decision aids for the clothing industry) (Aksoy, Ozturk, & Sucky, 2012; Thomassey, 2010; Thomassey, Happiette, & Castelain, 2005). The standard forecasting process – as described in the literature – is illustrated in Figure 3.

Figure 3: Standard forecasting process with managerial judgmental adjustment



Notes: This figure illustrates the common forecasting process with algorithmic decision aids. Numbers indicate temporal sequence of actions.

Sources: Author's interpretation, adapted from Lawrence et al. (2006, p. 494).

First, algorithmic decision aids create forecasts based on historical data. History data is past data on the variable that is to be forecasted and describes the trend, growth rate, and seasonality. In general, there are three different types of possible forecasts: Point forecasts, probability forecasts, and interval forecasts. Point forecasts represent the most likely future realized value. Probability forecasts are used to express uncertainty by providing subjective probabilities for each possible future value. Interval forecasts have lower and upper prediction limits which describe the possible range the future value will be in with a certain probability (Alvarado-Valencia & Barrero, 2014; Lawrence et al., 2006).

Second, managers can judgmentally adjust the recommended forecasts based on historical data because they might have non history data. Non history data or contextual data is information that is not included in the history data. This can be quantitative calculable facts like increased promotion budget or soft qualitative information like a competitor's reaction to an increase in promotion budget (Alvarado-Valencia & Barrero, 2014; Lawrence et al., 2006). Salehzadeh et al. (2020) argue that mixed forecasting methods, a combination of quantitative forecasts (e.g., algorithmic decision aids) and managerial adjustments, increase competitive performance by improving forecast accuracy.

The fact that managers receive forecast recommendations (advice) and have to decide whether they want to accept them or make adjustments (advice utilization) is identical to managerial advice-taking from human advisors (see chapter 2.1). Making forecasts is just a specific task type factor on the IPOm Environmental-level (see Figure 2). In line with prior advice-taking studies with human advisors, researchers study advice utilization of algorithmic decision aids – depending on the degree of observed adjustments – focusing on increasing forecast accuracy. Due to the specific forecasting setting and the potentially large negative economic effects caused by high forecast errors, increasing decision accuracy (i.e., forecast accuracy) is considered especially important compared to other advice-taking settings (Lawrence et al., 2006; Salehzadeh et al., 2020). Since literature on advice utilization in forecasting settings has many similarities with general advice-taking literature and represents a specific field of application for algorithmic decision aids as nonhuman advisors, I refer to managers making forecasts as judges.

Advice utilization as an IPOm Output-Dimension factor in forecasting settings is usually measured by the *mean absolute percentage adjustment* (*MAPA*) which focuses on the magnitude of adjustments and is very similar to *WOA* (see Equation 1) (Fildes et al., 2009; Goodwin, Fildes, Lawrence, & Nikolopoulos, 2007). Equation 3 shows the formula for calculating *MAPA*:

Equation 3: $$MAPA = mean(\left|\frac{Own\ Forecast - Recommended\ Forecast}{Recommended\ Forecast}\right| * 100)$$

The common measure for decision accuracy in the form of forecast accuracy is the *mean absolute percentage error* (MAPE) (Davydenko & Fildes, 2013; Fildes et al., 2009; Goodwin et al., 2007; Hyndman & Koehler, 2006). Equation 4 shows the formula for calculating *MAPE*:

Equation 4: $$MAPE = mean(\left|\frac{Ist - Forecast}{Ist}\right| * 100)$$

Overall, algorithmic decision aids help judges to make better forecasting decisions (e.g., Fildes et al., 2009). In line with advice-taking from human advisors, judges have to decide to what extent they want to integrate advice in their decision-making (i.e., accepting forecast recommendations or making forecast adjustments). The next chapter describes prior literature analyzing factors which influence judges' tendency to make forecast adjustments and their effects on forecast accuracy.

2.2.2.2 Factors influencing managerial advice-taking from algorithmic decision aids in forecasting settings

Prior research on advice utilization in forecasting settings identifies four central reasons why judges only partly use advice from algorithmic decision aids and make adjustments: (1) domain knowledge, (2) behavioral biases and noise, (3) lack of autonomy and understanding as well as (4) internal politics (Petropoulos, Fildes, & Goodwin, 2016; Syntetos et al., 2016). Referring to the IPOm framework, the first three reasons can be allocated to the IPOm Individual-level because these are all individual judges' characteristics or biases. Internal politics can be considered as a factor of the IPOm Environmental-level (see Figure 2). Due to the large focus of advice-taking literature specialized in forecasting settings on IPOm Individual-level factors and their effect on forecast accuracy, I adapt the classification of prior literature and especially Syntetos et al. (2016) by reviewing current research focused on increasing forecast accuracy along these four dimensions to provide a more granular overview of relevant studies.[11]

Several forecasting studies find that integrating domain knowledge in forecasts recommended by algorithmic decision aids increases overall forecast accuracy (Blattberg & Hoch, 1990; Goodwin & Fildes, 1999; Lim & O'Connor, 1996b; Mathews & Diamantopoulos, 1986; McNees, 1990; Syntetos et al., 2010; Syntetos et al., 2016; Trapero et al., 2013). Combining judgments and forecast recommendations of algorithmic decision aids is especially useful when there are stable patterns and trends which are disrupted by rare singular events (e.g., a large marketing campaign or new product launches). Moreover, adjustments tend to be more beneficial in high data variability settings due to higher uncertainty than in low data variability settings due to a more consistent pattern. Therefore, particularly large subjective adjustments usually positively contribute to forecast accuracy. Main condition for a successful integration of domain knowledge is that adjustments are based on additional information that are not processed by algorithmic decision aids and cannot be easily integrated (Davydenko & Fildes, 2013; Fildes & Goodwin, 2007b; Goodwin & Fildes, 1999; Lin, 2019; Syntetos, Nikolopoulos, Boylan, Fildes, & Goodwin, 2009). Apart from integrating missing information in the forecast, combining the strengths of several different algorithmic decision aids with the respective strength of human judgment can increase forecast accuracy (Armstrong, 2001; Eroglu & Knemeyer, 2010). Specifically, De Baets & Harvey (2018) show that judges underestimate the sales volume in times of promotion and overestimate the sales volume in normal periods. However, the integration of algorithmic decision aids in human

[11] Syntetos et al. (2016) differ between four reasons for judgmental adjustments in a forecasting setting: (1) domain knowledge, (2) behavioral biases and noise, (3) lack of autonomy and understanding as well as (4) internal politics.

judgment improves forecast accuracy, not because these biases are eliminated but by reducing random error.

Despite these legitimate reasons to adjust forecasts recommended by algorithmic decision aids, judges tend to make these adjustments too often without convincing evidence and relevant domain knowledge (Fildes et al., 2009; Fildes & Goodwin, 2007a, 2007b; Goodwin, 2000). Reasons for this behavior are that human judges are easy to confuse with noise and are behaviorally biased – similarly to advice-taking from human advisors (see chapter 2.1.2.1) (Alvarado-Valencia & Barrero, 2014; Eroglu & Croxton, 2010; Petropoulos et al., 2016).

A possible bias influencing judges is an optimism bias which describes the judges' tendency to be too optimistic and make too high forecasts by positively adjusting the recommended forecasts resulting in many positive forecast errors (Eroglu & Croxton, 2010; Fildes et al., 2009; Fildes & Goodwin, 2007b). Moreover, judges are affected by an anchoring bias causing them to stay too close to the anchor, the proposed forecast (Eroglu & Croxton, 2010; Theocharis, Smith, & Harvey, 2019). However, Theocharis & Harvey (2016) demonstrate that end-anchoring - making forecasts with different time horizons in a strictly increasing or decreasing order - increases forecast accuracy by mitigating the anchoring bias. In addition to an optimism bias and an anchoring bias, judges also exhibit an overreaction bias. This bias causes judges to make too large adjustments in the right direction which are justified by additional domain knowledge (Eroglu & Croxton, 2010). Specifically, Petropoulos et al. (2016) show that when judges cause a major forecast error due to their own adjustment, they try to correct it by making a large adjustment in the opposite direction in the next forecasting period resulting in an even worse forecast. Finally, Eroglu & Croxton (2010) argue that an optimism bias, an anchoring bias, and an overreaction bias are influenced by judges' individual factors like personality and internal or external motivation. In line with this argumentation, Eroglu &

Knemeyer (2010) analyze that adjustments are influenced by the judges' motivation and sex. Female judges focused on compensation as an external motivation make better adjustments than male ones, whereas male judges focused on enjoyment of the forecasting task as an internal motivation make better judgmental adjustments than female ones. Judges' sex influences the effects of motivation on the task performance of making adjustments.

An additional important factor reducing judges' task performance is their inflated self-confidence when making adjustments. Specifically, an overconfidence bias causes judges to be too convinced of their own opinion and make too large adjustments (Blattberg & Hoch, 1990). This effect is similar to an egocentric bias in the form of overweighting one's own opinion or forecast compared to the received advice (see chapter 2.1.2.1) (e.g., Yaniv & Choshen-Hillel, 2012; Larson et al., 2020; Franses & Legerstee, 2009; Yaniv, 2004b). This egocentric bias or overconfidence bias is especially strong when judges already made an own forecast before receiving advice in the form of the recommended forecast (Harvey & Harries, 2004). Additionally, Önkal, Gönül, & Lawrence (2008) find a framing effect. Forecasts that are labeled as already adjusted are less adjusted than identical unlabeled forecast. Moreover, the provision of an explanation of the prior adjustment further reduces judges' tendency to adjust the forecast.

Despite prior studies finding adjustments to be beneficial (e.g., Syntetos et al., 2010; Trapero et al., 2013), other researchers also find adjustments to be damaging to forecast accuracy (e.g., Fildes et al., 2009; Fildes & Goodwin, 2007a; Goodwin, 2000; Harvey, 1995). The central reason for this – in addition to the numerous previously mentioned behavioral biases – is that judges tend to react to very small, inconsequential statistical noise (Fildes & Goodwin, 2007b; Goodwin, 2000; Kahneman & Tversky, 1982; McNees, 1990). Kahneman & Tversky (1982) describe this phenomenon as the "major error of intuitive prediction" (p. 416). Specifically, Theocharis et al. (2019)

demonstrate that judges' tendency to believe in being be able to identify a pattern is stronger when historical data is displayed as a continuous line compared to discrete data points. Consequently, judges should not adjust recommended forecasts if they have no convincing reasons for it. Moritz, Siemsen, & Kremer (2014) argue that the decisive factor whether adjustments are beneficial due to additional domain knowledge or damaging due to behavioral biases and a reaction to inconsequential statistical noise, is whether judges can balance their intuitive and rational decision-making. Specifically, Moritz et al. (2014) demonstrate that judges who can balance intuitive judgment and rational deliberation, have higher forecaster accuracy compared to very fast or very slow deciding judges.

Apart from domain knowledge, behavioral biases, and statistical noise, judges' lack of autonomy and understanding is another reason for unnecessarily adjusted forecasts. Goodwin (2002) stresses that the adoption of recommended forecasts should not be forced and has to be voluntary, otherwise the forecasts will not be accepted. Judges always need to have the opportunity to make adjustments and believe that it is still their decision even if they completely adapt the recommended decisions. Moreover, judges need to superficially understand how the algorithmic decision aids are technically working. If they cannot understand the calculations of the algorithmic decision aids due to a lack of training in forecasting and utilization of algorithmic decision aids, judges will make adjustments just to get a better understanding and feeling for the forecast (Dietvorst, Simmons, & Massey, 2016; Syntetos et al., 2016). In line with this, Gönül et al. (2009) demonstrate that judges make smaller adjustments when the forecast is recommended by a well-known source and they can understand the underlying theoretical assumptions and explanations of the algorithmic decision aid. In line with this, Legerstee & Franses (2014) and Kim, Lee, & Jun (2019) show that if judges are trained and receive feedback, they reduce their adjustments and have higher forecast accuracy. Moreover, De Baets &

Harvey (2020) find that judges realize which algorithmic decision aids are providing better recommendations over time and can improve forecast accuracy by choosing and integrating the right algorithmic decision aids. Overall, training judges in the utilization and calculations of algorithmic decisions aids is a central part in avoiding unnecessary adjustments.

So far, judges predominantly concentrated on improving forecast accuracy by integrating domain knowledge but were limited due to IPOm Individual-level factors like behavioral biases, distorted perceptions caused by statistical noise or a lack of training and perceived autonomy. However, judges can also have different intentions like complying to internal politics when adjusting recommended forecasts. Consequently, IPOm Environmental-level factors like organizational frameworks and expectations can affect adjustments. If the forecasting process explicitly intends judges to make adjustments and even considers the judges' needed working hour capacity for this, then judges can feel organizationally forced to intervene. Moreover in practice, companies use forecasts to reach a commitment among different business unit managers and are willing to dilute the final forecast and worsen forecast accuracy for this (Lawrence, O'Connor, & Edmundson, 2000). However, not only companies on an organizational level but also individuals misuse forecasts for other motives. For example, sales managers can consciously positively adjust the recommended sales forecasts to guarantee not to run out of possible sales products. This way, sales managers do not risk missing their individual sales targets due to low inventory levels by dysfunctionally causing increased organizational costs (Syntetos et al., 2016).

So far, prior research on algorithmic decision aids in forecasting settings has identified mainly IPOm Individual-level factors influencing advice utilization focused on increasing decision accuracy. Due to the error based nature of forecasts, it is obvious that most studies analyze how forecasts in a business context can be as accurate as possible and minimize financial costs due to forecast errors (Fildes et al., 2009; Moon et al., 2003; Salehzadeh et al., 2020). Specifically, integrating judges' domain knowledge (e.g., a large rare marketing campaign) that is not represented in forecasting data is one main argument supporting forecast adjustments (e.g., Trapero et al., 2013). However, prior research also finds that judges tend to make too many unnecessary forecast adjustments due to behavioral biases (e.g., anchoring bias) and distractions by random noise (e.g., Fildes et al., 2009 and Eroglu & Croxton, 2010). Nonetheless, judges can increasingly avoid accuracy damaging forecast adjustments when being trained to understand the forecast calculations of the algorithmic decision aids (e.g., Kim et al., 2019). Consequently, (1) having important domain knowledge, (2) being aware of potential behavioral biases and statistical noise, and (3) being trained to use algorithmic decision aids are central judges' characteristics on an IPOm Individual-level when making forecasting decisions focused on increasing forecast accuracy. In the next chapter I introduce sharing responsibility with algorithmic decision aids as an additional motive for forecast adjustments and identify the research gap on adjustments in managerial forecasting settings.

2.2.2.3 Identified research gap on managerial advice-taking from algorithmic decision aids in forecasting settings

Judges use algorithmic decision aids very similar to human advice – listening to it and then deciding how much to utilize it. These algorithmic decisions aids are traditionally classical statistical methods and have been in place in managerial forecasting settings for decades (Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011; van Swol et al., 2018). However, with increasing technological sophistication, algorithmic decision aids (e.g., AI) can be used in more and more complex settings (Floridi et al., 2018; Sutherland et al., 2016). Nonetheless, advice from algorithmic decision aids is often adjusted. Fildes et al. (2009) find in a field study that a single company in their sample adjusted 91% of all inventory forecasts indicating too many unnecessary adjustments.

Advice-taking literature proposes two motives for advice utilization: (1) increasing decision accuracy and (2) sharing responsibility (Bonaccio & Dalal, 2006). Current advice-taking literature specialized in forecasting settings focuses on how to allow justified adjustments dependent on domain knowledge and avoid unnecessary adjustments mainly caused by behavioral biases and lack of training. Table 3 presents a consolidated overview of important studies on judgmental adjustments in managerial forecasting settings along the dimensions proposed by Syntetos et al. (2016). Nonetheless, all these factors are only studied in regard to their influence on forecast accuracy. Research about the second advice-taking motive – sharing responsibility – in a forecasting context with algorithmic decision aids is scarce. If at all, then forecasting research predominantly focused on forecast accuracy contributes to the advice-taking motive sharing responsibility in the form of unintended additional findings.

Specifically, Gönül et al. (2009) already show the relevance of judges' responsibility in making judgmental adjustments. They note as an additional finding that judges' adjustments depend on their wish to assume responsibility for the forecasts. Interestingly, Gönül et al. (2009) find that assuming responsibility by increasing adjustments is more relevant than avoiding responsibility by reducing adjustments. This finding is a striking parallel to the advice-taking motive sharing responsibility. The higher the judges' advice utilization, the more judges and advisors (e.g., algorithmic decision aids) share responsibility. In contrast to current advice-taking literature specialized in forecasting settings, I do not focus on improving forecast accuracy by studying factors which prevent judges from making unnecessary adjustments (see Table 3). Instead, I transfer the second general advice-taking motive sharing responsibility to specialized forecasting settings with algorithmic decision aids.

The question of responsibility attribution to nonhuman blamable algorithmic decision aids (analogous to blamable human advisors – see chapters 2.1.2.2 and 3.2.2) is becoming more and more relevant with increasing technological sophistication and additional fields of application. A panel consisting of academia, business, and government participants identifies responsibility attribution to algorithmic decision aids as a central challenge (Robert, Bansal, & Lütge, 2020). Specifically, current philosophical research already studies whether nonhuman things like algorithmic decisions aids can normatively assume responsibility for their actions (e.g., Ashrafian, 2015; Coeckelbergh, 2020). Building on the two conditions of responsibility by Aristotle, one is generally considered responsible when (1) one has control over one's actions and (2) is aware of the resulting consequences (Coeckelbergh, 2020). Transferring this argumentation to nonhuman advisors means that algorithmic decision aids are only normatively responsible when they have an own consciousness and can fully control their own actions as well as understand the resulting consequences (Ashrafian, 2015; Coeckelbergh, 2020).

However, my main focus is not on whether algorithmic decisions aids improve forecast accuracy or whether they can normatively assume responsibility. Instead, I study whether judges (e.g., managers) perceive nonhuman advisors in the form of blamable algorithmic decisions aids to be responsible for bad decision outcomes (e.g., major forecast errors) by consciously attributing responsibility to them and on which factors this depends. Managers not focused on increasing decision accuracy but on sharing responsibility with blamable algorithmic decision aids can have adverse effects on the economic success of companies due to higher operational costs and wrong demand forecasts as well as worsen organizational competitiveness (Fildes et al., 2009; Moon et al., 2003; Salehzadeh et al., 2020). Therefore, I study the following research question:

<u>Research question 3:</u> Do managers utilize nonhuman advice by blamable algorithmic decision aids to share responsibility?

This research question contributes to advice-taking literature by studying advice utilization focused on sharing responsibility as an IPOm Output-Dimension factor. Moreover, I am the first to study the blame potential of nonhuman algorithmic decision aids as an IPOm Individual-level factor (see Figure 2). The next chapter compares managerial advice-taking from human advisors (see chapter 2.1) and algorithmic decision aids as nonhuman advisors (see chapter 2.2).

Table 3: Overview of important research studies on judgmental forecast adjustments

Reasons for adjustments by Syntetos et al. (2016)	Study	Main findings
Judgmental forecast adjustment focused on decision accuracy		
Existence of domain knowledge	Trapero et al. (2013); Goodwin & Fildes (1999); Syntetos et al. (2009); De Baets & Harvey (2018)	Judges implementing domain knowledge (e.g., promotion activity) increase forecast accuracy.
	Lin (2019)	Adjustments are only beneficial in high data variability settings due to the possible integration of potential domain knowledge.
	Syntetos et al. (2016); Davydenko & Fildes (2013)	Adjustments can improve forecast accuracy and reduce inventory costs.
Confusion by random noise and biases	Eroglu & Croxton (2010); Alvarado-Valencia & Barrero (2014); Fildes & Goodwin (2007b); Harvey & Harries (2004); Franses & Legerstee (2009)	Judges are affected by anchoring, overoptimism, egocentric, and overreaction biases when making adjustments.
	Theocharis & Harvey (2016)	End-anchoring, sequential forecasting of increasing/decreasing time horizons, increases accuracy.
	Petropoulos et al. (2016)	Judges overreact to forecast errors by overadjusting in the opposite direction.
	Fildes et al. (2009)	Large adjustments increase forecast accuracy, smaller adjustments reduce it.
	Theocharis et al. (2019)	Judges see fictitious patterns when historical data is displayed as a continuous line.
	Önkal et al. (2008)	Forecasts labeled "adjusted" are less adjusted than unlabeled forecasts.
	Moritz et al. (2014)	Judges making fast, intuitive or slow, rational adjustments have lower accuracy than judges balancing intuitive and rational decision-making.
	Eroglu & Knemeyer (2010)	Benefits of adjustments depend on the judges' sex and motivational orientation. Compensation-seeking female and enjoyment-seeking male judges make better adjustments.
	Fildes & Goodwin (2007a); Goodwin (2000)	Judges avoid unnecessary adjustments by documenting reasons.
Lack of autonomy and understanding	Dietvorst et al. (2016); Goodwin (2002)	Judges make adjustments to feel in control and to better understand it.
	Legerstee & Franses (2014); Kim et al. (2019)	Trained judges make smaller adjustments and have higher forecast accuracy.
	De Baets & Harvey (2020)	Judges recognize advice quality of algorithmic decision aids and utilize it accordingly.
	Gönül et al. (2009)	Judges decrease adjustments if they can understand the underlying forecasting assumptions.
Internal politics	Lawrence et al. (2000)	Judges make adjustments because it is organizationally expected from them.
Judgmental forecast adjustment focused on sharing responsibility		
Lack of autonomy and understanding	Gönül et al. (2009)	Judges increase adjustments if they want to assume responsibility.

Notes: Only selected studies discussed in chapter 2.2.2 are shown. All studies are allocated to the four reasons for forecast adjustments by Syntetos et al. (2016) depending on their main contribution. Only, Gönül et al. (2009) is included twice due to their important additional finding of judges' potential motive of sharing responsibility. Moreover, all reasons for judgmental adjustments can also be allocated to the IPOm framework. Existence of domain knowledge, confusion by random noise and biases as well as lack of autonomy and understanding describe IPOm Individual-level factors, whereas internal politics represent an IPOm Environmental-level factor.

Source: Author

2.3 Algorithm aversion in managerial advice-taking

2.3.1 General drivers of algorithm aversion in managerial advice-taking

When managers receive and utilize advice, there are many parallels between human advisors and algorithmic decision aids. In the end, taking advice from algorithmic decision aids is just a special variation of general advice-taking from advisors (see Figure 2). In line with this, prior literature finds similar IPOm Individual-level factors – especially behavioral biases – for advice-taking from human advisors and algorithmic decisions aids.

Specifically, judges underutilize human advice due to an egocentric bias (e.g., Yaniv & Kleinberger, 2000; Yaniv & Choshen-Hillel, 2012) as well as make many unnecessary adjustments of advice from algorithmic decision aids due to an overconfidence or egocentric bias (e.g., Harvey & Harries, 2004; Eroglu & Croxton, 2010). Moreover, judges are similarly affected by an anchoring bias caused by human advisors (e.g., Bonaccio & Dalal, 2006; Schultze et al., 2017) and algorithmic decision aids (e.g., Eroglu & Croxton, 2010; Theocharis et al., 2019). Additionally, the more competent human advisors are perceived, the higher advice utilization (Bonaccio & Dalal, 2006; Harvey & Fischer, 1997; Soll & Larrick, 2009; Yaniv & Kleinberger, 2000). This is also the case for algorithmic decision aids (De Baets & Harvey, 2020; Dietvorst et al., 2016). These parallels concerning judges‘ individual behavioral biases are not surprising because the reasons for these rest within the judges’ bounded rationality and not in the advisors’ nature (human advisors vs. algorithmic decision aids). Consequently, Hütter & Fiedler (2019) find no difference in judges’ advice utilization when framing the identical advice with a human advisor or an algorithmic decision aid.

However and contradicting Hütter & Fiedler (2019), there are several other advice-taking studies which find that judges prefer human advisors compared to algorithmic decision aids in regard to increasing decision accuracy (e.g., Burton et al., 2020; Önkal et al., 2009; Dietvorst et al., 2015, 2016). Specifically, Önkal et al. (2009) demonstrate that the identical recommended forecast is utilized more and less adjusted if it is recommended by a human advisor compared to an algorithmic decision aid. Moreover, judges are perceived more negatively when they seek advice from algorithmic decision aids compared to human expert advice (Shaffer, Probst, Merkle, Arkes, & Medow, 2013). Research describes this phenomenon as "algorithm aversion". This term implies that judges systematically prefer their own human opinion or other human advisors compared to algorithmic decision aids (Burton et al., 2020; Dietvorst et al., 2015, 2016; Prahl & van Swol, 2017). While there are several behavioral biases which similarly affect judges' advice-taking from human advisors and algorithmic decision aids, the bias algorithm aversion causes judges to systematically discount advice from algorithmic decisions aids. Burton et al. (2020) propose five possible dimensions for analyzing the reasons for algorithm aversion and observed underutilization of algorithmic advice: (1) Judges' expectations and expertise, (2) incentivization, (3) decision autonomy, (4) cognitive compatibility, and (5) divergent rationalities. In the following, I review prior literature on algorithm aversion along these dimensions.

An important reason for algorithm aversion is that judges have too high expectations of algorithmic decision aids caused by existing prejudices (Burton et al., 2020). There is a "persistent belief that human error is random and repairable whereas algorithmic error is systematic" (Burton et al., 2020, p. 223). Moreover, Prahl & van Swol (2017) argue that „humans generally expect automation to be 'perfect' (i.e., with an error rate of zero), whereas a human is expected to be imperfect and to make mistakes" (p. 693). These unequal expectations cause algorithm aversion because judges lose trust faster in algorithmic decision aids than human advisors when observing identical mistakes and reduce advice utilization stronger (Dietvorst et al., 2015; Prahl & van Swol, 2017). Furthermore, Longoni, Bonezzi, & Morewedge (2019) find that judges exhibit algorithm aversion because they doubt that algorithms can consider personal and individual circumstances. Consequently, judges dislike imperfect algorithmic decision aids, even when they are objectively better than their human counterparts (Dietvorst et al., 2016). Nonetheless, there are also contradicting findings. Goodyear et al. (2016) find the exact opposite by demonstrating that judges reduce advice utilization stronger for human advisors than for algorithmic decision aids when observing the identical error. In line with this, Logg, Minson, & Moore (2019) argue that judges utilize algorithmic decision aids more than human advisors but show increasing algorithm aversion with higher task expertise. While there are some contradicting findings on algorithm aversion, too high and unrealistic expectations are a central factor. Burton et al. (2020) propose that an increase in algorithmic literacy by training judges to interpret statistical results and avoid overstressing a statistical miss due to random noise lowers overall algorithm aversion and increases overall decision accuracy.

In addition to training judges, directly incentivizing the utilization of algorithmic decision aids is an obvious way of trying to convince judges. Burton et al. (2020) propose two different types of incentives which influence algorithm aversion: (1) monetary and (2) social incentivization. Monetary incentives reward judges financially for making good decisions, whereas social incentives allow judges to gain social reputation among their peers. There are contradicting findings on the usefulness of financial rewards on influencing algorithm aversion. Prahl & van Swol (2017) find no algorithm aversion when using financial rewards, whereas Önkal et al. (2009) demonstrate persisting algorithm aversion despite financial incentives. There is no clear evidence that financial incentives really reduce algorithm aversion and convince judges to utilize algorithmic decisions aids similar to human advisors. However, the implementation of social incentives is more promising (Burton et al., 2020). Specifically, Alexander et al. (2018) demonstrate that judges exhibit higher utilization of algorithmic decision aids when they are informed that other human judges already use these algorithmic decision aids strongly. This information is even more effective than detailed information on the statistical accuracy of algorithmic decision aids. All that matters is that other human judges already trust specific algorithmic decision aids. Consequently, the informed judges also trust and utilize them.

Another possible reason for reduced advice utilization of algorithmic decision aids is perceived limited decision autonomy. Judges want to believe that they have complete control over the decision and dislike deviating from their own intuition (Burton et al., 2020). In line with this, Scherer, Vries, Zikmund-Fisher, Witteman, & Fagerlin (2015) demonstrate that judges become more confident, the more they deliberately make a decision by slow and effortful thinking. This is true, even if judges make the exact same decision. The process of carefully debating what to choose and feeling in control is more important to judges than the realized decision. Moreover, Highhouse (2008) argues that judges are convinced that their decision accuracy is positively influenced by increasing experience and resist viewing decisions as probabilistic. Therefore, they prefer individual human intuition and human advice to algorithmic decision aids. Addressing the judges' need for feeling in control, Dietvorst et al. (2016) demonstrate that advice utilization of algorithmic decision aids is increased if judges can modify and adjust the recommended advice. Increased advice utilization is still observed when the adjustments are extremely limited and merely symbolic. Decisive factor for judges adopting advice from algorithmic decision aids and lowering algorithm aversion is their feeling of control over the decision (Burton et al., 2020; Dietvorst et al., 2016).

Apart from feeling in control, judges only utilize algorithmic decisions aids when they also understand the underlying decision processes and are cognitively compatible (Yeomans, Shah, Mullainathan, & Kleinberg, 2019). This means that judges try to integrate and combine their decision-making consisting of human intuition with algorithmic decision aids (Burton et al., 2020). Jarrahi (2018) and Patterson (2017) argue that algorithmic decision aids can improve analytic decisions parts but should augment and not replace human intuition which provides a suitable holistic view on uncertain decision-making environments. „Without cognitive compatibility, algorithmic aids simply combat rather than engage human intuition" (Burton et al., 2020, p. 225) In line with this, Shin (2020) and Önkal, Gönül, & De Baets (2019) demonstrate that when algorithmic decisions aids are perceived to be more transparent, fairer, and better to comprehend, then trust is increased and algorithmic decision aids are more utilized. Current literature mainly focuses on biases preventing judges from adopting algorithmic advice (e.g., Alexander et al., 2018; Dietvorst et al., 2015), but ignores the judges' own black box – human intuition. Specifically, judges are generally expected to adapt their own intuition and follow the recommended advice. However, to permanently reduce algorithm aversion, algorithmic decision aids need to augment human intuition by supporting and complementing it (Brown, 2015; Burton et al., 2020; Patterson, 2017).

Even if human intuition is augmented by algorithmic decision aids, judges still may have divergent rationalities than algorithmic decision aids when making decisions in different environmental settings. Judges (e.g., managers) usually make decisions under uncertainty and do not know all alternatives with probabilities, whereas algorithmic decision aids are specialized in decisions under risk with known alternatives and corresponding probabilities. However, the best decision under uncertainty is not necessarily the best decision under risk. Therefore, judges may pursue different decision outcomes depending on their decision environment (Arkes, Gigerenzer, & Hertwig, 2016; Burton et al., 2020; Hafenbrädl, Waeger, Marewski, & Gigerenzer, 2016). Interestingly and despite the fact that algorithmic decision aids are optimized for structured decision problems, some previous studies find increased utilization of algorithmic decisions aids in unstructured, unpredictable decision environments (Burton et al., 2020; Carey &

Kacmar, 2003; Sutherland et al., 2016). In contrast to that Dietvorst & Bharti (2020) demonstrate that judges exhibit increased algorithm aversion for uncertain decision environments due individuals' preference for making a perfect decision (e.g., making a forecast decision with no forecast error). Specifically, individuals try in vain to counterbalance higher noise of uncertain decision environments with human judgment by adjusting highly probable statistical recommendations. Moreover, Castelo, Bos, & Lehmann (2019) show that judges exhibit higher algorithm aversion for perceived subjective tasks than for objective tasks. However, increasing algorithmic decision aids perceived human-likeness (e.g., creating art and music, understanding human emotion) reduces algorithm aversion. Specifically, Lowens (2020) and Castelo et al. (2019) argue that not psychological biases but a task-mismatch is the main cause for algorithm aversion. Only if judges deem algorithmic decision aids suitable for supporting a specific task type, they utilize their advice (e.g., higher algorithm aversion for subjective than objective tasks).

Finally, algorithm aversion is a consistent finding of current research across many different contexts and is caused by cognitive reasons (e.g., too high expectations, lack of perceived decision autonomy, and low cognitive compatibility) as well as environmental factors (e.g., incentivization and divergent rationalities due to a task-mismatch) (Burton et al., 2020). These reasons for algorithm aversion can be allocated to the IPOm framework and be considered as IPOm Individual-level and IPOm Environmental-level factors influencing advice utilization of algorithmic decision aids (see Figure 2). The next chapter discusses the identified research gap on algorithm aversion.

2.3.2 Identified research gap on algorithm aversion in managerial advice-taking

Current advice-taking literature finds systematic algorithm aversion. Specifically, judges tend to underutilize the identical beneficial advice from algorithmic decision aids compared to human advisors for many different reasons (e.g., Burton et al., 2020). A central reason is that judges believe they can make better decisions with human advisors than algorithmic decision aids and thereby increase overall decision accuracy. In line with this, research on algorithm aversion predominantly assumes that judges focus on increasing decision accuracy and analyzes how human advisors or algorithmic decision aids are utilized in regard to this advice-taking motive (see chapter 2.3.1) (e.g., Prahl & van Swol, 2017; Dietvorst et al., 2016; Önkal et al., 2009). Additionally, important studies on algorithm aversion are illustrated in Table 4.

However, despite the fact that advice-taking literature has identified the importance of the second possible reason for advice utilization – sharing responsibility, there is no research on algorithm aversion for this motive. Specifically, Harvey & Fischer (1997) and Palmeira et al. (2015) demonstrate the relevance of this motive for advice-taking from blamable human advisors (see chapters 2.1.2.3 and 3.2.2), whereas Gönül et al. (2009) explain it for advice-taking from blamable algorithmic decision aids (see chapters 2.2.2.3 and 3.2.2). Additionally, Niewiem & Richter (2006) stress the importance of this advice-taking motive for manager practitioners.

Especially, the findings of Lowens (2020) and Castelo et al. (2019) are interesting because they propose a task dependent influence on algorithm aversion which is stronger for subjective decision tasks. One could argue that sharing responsibility with blamable advisors is a more subjective decision task because there is no objectively optimal answer but just a perceived shift in responsibility. Therefore, I study the following research question:

<u>Research question 4:</u> Do managers exhibit algorithm aversion when utilizing blamable advice to share responsibility?

This research question contributes to advice-taking literature by studying advice utilization focused on sharing responsibility as an IPOm Output-Dimension factor and algorithm aversion in the form of advisors' nature (human advisors vs. algorithmic decision aids) as an IPOm Individual-level factor (see Figure 2).

Finally, chapter 2 summarizes prior research on managerial advice-taking from human advisors (see chapter 2.1) and from algorithmic decision aids (see chapter 2.2) as well as their corresponding differences in the form of algorithm aversion (see chapter 2.3). Specifically, advice-taking research identifies two main reasons for advice utilization: (1) increasing decision accuracy and (2) sharing responsibility (Bonaccio & Dalal, 2006). I develop my research questions focusing on the advice-taking motive sharing responsibility with human advisor (e.g., Harvey & Fischer, 1997) and algorithmic decisions aids (e.g., Gönül et al., 2009). Consequently, the central assumption of my research questions in this thesis is that judges or managers want to share responsibility with advisors, irrespective of the potential consequences for decision accuracy. Specifically, this thesis studies what IPOm Individual-level factors (i.e., manager's risk perception, advisor's blame potential, and algorithm aversion in the form of advisor's nature) impact managerial advice-taking focused on sharing responsibility as an IPOm Output-Dimension factor (see chapters 2.1.2.3, 2.2.2.3, and 2.3.2). The next chapter discusses why managers are motivated to avoid personal blame and what blame avoiding strategies they can use (e.g., sharing responsibility with advisors).

Table 4: Overview of important research studies on algorithm aversion

Reasons for algorithm aversion by Burton et al. (2020)	Study	Main findings
Expectation and expertise	Dietvorst et al. (2015, 2016); Prahl & van Swol (2017)	When observing errors, judges lose trust faster in algorithmic decision aids than human advisors.
	Goodyear et al. (2016)	When observing errors, judges lose trust faster in human advisors than algorithmic decision aids.
	Logg et al. (2019)	Experts show higher algorithm aversion than novices.
	Longoni et al. (2019)	Judges doubt algorithms can consider individual personal circumstances.
Decision autonomy	Scherer et al. (2015)	Judges gain more confidence, the longer they deliberately think about a decision because they perceive an increase of control although the final decision does not change.
	Dietvorst et al. (2016)	Allowing judges to modify irrelevant, superficial settings, decreases algorithm aversion.
	Highhouse (2008)	Judges resist using algorithmic decision aids and trust their intuition due to a wrong believe of being able to see a pattern in statistical noise.
Incentivization	Prahl & van Swol (2017)	Judges show no algorithm aversion when financially incentivizing decision accuracy.
	Önkal et al. (2009)	Judges show algorithm aversion when financially incentivizing decision accuracy.
	Alexander et al. (2018)	Social incentivization like informing about utilization by colleagues reduces algorithm aversion.
Cognitive compatibility	Brown (2015); Jarrahi (2018)	Algorithm aversion can only be reduced if it does not compete with judges' intuitive decision-making but supports it.
	Yeomans et al. (2019)	Judges exhibit algorithm aversion due to a lack of understanding of algorithmic decision processes.
	Shin (2020); Önkal et al. (2019)	Judges trust algorithmic decision aids more and utilize them if they are perceived as transparent and fair.
	Patterson (2017)	Intuition dominates human decision-making and has to be considered by algorithm decisions aids.
Divergent rationalities	Arkes et al. (2016)	Depending on environmental factors, deliberate or fast-and-frugal decisions can be rational.
	Sutherland et al. (2016)	Overutilization (Underutilization) of algorithms in less (more) predictable environments.
	Dietvorst & Bharti (2020)	High algorithm aversion in unpredictable environments as individuals try in vain to adjust highly probable recommendations to make perfect decisions with no error term.
	Castelo et al. (2019)	Higher algorithm aversion for subjective than for objective task. Increasing perceived level of human-likeness of algorithmic decision aids can reduce algorithm aversion.
	Lowens (2020)	Task-mismatch, not behavioral biases, drives algorithm aversion.

Notes: Only selected studies discussed in chapter 2.3 are shown. All studies are allocated to the five reasons for algorithm aversion depending on their main contribution. Prahl & van Swol (2017) and Dietvorst et al. (2016) are mentioned twice due to their broader contribution to several reasons on algorithm aversion. Moreover, all reasons for algorithm aversion can also be allocated to the IPOm framework. Expectation and expertise, decision autonomy, and cognitive compatibility represent IPOm Individual-level factors, whereas incentivization and divergent rationalities due to a task-mismatch are IPOm Environmental-level factors.

Source: Author, adapted from Burton et al. (2020, p. 232-239).

3 Managerial blame assignment and avoidance

3.1 Managerial blame assignment and organizational consequences

3.1.1 Motives and biases influencing managerial blame assignment

Blaming others is a general human phenomenon which can be observed in many different industries ranging from healthcare organizations (e.g., Mitchell, 2014; Khatri, Brown, & Hicks, 2009) to public sector institutions (e.g., James et al., 2016; Bach & Wegrich, 2019) as well as private sector companies (e.g., Skarlicki et al., 2017). Malle, Guglielmo, & Monroe (2014) describe blame as "a unique moral judgment that is both cognitive and social [..] [which] regulates social behavior" (p. 147). Specifically, Skarlicki et al. (2017) differ managerial blame assignment in two main dimensions: (1) assigning responsibility and (2) holding the blamed individual accountable by choosing an appropriate punishment (e.g., disciplinary actions like warning or dismissing employees). Assigning responsibility is a cognitive process which decides if and by how much someone is responsible for a mistake, whereas choosing punishment ensures social regulation (Alicke, 2000; Malle et al., 2014; Skarlicki et al., 2017).

Skarlicki et al. (2017) identify three main reasons for managers assigning responsibility: (1) Organizational factors, (2) legal obligations or societal expectations, and (3) behavioral reasons. Organizational factors describe managers' tendency to blame others because they believe this reaction is organizationally excepted from them when employees make mistakes. This way managers try to signal other employees what happens to individuals who violate organizational structure by not doing their work properly and motivate them. Moreover, legal obligations (e.g., pursuing and stopping sexual harassment in the work place) or general societal expectations (e.g., preventing employees from violating corporate social responsibility actions) can force managers to assign blame. Additionally, behavioral biases can cause managers to blame others (Skarlicki et al., 2017). Especially, people with high self-esteem tend to accuse others for personal failure because they want to protect themselves and avoid admitting they made mistakes (Crocker & Park, 2004). It is important to note that the decision to assign responsibility is an intuitive and reflexive cognitive process that happens automatically (Alicke, 2000).

The reason for this intuitive cognitive process of assigning responsibility and blame is founded in human evolution. Human evolution has been aided with the introduction of social norms – learned behavioral standards controlled by the community. Adhering to norms resulted in positive social relationships and shared resources, whereas ignoring norms resulted in punishment because it endangered the survival of the community (Chudek & Henrich, 2011). Humans are social beings who ostracize everyone who endangers their common goals and threatens survival (Alicke, 2000; Skarlicki et al., 2017). Consequently, assigning responsibility and blaming others is used as a corrective or punishment mechanism to ensure prosocial behavior and is deeply evolutionary ingrained in humans. The more damage the anti-social behavior causes, the harsher the punishment (Cushman, 2013). Mitchell (2014) argues that blame has a very negative connotation and feels bad for the blamed individual due to feelings of social exclusion (e.g., ostracizing and shunning) and shame which causes a general fear of being blamed. In line with this, Gorini, Miglioretti, & Pravettoni (2012) find that individuals are more afraid of being blamed than being punished. Depending on the specific situation and the negative (economic) impact, managers have a broad range for choosing appropriate punishments from providing private confidential criticism to public reprimands or even laying off the blamed employee (Skarlicki et al., 2017). Finally, managers assign responsibility and punish employees because they want to enforce prosocial behavior – desired behavior from the companies’ perspective – by reminding other employees of the consequences of misbehavior.

Since blame assignment happens intuitively based on predisposing evolutionary ingrained biases when someone deviates from social norms, motivational cognitive biases play a central role in influencing responsibility assignment compared to organizational factors or legal obligations (Alicke, 2000; Skarlicki et al., 2017). Specifically, a self-serving bias determines someone's general tendency to blame others (Crocker & Park, 2004; Skarlicki et al., 2017). This means that success is attributed to oneself, whereas failure is attributed to external factors like bad luck or other individuals' incompetence. Managers with high self-esteem increase own self-esteem by claiming successes and protect their self-esteem by blaming others in the case of failure (Coleman, 2011). Moreover, managers exhibit a correspondence bias. They associate observed mistakes by employees automatically with the employees' characteristics (e.g., being sloppy) and ignore potential context information that might explain these mistakes (e.g., being under severe time pressure) (Howell & Shepperd, 2011; Skarlicki et al., 2017).

Additionally, judging the blamed individuals' causal attribution and influence on mistakes is biased. Paharia, Kassam, Greene, & Bazerman (2009) explain that individuals perceive negative actions done indirectly as less negatively than direct negative actions.[12] However, this is only the case when making these judgments independently. If these actions are directly compared, the indirect action is perceived to be more blameworthy. Moreover, Lagnado & Channon (2008) demonstrate that intentional actions which lead to harm are more blameworthy than unintentional actions. Interestingly, the location of the action on the causal timeline to the final blameworthy effect also has an influence on perceived blame attribution. The closer the action to the final negative event and the more

[12] A possible setting is that a healthcare company directly increases drug prices (direct action) or sells the drug license to another healthcare company which has to make an even larger price increase due to high license costs (indirect action) (Paharia et al., 2009; Berenson, 2006).

foreseeable the negative consequence is, the more blamable the action. Consequently, managers are influenced by many biases when assigning responsibility.

In line with assigning responsibility, punishing the blamed employees is also influenced by biases. Choosing an adequate punishment is associated with negative emotions like anger, contempt, and disgust (Haidt, 2003; Skarlicki et al., 2017). Specifically, managers are affected by a negativity bias causing them to focus more on negative than on positive experiences. This causes managers to choose too harsh and inappropriate punishments (Rozin & Royzman, 2001; Skarlicki et al., 2017). This is especially problematic because Andrade & Ariely (2009) explain that even prior outdated negative incidental emotions can build the basis for future negative evaluations that have nothing to do with their original cause. Consequently, managers choosing punishments are biased.

Finally, blame assignment is an intuitive evolutionary process focusing on ostracizing individuals who deviate from social expectations and thereby endanger the survival of the community. This intuitive process of assigning responsibility and choosing an appropriate punishment is influenced by different behavioral biases (e.g., self-serving bias, negativity bias). Consequently, managers often unwarrantedly assign blame to employees and choose too harsh punishments (Alicke, 2000; Chudek & Henrich, 2011; Crocker & Park, 2004; Rozin & Royzman, 2001; Skarlicki et al., 2017). The next chapter summarizes possible negative organizational consequences resulting from unwarranted managerial blame.

3.1.2 Organizational consequences of managerial blame assignment

Managers blaming and punishing employees warrantedly or unwarrantedly can cause severe negative consequences for organizations by negatively influencing employees' behavior. Blaming colleagues can destroy interpersonal compassionate relationships and create a downward spiral of interpersonal conflicts as well as antisocial and aggressive behavior (Andersson & Pearson, 1999; Atkins & Parker, 2012). Moreover, people who feel treated unfairly try to seek revenge to restore justice (Tripp & Bies, 2010). These interpersonal conflicts and loss of mutual trust reduce individual employee's performance and thereby also organizational performance because resources are only personally utilized and no longer shared with colleagues (Dirks & Skarlicki, 2009). Consequently, a blame culture emerges which causes employees to avoid taking risks and desperately try to avoid personal blame (Gorini et al., 2012; Khatri et al., 2009; Mitchell, 2014). Therefore, an organizational blame culture increases organizational inefficiencies and reduces organizational performance (Dingwall & Hillier, 2015; Skarlicki et al., 2017).

Moreover, a prevailing blame culture focused on avoiding personal blame can also lead to a culture of blame storming. Blame storming describes the fact that employees do not focus on discussing why things failed but on who is responsible for failure. Consequently, a blame storming culture hinders communication of errors and organizational learning (Catino, 2009; Dingwall & Hillier, 2015; Skarlicki et al., 2017). Specifically, Knapp (2016) argues that employees' interpersonal beliefs of psychological safety positively influence their team learning behavior. Only if all employees or team members believe to be psychologically safe, they are ready for interpersonal risk-taking and learning (Edmondson, 1999). Sufficient mutual trust is a central basis for employees to openly discuss mistakes and collectively learn from them (Khatri et al., 2009). Additionally, Baas, Dreu, & Nijstad (2008) demonstrate that positive emotions (e.g., happiness) encourage creative thinking, whereas negative emotions (e.g., fear) hinder creativity. In contrast, a managerial focus on blaming mistakes causes employees' risk aversion for trying out new innovative things and decreases organizational learning by threatening blame for failures and hindering open communication between colleagues.

Moreover, it restricts employees' creative thinking and reduces organizational innovativeness (Skarlicki et al., 2017).

In addition to lower organizational learning, Skarlicki et al. (2017) argue that a blame culture also decreases overall employees' job satisfaction and increases absenteeism as well as overall voluntary employee initiated turnovers and (unwarranted) employee dismissals. Higher employee turnover increases organizational hiring costs and reduces public reputation as an employer. Moreover, Cable & Turban (2003) explain that employees are even willing to forgo a higher salary to work for a more reputable company. This can make it difficult for companies with a blame culture to hire and retain high quality employees.

Overall, excessive blaming of employees damages collaboration, reduces innovativeness, and increases organizational inefficiencies as well as employee fluctuation as employees desperately try to avoid personal blame (Dirks & Skarlicki, 2009; Knapp, 2016; Skarlicki et al., 2017). The next chapter explains what motives managers can have to avoid own personal blame and what blame avoiding strategies they can utilize.

3.2 Managerial blame avoidance and blame avoiding strategies

3.2.1 Motives and biases influencing managerial blame avoidance

Most negative organizational effects resulting from a blame culture are based on one central phenomenon – blame avoidance. Individuals adjust their behavior in such a way that their risk for personal individual blame is minimized and thereby cause negative organizational consequences (see chapter 3.1.2).

Blame avoidance theory (BAT) proposes that individuals will try to avoid personal blame to achieve personal goals. This theory originates and is still commonly used in the public management literature (e.g., Weaver, 1986; Hood, 2011; Nielsen &

Baekgaard, 2015; George, Desmidt, Nielsen, & Beakgaard, 2016). Original focus of the BAT is to explain politicians' behavior. Due to the biases influencing blame assignment, especially the negativity bias, people tend to remember negative experiences more than positive ones. Therefore, negative information has a larger impact on individuals' attitude towards someone because, in contrast to positive events, even past outdated negative events are used for current personal evaluations. However, if politicians' main goal is to be reelected, they have to decrease their negative and increase their positive media attention. Due to the asymmetric perception of positive and negative information caused by a general negativity bias, politicians tend to consciously make inefficient (i.e., blame avoiding) decisions because they cannot risk making a good decision that might fail and cause greater harm than benefit (Andrade & Ariely, 2009; Rozin & Royzman, 2001; Soroka, 2006; Weaver, 1986).

Consequently, BAT describes individuals' tendency to adjust their behavior in such a way that their future blame potential is minimized and they thereby increase their chances for achieving personal goals. Blame avoidance is just the natural counterpart of blame assignment. For the identical reasons people blame others (i.e., social regulation to enforce cooperation), people want to avoid personal blame (i.e., avoiding social ostracism and being excluded from cooperation) (Alicke, 2000; Chudek & Henrich, 2011; Cushman, 2013; Mitchell, 2014; Skarlicki et al., 2017). Similar to blame assignment, avoiding blame is also an evolutionary ingrained cognitive and intuitive human process (Chudek & Henrich, 2011; Cushman, 2013). Assigning blame and avoiding blame are both the identical reciprocal cognitive process (see chapter 3.1.1).

I differ between internal and external motives for managers to avoid personal blame. Internal motives describe attributes that rest within an individual manager. Specifically, Mitchell (2014) argues that an individual's fear of blame and higher stress levels can increase blame avoiding behavior. Moreover, possible biases influencing blame assignment also affect blame avoiding behavior (see chapter 3.1.1) (e.g., Skarlicki et al., 2017). For example, a self-serving bias causes more blame avoiding behavior, the higher managers' self-esteem and the more they want to protect it (Crocker & Park, 2004). Additionally, personal career ambitions and avoiding own layoffs can positively affect managers' blame avoiding behavior because they try to avoid personal punishments due to blame assignment (see chapter 3.1.1) (e.g., Skarlicki et al., 2017; Park et al., 2014; Gangloff et al., 2014).

In contrast to these internal factors, there are also external environmental factors like organizational factors or societal expectations influencing blame assignment and therefore, reciprocally also blame avoidance (see chapter 3.1.1) (Skarlicki et al., 2017). A possible organizational factor is organizational culture. The more organizational culture is focused on blaming others, the higher individual blame avoidance (Dingwall & Hillier, 2015; Khatri et al., 2009; Mitchell, 2014; Skarlicki et al., 2017). However, managers' national culture and societal expectations also influence blame avoiding behavior. Specifically, Keil, Im, & Mähring (2007) demonstrate that individuals from western cultures tend to blame others if possible, whereas individuals from eastern cultures do not because they do not want to appear immorally.

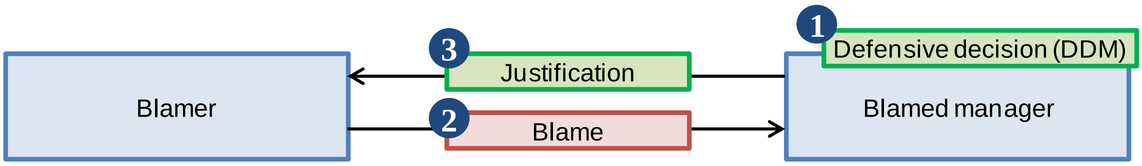
Finally, BAT proposes that individuals behave in such a way they least expect to be blamed. Specifically, there are internal (e.g., personal career ambition, self-serving bias) and external (e.g., organizational culture) motives to avoid personal blame (Park et al., 2014; Skarlicki et al., 2017). The next chapter discusses possible blame avoiding strategies for managers.

3.2.2 Managerial blame avoiding strategies

Previous literature has developed different blame avoiding strategies. In the end, two main topics emerge: (1) defending blame and (2) deflecting blame (e.g., Weaver, 1986; Hood, 2011; Mitchell, 2014; Artinger, Artinger, & Gigerenzer, 2019).

The first main blame avoiding strategy – defending blame – is consciously making decisions that limit own future blame potential and avoid extreme forms of blame. Additionally, blamed managers argue or justify by themselves why it is not their fault if something bad happens nonetheless. As proposed by Artinger et al. (2019), I call this blame avoiding strategy "defensive decision-making" (DDM) (see Figure 4).

Figure 4: Blame avoiding strategy – Defensive decision-making



Notes: This figure abstractly illustrates the blame avoiding strategy DDM. Green actions are done by blamed managers, whereas red actions are done by individuals blaming managers. Numbers indicate temporal sequence of actions.

Sources: Author's interpretation.

Figure 4 shows three steps for DDM as a blame avoiding strategy. DDM means that managers expect to be sooner or later be blamed for something by someone (blamer). To reduce their personal risk, they predominantly make defensive decisions with low future blame potential, although these might not always be the objectively best decisions for their companies (Artinger et al., 2019) (step 1). In the case they are blamed (step 2), managers try to justify their decisions by providing arguments supporting their decisions, diverting attention to positive successes, preemptively apologizing for errors, or even completely avoiding a statement hoping criticism will vanish (step 3) (Hood, 2011; Mitchell, 2014; Weaver, 1986).

Empirical evidence for DDM has mainly been found in public sector and medical contexts. In line with DDM, medical doctors propose suboptimal medical treatments to patients by ordering unnecessary treatments or avoiding appropriate risky treatments because they are afraid of malpractice litigations (Catino, 2009; Garcia-Retamero & Galesic, 2014; Gorini et al., 2012; Kristiansen et al., 2001). Moreover, Mitchell (2014) interviews managers in the healthcare sector who describe the negative impacts of blame. One manager answered:

> "People spend a lot of time, a lot of unnecessary time and energy and worry, trying to justify everything they're doing because they don't know where the next set of blame might be coming from. So if you're over budget or you're understaffed or you're whatever ... depending on whom you're reporting to and stuff, the big focus is where's the next kind of blame coming from" (p. 82).

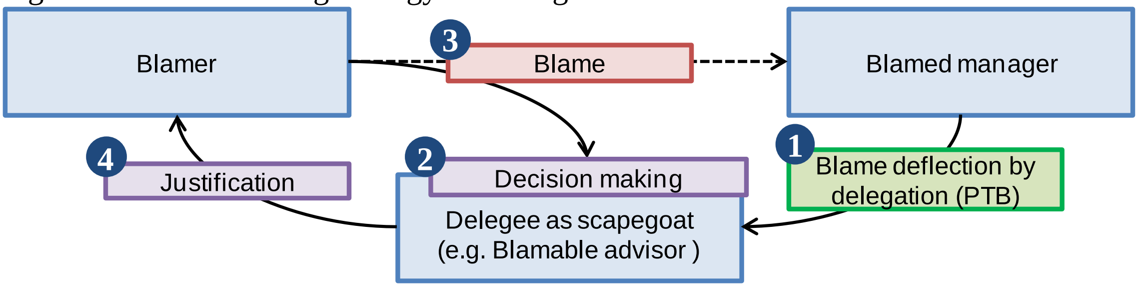
A main focus of DDM is to consciously adjust current decision-making to minimize future blame potential independent of the possible negative influence on decision quality (Artinger et al., 2019).

Similar to medical doctors, politicians and public sector managers also exhibit DDM behavior. Specifically, Nielsen & Baekgaard (2015) and George et al. (2016) explain that politicians tend to increasingly invest public resources in low performing public sector organizations to explicitly demonstrate their support – but do not show a higher preference for reforms – to avoid personal blame and maximize their chances for reelection. The higher investment is a just preemptive argument in case the low performing public sector organizations make mistakes. In line with this, Lindermüller, Sohn, & Hirsch (2021) argue that politicians increase financial spending with more negative media attention, especially for low performing public services. Furthermore, in a survey with public sector managers, Artinger et al. (2019) find that 80% of them admit that they consciously make inferior decisions because they want to avoid personal blame and protect themselves.

There are even first findings of DDM behavior in contexts with private sector managers. Despite making no explicit connection to BAT or DDM, Barros, Verga Matos, Miranda Sarmento, & Rino Vieira (2021) demonstrate that private sector managers adjust their dividend policy to mollify activist shareholders and protect themselves at the cost of higher dividend level volatility. Finally, the blame avoiding strategy DDM can be found in many different contexts and represents a valid option for blame avoiding managers.

The second main blame avoiding strategy is delegating decisions with high blame potential to someone else and deflecting blame. As proposed by Weaver (1986), I call this strategy "Passing the buck" (PTB) (see Figure 5).

Figure 5: Blame avoiding strategy – Passing the buck



Notes: This figure abstractly illustrates the blame avoiding strategy PTB. Green actions are done by blamed managers and violet actions are done by delegees, whereas red actions are done by individuals blaming managers. Numbers indicate temporal sequence of actions.

Sources: Author's interpretation.

Figure 5 describes four steps for the blame avoiding strategy PTB. PTB means that managers delegate decisions with high future blame potential to delegees (e.g., advisors) (step 1) who have to make these decisions instead (step 2) and can then assume responsibility in the form of scapegoats for potential blame (step 3) as well as justify the delegated decisions and protect blame avoiding managers (step 4). With this blame avoiding strategy, managers try to achieve their personal goals (e.g., personal career ambitions) by redirecting and deflecting possible blame that is originally focused on them to delegees (e.g., advisors) (Hood, 2011; Mitchell, 2014; Weaver, 1986).

Specifically, blamed managers who are initially responsible for the blamed decision try to share, dilute, and shift own responsibility to delegees. Blame avoiding managers set up delegees as scapegoats to guarantee successful blame avoidance. Either delegees make good decisions and cause no blame assignment or the decisions fail and managers can reprimand the delegees for their bad decisions and join other individuals or organizations (blamers) blaming the delegees. Then, managers can hide behind the delegees as scapegoats and support assigning punishment (e.g., laying off the scapegoats). "A key idea underlying the scapegoating perspective is that fault is ascribed and isolated to an individual who is dismissed with relatively minimal disruption" (Gangloff et al., 2014, p. 1617). Moreover, Steffel, Williams, & Perrmann-Graham (2016) explain that especially decisions with possible negative consequences are delegated. Main delegation criterium is the delegees' ability to assume responsibility. All that matters to blame avoiding managers is the fact that blamers perceive a shift in responsibility for blamed decisions to delegees and redirect their blame accordingly. I refer to advisors in the form of delegees with these attributes as "blamable advisors". Blamable advisors are potential delegees whose advice or decision recommendations are considered competent and valuable by blamers which results in foregoing blame assignment to blame avoiding managers due to an understandable delegation to supposedly experts. Consequently, blame avoiding managers use blamable advisors as scapegoats by having them justify made decisions to blamers and assume responsibility for potential blame.

Similar to DDM, PTB has been found in empirical public and private management contexts. James et al. (2016) find that politicians can avoid citizens' blame for public service failure by delegating public services to public sector managers. Moreover, Bach & Wegrich (2019) demonstrate that a complex delegation structure results in blame diffusion among the different participants. In addition to politicians, private sector managers and companies also delegate difficult decisions to avoid personal blame. Specifically, private sector organizations lay off responsible managers after technological issues like data security breaches to avoid public blame and ensure organizational legitimacy (Banker & Feng, 2019; Haislip, Masli, Richardson, & Sanchez, 2016). Furthermore, Gangloff et al. (2014) explain that private sector companies try to avoid blame from their shareholders by laying off their chief executive officer (CEO) after financial misconduct. In line with this, Park et al. (2014) argue that CEOs are less likely to be laid off with increasing celebrity and instead lay off less powerful managers after poor financial performance. Moreover, Paharia et al. (2009) find that direct price increases are perceived more unethical and blameworthy than indirect price increases by selling the product to a competitor or even a subsidiary (as a scapegoat) and requiring a price increase due to high acquisition costs.[13]

While there are many empirical findings which indicate the relevance of PTB in real-world settings, most findings on possible influencing factors on PTB are from research in fictitious economic dictator games with student samples. Students in economic dictator games with punishment options also exhibit blame avoiding behavior. The classical procedure is that dictators choose a fair or unfair distribution of available budget as compensation for themselves and the respondents, or delegate the whole decision to delegees. After receiving the dictators' or delegees' decision, the respondents have to accept the proposed offer but have the option the punish the dictators or delegees for their decision and retribute by reducing their compensation. The dictators' delegation of an unpopular decision to delegees reduces the dictators' perceived responsibility and increases their negotiation power. Consequently, participants tend to punish the delegees instead of the dictators (e.g., Bartling & Fischbacher, 2012; Coffman, 2011; Fershtman & Gneezy, 2001). Moreover, Oexl & Grossman (2013) demonstrate that these findings still hold when dictators force delegees to choose between two unfair distributions of compensation.

Furthermore, another influencing factor for advice utilization is competition among delegees. Dictators tend to choose the delegee who announces to act the most in the dictators' interests. This results in even greater negotiation power for dictators. Additionally, dictators do not perceive their actions as immoral and do not feel responsible for the decision because it was the delegees' decision, not theirs (Hamman,

[13] Specifically, in 2005 a pharmaceutical company sold the rights for a specific cancer drug to another pharmaceutical company. After that sale, the patients' monthly cost for the drug increased from $160 to $1,100 (Berenson, 2006).

Loewenstein, & Weber, 2010). Moreover, Sutan & Vranceanu (2016) demonstrate that dictators even straight out lie about having delegated an unfair decision and only very few delegees resist against an instrumentalization as a scapegoat if they have to forgo or reduce their own compensation for it. This behavior increases dictators' negotiation power because respondents tend to accept the supposedly delegated unfair decision. Adding to these findings, Garofalo & Rott (2018) explain that the way of communicating the unfair decision to the respondents affects their punishment decisions. Regardless of who – dictator or delegee – is communicating the bad decision, communications referring to emotions and regret are punished more than rational argumentation.

Finally, individuals can avoid personal blame by utilizing the blame avoiding strategies DDM and PTB. DDM focuses on making decisions in such a way that blame risk is minimized independent of its consequences on decision quality, whereas PTB focuses on shifting responsibility to someone else (Artinger et al., 2019; Hood, 2011; Mitchell, 2014; Weaver, 1986). Specifically, a consistent finding across all real-world contexts and fictitious experimental settings is that the introduction of a delegee increases the decision makers' decision power and reduces their perceived responsibility for an unpopular decision. Therefore, managers can utilize the blame avoiding strategy PTB by delegating difficult decisions with high blame potential to others and deflect blame by blaming them as scapegoats instead. Mitchell (2014) argues that one way to avoid blame is to blame someone else and describes this as blame cycle. The managers' fear of own blame causes blame avoiding behavior which can be achieved by own (unwarranted) blame assignment. The next chapter explains the identified research gap on the blame avoiding strategy PTB.

3.3 Identified research gap on the managerial blame avoiding strategy "passing the buck" with human advisors and algorithmic decision aids

There is lots of empirical evidence for blame avoiding behavior in different contexts. Table 5 presents an overview of important studies focused on the two blame avoiding strategies DDM and PTB. Specifically, PTB as a blame avoiding strategy (see chapter 3.2.2) has large similarities with the advice-taking motive sharing responsibility (see chapters 2.1.1 and 2.1.2.2). In both cases, the main reason for seeking advice or completely delegating the decision is not to increase overall decision accuracy but to decrease own responsibility. PTB provides more insights into why managers could want to share responsibility with blamable advisors. Due to these large similarities between the advice-taking motive sharing responsibility and the blame avoiding strategy PTB, I use both terms synonymously. Sutan & Vranceanu (2016) fittingly say:

> "Our results shed some light on the role of external advisors hired by decision makers when they must pass unpopular reforms. Policymakers might not only might try to "shift the blame", as shown by experimental economic studies [in fictitious settings] [...], but some of the observed "blame shift" might be spurious; the "expert" merely plays a scapegoat role with no real decision power" (p. 39).

Nonetheless, there is no research yet which focuses on real-world individual managers' causal reasons to share responsibility and utilize advisors for the blame avoiding strategy PTB in realistic managerial everyday tasks. There are only some studies in the private sector management context which hint in this direction. Banker & Feng (2019), Haislip et al. (2016), and Gangloff et al. (2014) find that private sector companies blame managers to appease public stakeholders and Park et al. (2014) demonstrate that private sector managers can avoid their own layoff with increasing celebrity and laying off less powerful colleagues. Sharing responsibility and PTB seem to be a highly relevant topic for managerial decision-making with potentially large negative effects for organizations. Individual managers consciously making different decisions just to avoid personal blame and exclusively hiring expensive external consultants not for their expertise but for their role as scapegoats can result in increased organizational inefficiencies. However, PTB can also be beneficial when companies strategically consider when to consciously delegate or outsource unpopular decisions (e.g., price increases) to avoid own external blame (e.g., Paharia et al., 2009).

So far, there is some literature studying factors which influence general blame avoiding behavior. Factors affecting internal motives like managers' self-esteem (e.g., Crocker & Park, 2004) or stress level (e.g., Mitchell, 2014) increase blame avoiding behavior. Similarly, external motives like environmental factors (e.g., organizational blame culture) cause blame avoiding behavior (Dingwall & Hillier, 2015; Khatri et al., 2009; Mitchell, 2014; Skarlicki et al., 2017).

Prior research mostly focuses on individuals' tendency to generally avoid blame but not on how and when a specific blame avoiding strategy like PTB is utilized and what factors influence the adoption of PTB. Only, Keil et al. (2007), studying individuals' cultural influence, and research in fictitious economic dictator games (e.g., Bartling & Fischbacher, 2012; Sutan & Vranceanu, 2016) exclusively focus on factors influencing the utilization of the blame avoiding strategy PTB or sharing responsibility with advisors. However, most of this research is conducted with student samples in purely fictitious surroundings and not with real-world manager practitioners. Therefore, I exclusively focus on factors influencing real-world managers' utilization of blamable advisors for the blame avoiding strategy PTB.

Following, I provide a consolidated overview of my research questions which I derived in the previous chapters and can be operationalized using the blame avoiding strategy PTB (see Table 1). Overall, I conduct two research studies.

Study 1 concentrates on whether managers utilize blamable human advisors to share responsibility with them and thereby try to avoid own blame by using the blame avoiding strategy PTB. Moreover, I analyze whether managers' individual risk perceptions affect their blame avoiding behavior in regard to PTB (see chapter 5).

<u>Research question 1:</u> Do managers utilize blamable human advisors to share responsibility? (see chapter 2.1.2.3)

<u>Research question 2:</u> Do managers' individual risk perceptions influence their advice utilization of blamable human advisors to share responsibility? (see chapter 2.1.2.3)

Study 2 concentrates on whether managers utilize nonhuman advice from blamable algorithmic decision aids to share responsibility with them and thereby try to avoid own blame by using the blame avoiding strategy PTB. Moreover, I analyze whether managers exhibit algorithm aversion in regard to PTB (see chapter 6).

<u>Research question 3:</u> Do managers utilize nonhuman advice by blamable algorithmic decision aids to share responsibility? (see chapter 2.2.2.3)

<u>Research question 4:</u> Do managers exhibit algorithm aversion when utilizing blamable advice to share responsibility? (see chapter 2.3.2)

Finally, chapter 3 summarizes prior literature on managerial blame assignment (see chapter 3.1) and blame avoidance (see chapter 3.2). Specifically, researchers argue that assigning external blame is an evolutionary ingrained intuitive cognitive process which focuses on punishing anti-social behavior to ensure social collaboration (Alicke, 2000; Chudek & Henrich, 2011; Cushman, 2013). However, this intuitive process is distorted by behavioral biases (e.g., self-serving bias, negativity bias) also causing unwarranted blame assignment (Crocker & Park, 2004; Rozin & Royzman, 2001).

Consequently, individuals develop different blame avoiding strategies to protect themselves and avoid social ostracism. PTB in the form of blaming someone else is a possible way of deflecting personal blame (Hood, 2011; Weaver, 1986). I contribute to the understanding of managerial advice-taking by connecting advice-taking literature (see chapter 2) and blame avoidance literature (see chapter 3). Both literature streams describe a similar phenomenon of sharing responsibility or PTB to achieve personal goals and avoid personal blame. My research concentrates on the managerial utilization of blamable advisors for the blame avoiding strategy PTB focused on sharing responsibility as an IPOm Output-Dimension factor. Specifically, I analyze what IPOm Individual-level factors – advisor's blame potential (Study 1 and Study 2), manager's individual risk perception (Study 1), and algorithm aversion in the form of the advisor's nature (human advisor vs. algorithmic decision aid) (Study 2) – affect managerial advice utilization. The next chapter explains general experimental designs and common experimental settings used in the advice-taking literature.

Table 5: Overview of important research studies on blame avoiding strategies

Observed context	Study	Main findings
Defensive decision-making as a blame avoiding strategy		
Medical sector	Catino (2009); Garcia-Retamero & Galesic (2014)	Medical doctors do not recommend appropriate high-risk treatments out of fear of malpractice litigations.
	Gorini et al. (2012); Mitchell (2014)	Medical professionals are more afraid of being blamed than being punished and try to avoid blame.
Public sector companies and politics	Nielsen & Baekgaard (2015); George et al. (2016)	Politicians invest in low performing public sector organizations to preemptively avoid blame and responsibility for possible public service failure but show no intentions to reform them.
	Lindermüller et al. (2021)	Politicians increase public spending with increasing negative media attention for low performing public services.
	Artinger et al. (2019)	Public sector managers consciously make inferior decisions to avoid personal blame.
Private sector companies	Barros et al. (2021)	Private sector managers adjust their dividend policy decisions in reaction to activist shareholders' negative attention.
Passing the buck as a blame avoiding strategy		
Public sector companies and politics	James et al. (2016)	Politicians can avoid citizens' blame for public service failure by delegating public services to public sector managers.
	Bach & Wegrich (2019)	Increasingly complex delegation structures cause a diffusion of responsibility among participants.
Private sector companies	Banker & Feng (2019); Haislip et al. (2016)	Private sector companies lay off responsible managers after technological issues like data security breaches.
	Gangloff et al. (2014)	Private sector companies can avoid blame from shareholders by laying off the CEO after financial misconduct.
	Park et al. (2014)	CEOs can avoid own layoffs after poor financial performance with increasing celebrity, resulting in layoffs of less powerful managers instead.
	Paharia et al. (2009)	Delegating/Outsourcing unpopular decisions (e.g., price increases) are perceived less blameworthy than making these decisions directly.
(Fictitious) economic experiments	Bartling & Fischbacher (2012); Oexl & Grossman (2013); Coffman (2011)	Delegating unpopular decisions, increases negotiation power and reduces blame.
	Hamman et al. (2010)	Judges choose the advisors who are most inclined of acting in their interests (i.e., taking blame).
	Sutan & Vranceanu (2016)	Advisors do not resist and make contradictions when judges publicly wrongly claim to have delegated unpopular decisions.
	Garofalo & Rott (2018)	Judges and blamable advisors increasingly reduce blame assignment by rationally arguing why this unpopular decision is necessary rather than making expressions of compassion.

Notes: Only selected studies discussed in chapter 3.2.2 are shown. All studies are allocated to the used blame avoiding strategy and the context in which this behavior has been observed.

Source: Author.

4 Experimental research in the advice-taking literature

4.1 Characteristics and types of experiments

Experimental research is useful to study direct causal relationships between different variables by manipulating independent variables and observing their effect on the dependent variable of interest (Aguinis & Bradley, 2014; James, Jilke, & van Ryzin, 2017a; Tanner, 2002; Tepe & Prokop, 2017). Shadish, Cook, & Campbell (2002) define an experiment as "a test under controlled conditions that is made to demonstrate a known truth, examine the validity of a hypothesis, or determine the efficacy of something untried" (p. 1).

General advice-taking literature almost exclusively uses experimental designs to identify possible causal effects influencing advice utilization (e.g., Bonaccio & Dalal, 2006). Additionally, advice-taking research specialized in forecasting settings (e.g., Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011) and studying algorithm aversion (e.g., Burton et al., 2020) also frequently use experimental research methods. Even blame avoidance literature increasingly uses experiments to isolate possible reasons for blame avoiding behavior (e.g., Bartling & Fischbacher, 2012; Keil et al., 2007; Lindermüller et al., 2021). Therefore, and in line with prior research, I test my research questions in two studies with context-rich experimental settings to isolate the influence of managers' blame avoiding behavior on advice-taking from human advisors and algorithmic decision aids.

Experimental research randomly splits participants in different experimental groups (treatment groups vs. control groups). Then, researchers manipulate independent variables of interest for the treatment groups while keeping other potential influencing factors constant and observing a potential change in the dependent variable across the experimental groups. The control groups are supposed to eliminate noise and other potential reasons for a change in the dependent variable. This way researchers can make sure that the participants in the experimental groups are statistically indistinguishable except in regard to the manipulated variables. The only difference and therefore reason for the change of the dependent variable is caused by the researchers' own manipulation of the treatment groups (Bryman & Bell, 2015; Shadish et al., 2002; Tanner, 2002).

Specifically, there are three different kinds of experimental research designs: between-subject, within-subject, and mixed-factorial designs. A between-subject research design manipulates an independent variable across participants in different experimental groups (treatment groups and control groups) and compares the effect on the dependent variable across different experimental groups, whereas a within-subject research design manipulates an independent variable within the same participant over time. Mixed-factorial research designs combine these two kinds of manipulations (Aguinis & Bradley, 2014; Tanner, 2002). Study 1 is a mixed-factorial experimental design (see chapter 5), whereas Study 2 is a between-subject experimental design (see chapter 6).

Main advantage of experimental research is the pure focus on causal relationships. In contrast to other research methods like surveys, experimental research does not only passively observe a correlation but can clearly identify a causal reason for an observed effect. High internal validity for experiments – observing a change in the dependent variable only because researchers manipulate a single independent variable – is very high (Bryman & Bell, 2015). However, in order to test complex theoretical research questions, the experimental setting has to be simplified. It is often questionable if the observed results in a controlled fictitious setting can be transferred to real-world problems. Therefore, experimental research usually has lower external validity as a cost for high internal validity (Aguinis & Bradley, 2014; James et al., 2017a; Shadish et al., 2002; Tanner, 2002; Tepe & Prokop, 2017). Low external validity is especially problematic if experimental researchers do not rely on real-world practitioners as experimental participants whose behavior researchers try to study. Specifically, Kirchler et al. (2018) find that the behavior of professionals differs from that of students in economic decision-making. However, it is often difficult to recruit professionals for experiments and therefore frequently graduate students are used (Aguinis & Bradley, 2014). Apart from hiring participants, experimental researchers also have to decide whether they want to use a naturalistic setting for experiments. An overview of the different types of experiments is provided in Table 6.

Table 6: Overview of experimental methods

	Intervention by researcher	Randomization	Naturalistic setting
Laboratory experiment	Yes	Yes	No
Field experiment	Yes	Yes	Yes
Survey experiment	Yes	Yes	No
Quasi-experiment	No	No	Yes
Natural experiment	No	Yes	Yes

Notes: This table provides an overview of the different types of experiments depending on a controlled manipulation by the researcher, the randomization of participants over different experimental groups, and the utilization of naturalistic settings.

Sources: Author's interpretation, adapted from James, Jilke, & van Ryzin (2017b, p. 7).

Natural experiments and quasi-experiments are a special variation of experiments because researchers do not consciously manipulate a variable. Instead, a natural experiment relies on a naturalistic setting or a natural event which allocates participants randomly to several groups with differing manipulations to study possible effects (e.g., an earthquake which randomly affects different areas) (James et al., 2017b). Quasi-experiments are like natural experiments but without being able to randomize participants because participants belong to a specific group of people in reality (e.g., studying employees' characteristics of different companies). The potential lack of randomization causes lower internal validity at the benefit of higher external validity for real-world settings (Bryman & Bell, 2015; James et al., 2017a, 2017b).

In contrast to natural experiments and quasi-experiments, laboratory experiments are conducted in a fictitious hypothetical setting in research laboratories. This ensures high control of the concrete setting and thereby the manipulation of the independent variables as well as eliminating potential noise. This results in higher internal validity at the cost of lower external validity (Bryman & Bell, 2015; Tanner, 2002).

Field experiments are like laboratory experiments in regard to manipulating independent variables and randomizing participants to different experimental groups. However, field experiments try to increase external validity by using real-world field settings at the cost of lower internal validity due to less direct control of variables and noise (Bryman & Bell, 2015; James, John, & Moseley, 2017).

Nonetheless, experiments are increasingly conducted online and not in research laboratories or field settings. Participants are usually recruited via online business networks (e.g., Amazon's Mechanical Turk (MTurk)). MTurk is an online labor market provided by the private sector company "Amazon" which is increasingly used for behavioral experiments. This enables researchers to easier recruit practitioners with work experience compared to laboratory experiments (Hunt & Scheetz, 2019; Jilke & van Ryzin, 2017; Knemeyer & Naylor, 2011; Lee, Seo, & Siemsen, 2018). In addition to recruiting practitioners, Aguinis & Bradley (2014) propose experimental vignette studies or context-rich experiments to increase external validity. Vignettes are short descriptions of a realistic environment or task which cause participants to act as if they were in their normal professional environment. Online vignette studies try to combine the advantages of laboratory experiments in the form of high internal validity with field experiments in the form of increased external validity.

Similarly, survey experiments try to combine the advantages of laboratory experiments and survey research designs. Researchers question participants via surveys while manipulating them by changing the wording, ordering, or combination of the questions and task descriptions. This way internal validity is increased without lowering external validity due to the utilization of robust survey scales (Atzmüller & Steiner, 2010; Jilke & van Ryzin, 2017).

Both conducted experiments, Study 1 (see chapter 5) and Study 2 (see chapter 6), are context-rich or vignette online experiments as recommended by Aguinis & Bradley (2014). I use vignettes to create a realistic setting and then manipulate variables of interest and observe possible effects. The next chapter describes the experimental design which is commonly used for JAS settings with human advisors in the advice-taking literature.

4.2 Established experimental designs in the advice-taking literature

The advice-taking literature has specifically developed the JAS as the standard experimental design to study different factors influencing advice utilization (e.g., Bonaccio & Dalal, 2006). The standard JAS design is a laboratory experiment with a random allocation of participants to the roles judge and advisor. Then, all participants read a short description of the decision task while researchers manipulate the variables of interest based on the IPOm framework (see Figure 1). Usually, the IPOm JAS-level factors define a setup for an independent judge. That means that the judges first make a decision on their own and then they receive recommendations from advisors and have the opportunity to adjust their final decision. Moreover, there are usually many small decision tasks to complete and researchers evaluate the average advice utilization of all recommendations over differently manipulated experimental groups. Judges are commonly financially rewarded depending on their decision accuracy (Bonaccio & Dalal, 2006; Sniezek & Buckley, 1995).

However, there a many possible variations of the standard JAS experimental design depending on varying IPOm factors (see Figure 1). The IPOm framework has been specifically developed to structure experimental advice-taking research (Bonaccio & Dalal, 2006). Especially, varying IPOm JAS-level factors, IPOm Environmental-level factors, and IPOm Process-Dimension factors define possible different experimental advice-taking settings.

Despite the fact that an IPOm JAS-level with an independent judge is common, there are some studies with cued or dependent judges. Cued judges are prohibited from making own decisions before advice-taking because they only receive information on the decision task simultaneously with the advisors' recommendations, whereas dependent judges receive no information related to the decision task at all and have to completely rely on their advisors (Bonaccio & Dalal, 2006; Sniezek & Buckley, 1995). Moreover, some researchers do not force judges to listen to advice but consciously provide them with the opportunity to seek advice if wanted. This is especially useful when the mere fact of seeking advice is examined (e.g., Schrah et al., 2006; Bonaccio & Dalal, 2006). Additionally, some studies even vary the number of advisors. While most studies use a dyad of one judge and one advisor, some experimental designs also analyze the effect of multiple advisors and have advisors compete with each other for advice-giving (Budescu & Rantilla, 2000; Radzevick & Moore, 2011).

Apart from different IPOm JAS-level factors, experimental designs also vary in regard to task type as an IPOm Environmental-level factor. Some researchers use multiple choice tasks for qualitative options (e.g., Sniezek & van Swol, 2001), whereas others prefer quantitative judgment tasks (e.g., Harvey, Harries, & Fischer, 2000).[14] This enables researchers to analyze varying advice utilization depending on different environmental settings in the form of discrete or continuous decision-making options.

Furthermore, researchers can define how the specific advice is provided. IPOm Process-Dimension factors describe whether advisors recommend a single decision,

[14] Experimental tasks are mainly about general knowledge like answering questions about computer knowledge or estimating the distance between two cities (e.g., Sniezek & van Swol, 2001; Schultze et al., 2017). However, some experiments also concentrate on practitioner related tasks like making sales forecasts or investment decisions (e.g., Harvey et al., 2000; Palmeira et al., 2015).

recommend against a specific option, or even provide additional unknown information for the present decision task (Dalal & Bonaccio, 2010). Additionally, the type of advisors' communication can vary across advice-taking research designs (e.g., oral or written advice).

In line with general advice-taking research with human advisors (e.g., Bonaccio & Dalal, 2006), prior studies specialized in forecasting settings with algorithmic decisions aids commonly use a very specific variation of the presented JAS experimental research designs. Researchers use a cued judge (e.g., forecaster) in a judgment task type (e.g., forecast) who receives a forecast recommendation from a single advisor (e.g., algorithmic decision aid) and then has to opportunity to adjust the recommendation (e.g., Lawrence et al., 2006; Goodwin et al., 2007; Harvey & Harries, 2004; Theocharis et al., 2019; De Baets & Harvey, 2018). In particular, the fact that the advisor is no human but an algorithmic decision aid is a specialty for advice-taking literature focused on forecasting settings and studying algorithm aversion.

Finally, chapter 4 summarizes established experimental research methodologies (see chapter 4.1) and common experimental designs in the advice-taking literature (see chapter 4.2). In line with Aguinis & Bradley's (2014) recommendation, I conduct vignette online experiments to have high internal validity as the main advantage of experimental research and at the same time increase external validity with highly realistic managerial tasks described in online vignettes. Moreover, I adopt the standard JAS experimental design for studying managerial advice-taking with blame avoiding intentions. Specifically, I analyze how managers utilize the blame avoiding strategy PTB and possible IPOm Individual-level factors influencing this behavior (see Study 1 and Study 2).

5 Study 1: How managers' risk perceptions affect their willingness to blame advisors as scapegoats[15]

5.1 Introduction and motivation Study 1

Business consulting represents a significant industry, which in 2018 created revenues of 188 billion USD worldwide (Healey et al., 2019). Managers usually hire external experts to help them make better-informed decisions. However, managers may have other motives for consulting advisors. One motive underlying managers' decision to seek such advice, which is often discussed but hardly empirically tested, is that they do so to be able to blame the advisor as a scapegoat (see chapter 3.2.2).

This study analyzes managers' blame avoiding decision-making in an advice-taking context. Specifically, I examine whether managers use advice to blame the advisor as a scapegoat and how this depends on their own risk perceptions and the advisors' blame potential. This provides a novel perspective on managers' advice-taking given that prior research on blame avoidance behavior has largely focused on why decision makers want to avoid personal blame (e.g., Andrade & Ariely, 2009; Rozin & Royzman, 2001), what individual traits (e.g., self-esteem) influence one's willingness to avoid blame (e.g., Crocker & Park, 2004), and which blame avoiding strategies individuals use (e.g., Bartling & Fischbacher, 2012; Steffel et al., 2016). Understanding the factors that influence blame avoiding behavior is important, as prior research has found that managers who excessively blame employees cause negative organizational consequences by creating a blame culture (Dingwall & Hillier, 2015; Skarlicki et al., 2017). This can lead to higher employee fluctuation, complicating new employee recruitment, and lowering organizational learning (see chapter 3.1.2) (Cable & Turban, 2003; Knapp, 2016).

[15] A modified version of this study should be published in the *European Management Journal*. In the publication process I am supported by Bernhard Hirsch (Bundeswehr University Munich, Germany) and Matthias Sohn (European University Viadrina, Germany).

Research suggests that across different settings, the introduction of an intermediary, delegee, or advisor helps decision makers to avoid personal blame and increases their chances of achieving personal goals.[16] I focus on two thus far neglected factors – the advisors' blame potential and managers' risk perceptions – which I deem particularly important in managerial blame avoiding decision-making. A context of an investment decision for an internal capital allocation task allows me to analyze the specific relevance of advice-taking for decisions with high impact and risk. Managers seek advice for investment decisions and increasingly delegate decisions as the number of divisions increases (Graham et al., 2015). They can avoid blame by delegating difficult decisions and blaming an advisor in the case of failure (Keil et al., 2007; Steffel et al., 2016). Investment decisions provide an ideal scenario for analyzing blame avoiding decision-making because such decisions can have a considerable economic impact and frequently involve advisors. Specifically, I study the following research questions (see Table 1 as well as chapters 2.1.2.3 and 3.3):

<u>Research question 1:</u> Do managers utilize blamable human advisors to share responsibility?

<u>Research question 2:</u> Do managers' individual risk perceptions influence their advice utilization of blamable human advisors to share responsibility?

Building on BAT, I propose that if there is a threat associated with not achieving a target (e.g., reputational loss within the company damaging personal career ambitions), managers tend to use advice more if it is given by a blamable advisor than by an unblamable advisor. Moreover, in line with CPT, I propose that managers perceive more (less) risk and make defensive (risky) investment decisions in an economic boom

[16] Such blame avoiding behavior has been observed in different contexts ranging from medical doctors (e.g., Garcia-Retamero & Galesic, 2014) to students in dictator games (e.g., Bartling & Fischbacher, 2012), public sector managers or politicians (e.g., Artinger et al., 2019; James et al., 2016), and students as proxies in private sector company settings (e.g., Keil et al., 2007) (see chapter 3.2.2).

(economic crisis). Importantly, I argue that managers' risk perceptions influence their investment decisions and their willingness to carry responsibility for their decisions. I expect a higher degree of blame avoiding decision-making – that is, a greater use of advice to share responsibility with advisors – in an economic boom than in an economic crisis.

As in most research on BAT (e.g., Bartling & Fischbacher, 2012; Keil et al., 2007; Lindermüller et al., 2021), I test my hypotheses in a context-rich experimental setting to isolate the effects of the advisors' blame potential and managers' risk perceptions on managerial advice-taking (see chapter 4). I conducted a fully anonymized and incentivized online experiment in a 2 (within-subject: no advisor vs. advisor) x 2 (between-subject: unblamable internal colleague vs. blamable external consultant) x 2 (between-subject: economic boom vs. economic crisis) incomplete mixed-factorial design. I relied on a sample of experienced managers, which enhances the external validity of my results. The participants were first asked to make a preliminary investment decision on their own. Then, they received advice and had the opportunity to adjust their preliminary investment decision (I refer to this as the final investment decision). The advisor was either blamable or not. The participants had to make their decision in an economic boom (gain scenario) or an economic crisis (loss scenario).

My results are largely in line with my hypotheses. Managers perceive lower risk in an economic crisis than in an economic boom when making investment decisions. In contrast to what I hypothesized, managers do not generally use advice more by a blamable advisor than by an unblamable advisor. However, managers' higher risk perceptions in an economic boom increase the scapegoating of blamable advisors due to the managers' increased concerns about personal threats. In an economic crisis, managers rely relatively more on unblamable advisors than on blamable advisors.

This study contributes to advice-taking literature and BAT literature by studying the use of advice as a possible blame avoiding strategy as an IPOm Output-Dimension factor and focusing on the advisors' blame potential in conjunction with managers' risk perceptions as IPOm Individual-level factors (see Figure 1). I demonstrate that the more risk managers perceive and the more they want to avoid blame, the more they tend to use an advisor as a scapegoat. Specifically, I identify advisors' blame potential and managers' individual risk perceptions as novel IPOm Individual-level factors for managerial blame avoiding decision-making with advisors (see chapters 2.1.2.3 and 3.3).

My findings also contribute to the theoretical understanding of how risk perceptions influence managerial decision-making. Previous literature mainly describes how monetary problem framing – choosing between gains or losses – affects a decision maker's risk perception (e.g., Tversky & Kahneman, 1992; Kahnemann & Tversky, 1979). Drawing on BAT, this study stresses the importance of nonfinancial problem framing in the form of blame avoiding decision-making; this implies a new form of nonfinancial risk – the threat of justification. I find that managers concentrate on avoiding nonfinancial losses (avoiding blame) in an economic boom and focus on avoiding financial losses in an economic crisis. Hence, understanding how financial and nonfinancial risk-taking affects managerial decision-making is important for theory building and business practice.

This study informs practitioners by highlighting why and under which circumstances managers tend to use advice (e.g., through external consulting firms) for difficult and high-risk management decisions. Although consulting external experts may help managers make better-informed decisions (Macdonald, 2006), my results indicate that there is another rationale for managers to use advice: managerial blame avoidance. Hence, advice cannot automatically be expected to increase decision accuracy, and companies should be aware of managers' opportunistic motives in hiring advisors.

The remainder of this chapter is structured as follows. Next, the hypotheses are developed (see chapter 5.2). Subsequently, the experimental method used to gather the data is explained (see chapter 5.3). Finally, the results are shown and discussed (see chapters 5.4 and 5.5).

5.2 Theoretical background and hypotheses development Study 1

5.2.1 Investment decision-making for internal capital allocations

In this study, I argue that whether managers use advice depends on the advisors' blame potential and the perceived riskiness of an investment decision as IPOm Individual-level factors. Deciding how much financial capital is invested in each internal corporate division is an essential task for managers (Busenbark, Wiseman, Arrfelt, & Woo, 2017). According to Busenbark et al. (2017), the predominant internal capital allocation strategies are winner-picking and diversification.[17]

In this research, I propose that the choice of winner-picking or diversification depends on the managers' risk perceptions. According to CPT, managers are risk-averse when choosing between gains and risk-seeking when choosing between losses (e.g., Tversky & Kahneman, 1992). Sitkin & Weingart (1995) explain this behavior with the influence of problem framing on the decision makers' risk perceptions. A gain scenario emphasizes possible threats to existing resources, causing managers to seek to avoid losing such resources. This results in a perception of higher risk and hence more risk-avoiding decisions. However, a loss scenario emphasizes the possibility of avoiding or regaining losses, resulting in a perception of lower risk and thus more risky decisions (Sitkin & Weingart, 1995). I propose that managers focus on risky capital allocation

[17] Winner-picking aims to allocate scarce financial resources solely to the division with the best future prospects and thereby tries to maximize future returns. Diversification concentrates on reducing risk by distributing scarce financial resources among multiple, unrelated business units to create a portfolio of uncorrelated cash flow streams that are less affected by financial and economic shocks (Busenbark et al., 2017).

strategies such as winner-picking in loss scenarios (such as an economic crisis) and risk-averse capital allocation strategies such as diversification in gain scenarios (such as an economic boom). This serves as my baseline hypothesis. Therefore, I formulate the following hypothesis:

H.1: Managers invest more defensively in an economic boom than in an economic crisis.

5.2.2 Influence of blamable advisors on investment decision-making

Building on BAT, I argue that managers avoid personal blame by instrumentalizing blamable advisors as scapegoats. Prior research differs between internal and external motives to avoid personal blame (see chapter 3.2.1). Internal blame avoiding motives are based on managers' individual personalities and personal goals. Managers with high self-esteem try to avoid criticism and fear failure, which would damage their self-worth (Crocker & Park, 2004). However, they can also try to avoid blame to realize personal goals (e.g., increase chances of being promoted, avoid justification to their superiors or avoid being laid off) (Gangloff et al., 2014; Park et al., 2014). External motives emerge from legal or societal expectations (e.g., corporate social responsibility) (Skarlicki et al., 2017). Additionally, corporate organizational cultures and national cultures also influence managers' blame avoiding behavior (Dingwall & Hillier, 2015; Keil et al., 2007; Skarlicki et al., 2017). In this study, I concentrate on managers' individual risk perceptions in regard to their personal career ambitions as an internal blame avoiding motive and the role of the advisors' blame potential.

Specifically, I focus on managers' internal reputational concerns as the main motive for blame avoiding decision-making. This hypothesis is motivated by prior research that has found that public sector managers focus on avoiding possible blame by delegating unpopular decisions to minimize personal blame (Artinger et al., 2019; James et al., 2016). Other research shows that using an intermediary to convey an economic offer in dictator games increases the dictator's negotiation power by shifting the respondent's blame and anger onto the intermediary (Bartling & Fischbacher, 2012). Additionally, prior research has found that powerful and famous CEOs can avoid their own layoff by blaming weaker executive managers after poor financial performance (Park et al., 2014). The strategy of consciously delegating difficult decisions to avoid being associated with possible future negative results is called PTB (see chapter 3.2.2) (Steffel et al., 2016; Weaver, 1986).

Managers can delegate difficult decisions to third parties – in my setting, external consultants – to be able to blame advisors in the case of failure and to avoid being held responsible or being punished for decisions that financially harm their companies (Steffel et al., 2016; Weaver, 1986). If managers aim to achieve their personal career ambitions and maximize their superiors' positive perception of them, they must minimize their blame potential by maximizing their chances of avoiding justifications for wrong decisions. In a similar context, Steffel et al. (2016) show that "people only delegate to others who can assume responsibility, regardless of their expertise" (p. 32).

Therefore, I propose that managers use advice to different degrees depending on the advisors' blame potential.[18] In my experimental setting, I therefore differ between two types of advisors: blamable advisors and unblamable advisors. Blamable advisors are advisors who can be made responsible for a bad decision outcome. Whether or not an advisor is blamable, is determined by the person or institution whose blame the managers are trying to avoid. I propose that managers use blamable advisors because they anticipate that such advisors draw superiors' wrath and negative emotions to the advisors rather than the managers. This reduces managers' responsibility for a bad decision (see chapter 3.2.2).

[18] Advice utilization describes the degree of following the advisor's recommendation (Bonaccio & Dalal, 2006; Schultze et al., 2017).

In practice, there are different levels of blame potential depending on the advisors' context-specific reputation as perceived by the managers' superiors. I expect that whether managers perceive an advisor to be blamable depends on their expectation that their superiors will respect the given advice and consider the advisors to be valuable and competent. The higher an advisor's perceived expertise, the easier it should be for a manager to blame the advisor. Prior research has already identified that advisors' characteristics are relevant to superiors (e.g., communication style) (Garofalo & Rott, 2018). Hence, I propose that managers try to avoid blame from their superiors by using blamable advisors as scapegoats who are held in high regard by their superiors (e.g., costly external consultants). Advisors with very low reputations are less blamable (e.g., a friend or spouse with no context-specific knowledge) and hence cannot serve as scapegoats in case of a bad decision.[19] Accordingly, I propose the following:

H.2: Managers use advice given by blamable advisors more than managers use advice given by unblamable advisors.

I argue above that managers use blamable advisors more than unblamable advisors when they want to avoid personal blame. I also propose this effect to be stronger, the more risk managers perceive in the form of a bad decision outcome and reputational losses. This hypothesis is motivated by Harvey & Fischer (1997), who argue that individuals use advice more and share responsibility with an advisor more when they perceive greater risks. This means that blaming advisors seems less risky for managers than making decisions on their own. By using advice, managers can reduce the risk of making an incorrect decision. If the recommended advice fails, it is the advisor's fault; if not, it was the right decision to trust the advisor. However, Harvey & Fischer (1997) also

[19] In my experimental setting, I manipulated the advisors' blame potential by differentiating between blamable (external consultants) and unblamable (internal colleagues) advisors. Specifically, superiors instructed the managers to use the advice of external consultants due to higher expertise. The advice by internal colleagues was provided unsolicitedly (see chapter 5.3.2).

admit that this is speculative and should be empirically tested with monetary incentivized participants. Consequently, I test this phenomenon in my experiment.

Specifically, I propose that in this context, managers' risk perceptions influence their investment decisions and their willingness to assume responsibility for those decisions (see chapter 2.1.2.2). I also know that – in line with CPT – the more (less) risk managers perceive, the more defensive (riskier) their decision-making will be (Sitkin & Weingart, 1995).[20] Therefore, I expect managers to be more likely to transfer responsibility to blamable advisors and reduce risk in an economic boom. In an economic crisis, managers are more inclined to assume responsibility because they perceive less risk. Building on BAT and CPT, I propose that identical threats are perceived as riskier and more valuable to avoid in an economic boom than in an economic crisis.[21] Hence, I formulate the following hypothesis:

H.3: Managers use advice given by blamable advisors more in an economic boom than in an economic crisis.

As argued above (H.2 and H.3), I propose that managers want to avoid blame. I now focus on providing more insights into why managers want to blame advisors in the form of the blame avoiding strategy PTB. Based on BAT, I argue that the main motive of PTB is to avoid being associated with failure. By delegating a decision to an advisor, decision makers seek to reduce their responsibility for the decision and to simultaneously decrease their chances of being held responsible for an incorrect decision (Steffel et al., 2016; Weaver, 1986). To better understand managers' reasoning behind using advice, I focus on whether managers believe they can transfer their own responsibility for decision

[20] In my experiment, the participants perceived more risk in an economic boom than in an economic crisis ($t(173) = -1.90$, $p = 0.059$).

[21] While one could argue that managers face greater threats in an economic crisis than in an economic boom and that the magnitude of personal threats influences blame avoiding decision-making, I deliberately use an experimental setting to hold personal threats constant and isolate the possible blame avoiding influence of individual risk perceptions (see chapter 5.3.2).

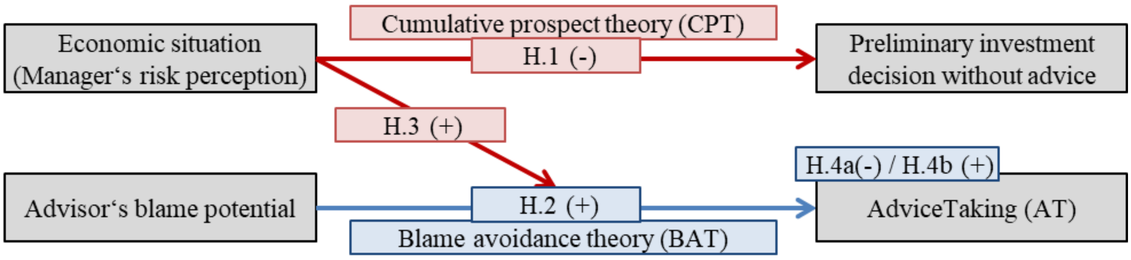
outcomes to advisors. Palmeira et al. (2015) find that advisors' responsibility for a decision outcome increases with higher advice utilization, which indicates a decrease in managers' responsibility. One form of responsibility is having to justify one's investment decision to one's superior (Steffel et al., 2016). Therefore, I argue that managers use advice because they want to avoid blame by minimizing their own responsibility and maximizing their chances of avoiding justification (see chapter 3.2.2). Hence, I propose that the more strongly managers rely on advisors, the more they believe they will thereby reduce their own responsibility and avoid justification. Accordingly, I formulate the following hypotheses:

H.4a: The more managers follow advice, the lower their perception of their own responsibility for the investment result.

H.4b: The more managers follow advice, the more they believe they can avoid justification.

Figure 6 summarizes my hypotheses and the theoretical model that I propose.

Figure 6: Theoretical model and corresponding hypotheses in Study 1



Notes: This figure abstractly summarizes the theoretical model of Study 1. Two independent IPOm Individual-level factors, namely advisors' blame potential and managers' risk perceptions (manipulated by the economic situation due to CPT) influence general investment decision behavior (H.1) and managerial advice-taking (H.2, H.3, H.4a, and H.4b). Specifically, H.1 proposes more defensive decision-making behavior in an economic boom than in an economic crisis. H.2. theorizes higher advice-taking for blamable advisors compared to unblamable advisors. H.3 expects this blame avoiding behavior to be stronger in an economic boom than in an economic crisis due to managers' varying risk perceptions. H.4a and H.4b propose perceived lower own responsibility and perceived higher chances of avoiding justification with increasing advice-taking.

Sources: Author's interpretation.

5.3 Method Study 1

5.3.1 Experimental design

I conduct a two-step online vignette experiment to study whether managerial blame avoiding advice-taking is influenced by the advisors' blame potential and the perceived riskiness of an investment decision as IPOm Individual-level factors (see chapter 4.1). In my setting, the participants were asked to make a preliminary investment decision on their own. Then, they received advice and had the opportunity to adjust their preliminary decision (final investment decision). Such an experimental setup is commonly used in the literature (see chapter 4.2) (Bonaccio & Dalal, 2006).

The hypotheses were tested using a 2x2x2 incomplete mixed-factorial design (see Table 7). The presence of advice (no advice vs. advice) is the within-subject factor. In line with Keil et al. (2007), the manipulation of the advisors' blame potential is a between-subjects factor (unblamable internal colleague vs. blamable external consultant).[22] Similar to Hirsch, Reichert, & Sohn (2017), the company's economic situation (economic boom vs. economic crisis) is a between-subject factor.

Table 7: 2x2x2 incomplete mixed-factorial experimental design in Study 1

2x2x2 experimental design		Presence of advice	
		Preliminary investment decision without advice	Final investment decision with advice
Economic situation	Economic boom	No advice (N = 94)	Advice from internal colleague (N = 37)
			Advice from external consultant (N = 50)
	Economic crisis	No advice (N = 81)	Advice from internal colleague (N = 38)
			Advice from external consultant (N = 32)

Notes: This table shows the experimental design and the number of participants within each experimental group. Due to the fact that the advisor recommended a riskier decision compared to the preliminary investment decision without advice, participants who already decided on the upper end of the decision scale on their own had to be excluded. Therefore, the number of participants for the final investment decision with advice decreases (see chapters 5.3.2 and 5.3.3 for more information).

Sources: Author's interpretation.

[22] This differentiation is necessary to isolate the advisors' blame avoiding influence and to nullify a possible anchoring effect.

5.3.2 Experimental task & procedure

The participants were asked to assume the role of a divisional business unit manager of a global industrial company. At the beginning of the experiment, each participant was randomly assigned to one condition.[23] The participants read a short description of the company's economic situation (see Appendix A.1), answered comprehension questions (see Appendix A.2 and chapter 5.3.3) and had to make an investment decision to allocate 100% of an investment budget in steps of 5% to two different investment plans.

In the boom situation, the first (second) investment plan, called "Stable Solutions" ("New Technology"), resembles the capital allocation strategy diversification (winner-picking) and finances established products (the development of a new product). The first (second) investment plan has been operationalized by a guaranteed outcome of 12.500.000€ (equally probable outcomes of 25.000.000€ or 1.250.000€). The two scenarios' expected payouts reflect a capital allocation of 100% to their corresponding investment plan. All possible variations of payouts resulting from the possible allocations of the budget were provided in a table (see Appendix A.3).

The participants received a fixed participation fee of 1.25€ and variable compensation of 0.00000005% of their realized investment result. Therefore, the total compensation ranged from 1.3125€ to 2.50€ (consisting of variable compensation ranging from 0.0625€ and 1.25€). The loss situation/economic crisis was created by subtracting 25.000.000€ from every positive investment result and by increasing the fixed compensation to 2.50€. The participants had positive variable compensation (gain scenario) in the economic boom and negative variable compensation (loss scenario) in the economic crisis. This resulted in the same compensation structure for both

[23] This way all experimental groups were statistically indistinguishable except in regard to the manipulated variables.

conditions.[24]

The participants were informed that the company's management board expected a minimum investment result of 15.000.000€ (-10.000.000€) in the boom (loss) situation.[25] If these targets were not met, the participants had to write a justification of at least 200 characters explaining the nonachievement. Furthermore, the decision makers were told that in the case of justification their own internal reputation would suffer and this would have negative consequences for their future career.

After the participants had made the preliminary investment decision, they were informed that an internal colleague or external consultant would support them. They were told that the internal colleague had participated in creating the two different investment plans and that he would like to share his own opinion informally with the participant. In the external advisor scenario, the participants were told that the company's management board had enacted a directive to always use an external consultant before making important decisions. Furthermore, it was stressed that the participants would not need to justify their decision if they followed the blamable consultant's advice, even if the expected investment result failed (see Appendix A.4).[26] Avoiding justification by following the recommendation resembles the main characteristic of a blamable advisor. In the experiment, both advisors – the internal colleague and the external consultant – always recommended a riskier investment decision (20% more investment in the investment plan "New Technology") than the participants' preliminary investment decision. Then, the participants could alter their preliminary investment decision.

[24] The participants' median compensation was 2.00€ with a median experimental duration of approximately twelve and a half minutes (743 seconds). This level of remuneration is in line with previous experimental research (e.g., Hunt & Scheetz, 2019).
[25] The expected investment results were set in such a way that the participants had to allocate at least 20% of the investment budget to the risky investment plan. Otherwise, they had no chance of achieving the expected investment result.
[26] The advisor recommended a 20% riskier investment decision than the participant's preliminary investment decision. The participant's final investment decision was considered to follow the advice if it did not deviate by more than 5% points from the recommended investment decision.

I included a series of questions (on 7-point Likert scales) in the interposed and post-experimental questionnaires. I asked for the participants' perceived own responsibility, perceived risk for the investment decisions, perceived chance of avoiding justification in the case of failure, and perceived advisors' competence. The participants answered questions after they made the preliminary investment decision (interposed questionnaire) and after they made the final investment decision (post-experimental questionnaire). Additionally, they reported their perceived own responsibility after being informed about the realized result of their final investment decision and being told whether they had achieved the expected investment result (see Appendix A.5).

Moreover, I controlled for the participants' individual risk propensity by using the risk propensity scale developed by Meertens & Lion (2008). Furthermore, the participants were asked on a 7-point Likert scale how risky the "Stable Solutions" and "New Technology" investment plans (1 = not risky, 7 = very risky) were and how good the economic situation (1 = very bad, 7 = very good) was (see Appendix A.6).

Finally, the participants were informed about their investment results and their corresponding variable compensation. Not using the external consultant as a scapegoat and missing the expected investment target resulted in the obligation to write a justification for the management board (see Appendix A.7).

5.3.3 Experimental participants

I ran the experiment online with experienced managers. I used the research agency "Respondi", which gave me access to a sample of managers from various industries of German-speaking countries. I received data from 257 managers. To ensure that all participants fully understood the experiment, I included a series of test questions, and the 257 participants were reduced to 175 through the comprehension screening (see

Appendix A.2 and Appendix A.4).[27]

Of the remaining 175 participants, 134 were male and 41 were female. The average age was 45.19 (SD = 18.50 years). Fourteen (8%), 51 (29%), 60 (34%), and 50 (29%) participants reported working experience of less than 10 years, between 10 and 20 years, between 20 and 30 years, and more than 30 years, respectively. Furthermore, 137 (78%) supervised fewer than or equal to 50 employees (I classify these managers as lower or middle managers in additional robustness checks), and 38 (22%) participants supervised more than 50 employees (who I classify as top managers). The participants worked in different industry sectors (2% telecommunication, 6% consumer goods, 3% energy, 8% finance, 6% healthcare, 17% industrial, 1% materials, 2% real estate, 2% utilities, 11% public sector, and 41% other).

To guarantee a fixed advice distance, participants whose preliminary investment decision was on the upper end of the scale, i.e., they invested more than 80% of the investment budget in the risky investment plan, could not receive the advice to invest 20% more in the riskier plan and, hence, had to be excluded from the analyses (see Table 7). Therefore, the sample size was reduced from 175 to 157 participants.

5.3.4 Dependent variables

InvestmentDecisionWithoutAdvice. The *InvestmentDecisionWithoutAdvice* (preliminary investment decision) is measured on a 21-point scale, with points ranging from 1 to 21 representing the 5% steps of possible capital allocation between the "Stable Solutions" (1 = 100% investment budget in "Stable Solutions") and "New Technology" (21 = 100% investment budget in "New Technology") investment plans.

[27] The comprehension screening consisted of two sets of comprehension questions. The first (second) set of comprehension questions tested the participants' understanding of the base situation (role of the advisor). The participants could continue with the experiment only when they had answered all comprehension questions correctly; otherwise, they were redirected to the corresponding description. A participant was included in the analyses if he or she needed four or fewer attempts with the first set of comprehension questions (6 questions) and two or fewer attempts with the second set of comprehension questions (3 questions).

AdviceTaking. *AdviceTaking* (*AT*) represents the change between the final investment decision after receiving advice and the preliminary investment decision without advice. Similar to prior research studying the influence of advisors, I use *AT* as a non-absolute version of the *WOA* variable to measure the decision maker's advice utilization (see Equation 2 and Equation 5) (Bonaccio & Dalal, 2006; Harvey & Fischer, 1997; Schultze et al., 2017).

Equation 5: $$AT = \frac{\text{Final investment decision} - \text{Preliminary investment decision}}{\text{Advisor's recommendation} - \text{Preliminary investment decision}}$$

AT is theoretically defined for values between 0 (no consideration of advice) and 1 (completely following the advisor's recommendation). Therefore, in previous studies, *AT* outliers have been reduced to their maximum (minimum) theoretical values (e.g., $AT > 1$ are set to 1 and $AT < 0$ are set to 0) (Schultze et al., 2017). I adopt this procedure and reduce the empirical *AT* results to their maximum (minimum) theoretical values. The final sample of 157 participants included nine positive *AT* outliers ($AT > 1$) and 19 negative *AT* outliers ($AT < 0$).[28]

5.3.5 Independent variables

***EconomicSituation*.** I manipulate the economic situation between-subjects in the case description (see Appendix A.1 and Appendix A.2). The participants are either in an economic crisis (loss scenario; dummy coded as 0) or in an economic boom (gain scenario; dummy coded as 1).

***BlamePotentialAdvisor*.** I manipulate advisor's blame potential between the participants (see Appendix A.4). The participants receive advice from either an unblamable internal colleague (dummy coded as 0) or a blamable external consultant (dummy coded as 1).

[28] However, I also conducted a multiple linear regression without adjusting the empirical *AT* results to their maximum (minimum) theoretical value. The results are shown in Model 5 of Table 11 (see chapter 5.4.3).

InvestmentDecisionWithoutAdvice. When studying the effect of advisors, the risk of the preliminary investment decision might influence *AT*. Thus, *InvestmentDecisionWithoutAdvice* (preliminary investment decision) is used as an independent variable for testing H.2, H.3, H.4a, and H.4b (see Appendix A.3).

PerceivedRiskWithoutAdvice. *PerceivedRiskWithoutAdvice* is a subjective measure of the perceived riskiness of the preliminary investment decision on a 7-point Likert scale (1 = no risk, 7 = very risky) (see Appendix A.5).

ΔPerceivedOwnResponsibility. *ΔPerceivedOwnResponsibility* measures the change in the participant's subjective responsibility between the final investment decision after being informed about the realized result of the final investment decision and the preliminary investment decision (measured on a 7-point Likert scale (1 = not responsible, 7 = completely responsible)) (see Appendix A.5).

ΔPerceivedChanceAvoidingJustification. *ΔPerceivedChanceAvoidingJustification* measures the change in the participant's subjective chance of avoiding a possible justification to the management board between the final and the preliminary investment decision (measured on a 7-point Likert scale (1 = avoiding justification is very unlikely, 7 = avoiding justification is very likely)) (see Appendix A.5).

5.3.6 Control variables

PerceivedRiskWithoutAdvice. *PerceivedRiskWithoutAdvice* is an independent variable analyzing advice utilization (see chapter 5.3.5). When studying CPT, a subjective measure of the preliminary investment decision's riskiness is a suitable control variable.

Confidence. *Confidence* in the preliminary investment decision is the participant's subjective feeling of having made the right preliminary investment decision for the company, measured on a 7-point Likert scale (1 = not confident, 7 = very confident) (see Appendix A.5).

ΔPerceivedRisk. *ΔPerceivedRisk* is the change in the decision maker's risk perception between the final and the preliminary investment decision (measured on a 7-point Likert scale (1 = not risky, 7 = very risky)) (see Appendix A.5).

RiskPropensity. *RiskPropensity* measures the participant's risk propensity as a trait using the risk propensity scale by Meertens & Lion (2008), with answers given on a 7-point Likert scale (1 = very risk-averse, 7 = very risk-seeking) (Cronbach's alpha is 0.76) (see Appendix A.6).

AdvisorCompetence. *AdvisorCompetence* measures the decision maker's perception of the advisor's competence on a 7-point Likert scale (1 = very incompetent, 7 = very competent) (see Appendix A.5).

TopManagement. *TopManagement* classifies manager participants into lower/middle managers supervising fewer than or equal to 50 employees (dummy coded as 0) or as top managers supervising more than 50 employees (dummy coded as 1).

Additional control variables. Additional control variables are the participant's *Sex* (0 = male, 1 = female), *Age* (measured in years), and *WorkingExperience* (1 = 0-5 years, 2 = 6-10 years, 3 = 11-15 years, 4 = 16-20 years, 5 = 21-25 years, 6 = 26-30 years, 7 = 31-35 years, 8 = more than 36 years).

5.4 Results Study 1

5.4.1 Manipulation checks

The participants perceived less risk for the "Stable Solutions" investment plan than for the "New Technology" investment plan ($t(174) = -8.17$, $p < 0.001$) and recognized the economic boom and the economic crisis ($t(173) = -10.29$, $p < 0.001$). There were no differences in the participants' risk propensity trait between the economic boom and economic crisis ($t(173) = -0.03$, $p = 0.973$). This indicates that both the manipulation and the randomization of participants across conditions were successful.

5.4.2 Influence of the economic situation on the preliminary investment decision

The participants' average preliminary investment decision was 10.70 (N = 94) in an economic boom and 11.32 (N = 81) in an economic crisis on a scale from 1 (100% investment budget in "Stable Solutions") to 21 (100% investment budget in "New Technology"). On average, the participants allocated 51.5% (48.4%) of their investment budget in the defensive investment plan in the economic boom (economic crisis).

The descriptive statistics – mean and standard deviation – and the pairwise correlations of the independent variables and control variables are shown in Table 8. Additionally, I conduct a multiple linear regression to test H.1; F(7, 167) = 3.68, $p < 0.001$, $R^2 = 0.17$ (see Table 9).

Table 8: Descriptive statistics and pairwise correlation matrix I in Study 1

Variables	M	SD	1	2	3	4	5	6	7
1. *EconomicSituation*	0.54	0.50	1.00						
2. *PerceivedRiskWithoutAdvice*	4.09	1.76	0.14*	1.00					
3. *Confidence*	4.97	1.39	0.13*	0.14*	1.00				
4. *TopManagement*	0.22	0.41	-0.01	-0.00	-0.05	1.00			
5. *Sex*	0.23	0.42	-0.05	-0.08	-0.21 ***	-0.10	1.00		
6. *Age*	45.19	18.50	0.05	-0.02	0.02	-0.03	-0.01	1.00	
7. *WorkingExperience*	5.20	1.84	0.16 **	0.09	-0.03	-0.03	-0.07	0.54 ***	1.00

Notes: This table shows mean (M), standard deviation (SD), and pairwise correlation for each independent variable and control variable for the 175 participants across all experimental groups. For more information on all variables, see chapters 5.3.5 and 5.3.6. P values are reported in the following way: * $p < 0.10$ (two-tailed tests), ** $p < 0.05$, and *** $p < 0.01$.

Sources: Author's interpretation.

Table 9: Results multiple linear regression – Preliminary investment decision and economic situation in Study 1

Dependent variable = *InvestmentDecisionWithoutAdvice*	Model 1		Model 2	
EconomicSituation			-1.25*	(0.099)
PerceivedRiskWithoutAdvice	1.10***	(0.000)	1.14***	(0.000)
Confidence	0.06	(0.825)	0.12	(0.674)
TopManagement	-0.21	(0.800)	-0.22	(0.792)
Sex	-0.00	(0.996)	-0.02	(0.983)
Age	0.03*	(0.063)	0.03**	(0.044)
WorkingExperience	-0.13	(0.539)	-0.07	(0.739)
Constant	5.52***	(0.002)	5.52***	(0.001)
Observations	**175**		**175**	
R-squared	**0.16**		**0.17**	

Notes: This table shows the results of a multiple linear regression testing H.1. The dependent variable is *InvestmentDecisionWithoutAdvice*, which represents the participant's preliminary investment decision, ranging from 1 (1 = 100% investment budget in "Stable Solutions") to 21 (21 = 100% investment budget in "New Technology"). For more information on all variables used in the regression, see chapters 5.3.4, 5.3.5, and 5.3.6. Regression coefficients are reported in conjunction with p values in parentheses at the individual level. P values are reported in the following way: * $p < 0.10$ (two-tailed tests), ** $p < 0.05$, and *** $p < 0.01$.

Sources: Author's interpretation.

Model 1 contains only the control variables. The more risk the participants took in allocating capital, the higher *PerceivedRiskWithoutAdvice* ($p < 0.001$).[29]

In Model 2, *EconomicSituation* is added to test CPT and H.1. Model 2 confirms a negative influence of the economic situation on *InvestmentDecisionWithoutAdvice* (preliminary investment decision). *EconomicSituation* has a negative effect ($p = 0.099$) on the preliminary investment decision, which confirms H.1. Managers tend to choose the riskier capital allocation strategy winner-picking in an economic crisis and the more risk-averse capital allocation strategy diversification in an economic boom. Additionally, I conduct a t-test to examine possible differences in *PerceivedRiskWithoutAdvice* between

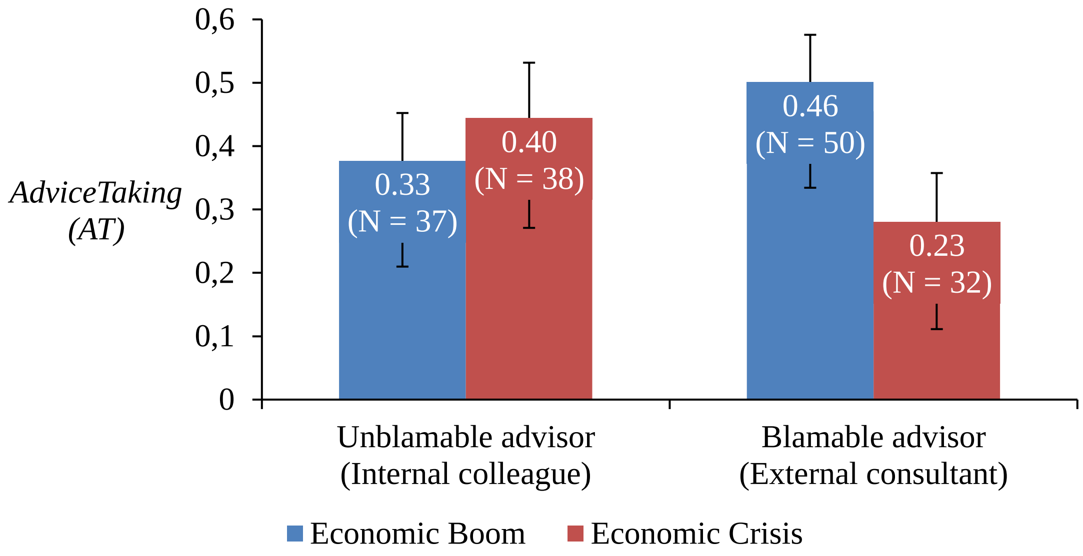
[29] The older the participants, the riskier their preliminary investment decision ($p = 0.063$).

an economic boom and an economic crisis (t(173) = -1.90, p = 0.059). Although the participants made riskier decisions in an economic crisis than in an economic boom, they perceived less risk in an economic crisis than in an economic boom, which further supports my hypothesis.

5.4.3 Influence of advisors' blame potential on advice-taking

Figure 7 shows the mean results of *AT* with 95% confidence intervals over the main groups, *EconomicSituation* and *BlamePotentialAdvisor*.

Figure 7: Means of *AdviceTaking (AT)* in Study 1



Notes: This figure shows the average *AdviceTaking (AT)* over the main groups *EconomicSituation* and *BlamePotentialAdvisor* (internal colleague as an unblamable advisor and external consultant as a blamable advisor) with 95% confidence intervals. In line with standard practice, empirical *AT* results are set to their maximum (minimum) theoretical value of 1 (0). For more information, see chapter 5.3.4. *AT* is 0 for no advice utilization and 1 for full advice utilization.

Sources: Author's interpretation.

The average *AT* for manager participants with unblamable internal colleagues (blamable external consultants) as advisors is 0.33 (0.46) in the economic boom and 0.40 (0.23) in the economic crisis. The descriptive statistics – mean and standard deviation – and the pairwise correlations of the independent variables and control variables are shown in Table 10. Additionally, I conduct a multiple linear regression to test the *AT* hypotheses; $F(15, 141) = 10.23$, $p < 0.001$, $R^2 = 0.355$ (see Table 11).

Table 10: Descriptive statistics and pairwise correlation matrix II in Study 1

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13
1. EconomicSituation	0.55	0.50	1.00												
2. BlamePotentialAdvisor	0.52	0.50	0.12	1.00											
3. ΔPerceivedOwnResponsibility	-0.32	1.87	-0.14*	-0.16*	1.00										
4. ΔPerceivedChanceAvoidingJustification	0.32	1.39	0.08	0.18 **	-0.18 **	1.00									
5. InvestmentDecisionWithoutAdvice	9.87	3.91	0.01	-0.01	-0.05	-0.07	1.00								
6. PerceivedRiskWithoutAdvice	3.85	1.62	0.17**	0.10	-0.03	-0.12	0.19 **	1.00							
7. ΔPerceivedRisk	0.54	1.67	0.05	-0.19 **	-0.11	0.23 ***	-0.13	-0.49 ***	1.00						
8. RiskPropensity	3.74	0.92	0.00	0.09	-0.11	-0.13	0.21 ***	0.20 **	-0.08	1.00					
9. AdvisorCompetence	5.00	1.27	0.08	-0.23 ***	-0.03	0.05	0.18 **	-0.03	0.19 **	0.10	1.00				
10. TopManagement	0.22	0.42	-0.01	-0.07	0.00	-0.06	0.03	0.02	-0.05	-0.03	0.11	1.00			
11. Sex	0.25	0.43	-0.05	0.05	0.01	0.04	0.05	-0.06	-0.04	-0.14*	-0.01	-0.10	1.00		
12. Age	44.90	19.29	0.07	-0.06	-0.04	-0.07	0.07	-0.03	0.00	-0.08	0.03	-0.03	0.00	1.00	
13. WorkingExperience	5.18	1.86	0.19 **	0.08	-0.06	-0.18 **	0.05	0.10	-0.13	-0.05	0.03	-0.04	-0.06	0.53 ***	1.00

Notes: This table shows mean (M), standard deviation (SD), and pairwise correlation for each independent variable and control variable for the 157 participants across all experimental groups. For more information on all variables, see chapters 5.3.5 and 5.3.6. P values are reported in the following way: * $p < 0.10$ (two-tailed tests), ** $p < 0.05$, and *** $p < 0.01$.

Sources: Author's interpretation.

Table 11: Results multiple linear regression – Advice-taking and blame avoidance in Study 1

Dependent variable = *AdviceTaking (AT)*	Model 1	Model 2	Model 3	Model 4	Model 5
EconomicSituation		-0.15* (0.093)	-0.20** (0.017)	-0.19** (0.019)	-0.25* (0.072)
BlamePotentialAdvisor		-0.14 (0.128)	-0.18** (0.048)	-0.17** (0.043)	-0.39** (0.024)
*EconomicSituation * BlamePotentialAdvisor*		0.38*** (0.002)	0.32*** (0.006)	0.28** (0.012)	0.54** (0.013)
ΔPerceivedOwn-Responsibility			-0.05*** (0.000)	-0.05*** (0.000)	-0.07** (0.027)
ΔPerceivedChance-AvoidingJustification			0.05*** (0.006)	-0.00 (0.932)	-0.11 (0.191)
*EconomicSituation * ΔPerceivedChance-AvoidingJustification*				0.09* (0.057)	0.21** (0.019)
InvestmentDecision-WithoutAdvice			-0.02*** (0.008)	-0.02** (0.012)	-0.07*** (0.000)
PerceivedRisk-WithoutAdvice			0.08*** (0.000)	0.08*** (0.000)	0.14*** (0.001)
ΔPerceivedRisk	0.03 (0.121)	0.04** (0.020)	0.05*** (0.003)	0.05*** (0.003)	0.04 (0.271)
RiskPropensity	-0.04 (0.230)	-0.04 (0.177)	-0.05 (0.121)	-0.05* (0.080)	-0.12* (0.063)
AdvisorCompetence	0.06** (0.022)	0.07*** (0.007)	0.07*** (0.002)	0.06*** (0.005)	0.02 (0.639)
TopManagement	0.04 (0.601)	0.04 (0.565)	0.05 (0.440)	0.06 (0.322)	0.14 (0.416)
Sex	-0.03 (0.684)	-0.01 (0.885)	0.01 (0.869)	0.00 (0.982)	0.06 (0.601)
Age	-0.00 (0.550)	-0.00 (0.672)	-0.00 (0.813)	-0.00 (0.789)	0.00 (0.795)
WorkingExperience	0.01 (0.532)	0.01 (0.685)	0.01 (0.507)	0.01 (0.678)	0.01 (0.816)
Constant	0.19 (0.333)	0.20 (0.308)	0.09 (0.603)	0.14 (0.391)	0.77** (0.031)
Adjusting *AT* outlier to min./max. theoretical value	Yes	Yes	Yes	Yes	No
Observations	157	157	157	157	157
R-squared	0.075	0.140	0.336	0.355	0.319

Notes: This table shows the results of the multiple linear regression testing H.2, H.3, H.4a, and H.4b. The dependent variable is *AdviceTaking (AT)*, which measures the change between the final and the preliminary investment decisions. In line with standard practice, empirical *AT* results are set to their maximum (minimum) theoretical value of 1 (0) for Models 1-4. Model 5 does not adjust empirical *AT* results. For more information on all variables used in the regression, see chapters 5.3.4, 5.3.5, and 5.3.6. Regression coefficients are reported in conjunction with p values in parentheses at the individual level. P values are reported in the following way: * p < 0.10 (two-tailed tests), ** p < 0.05, and *** p < 0.01.

Sources: Author's interpretation.

Model 1 contains control variables, and I find that *AdvisorCompetence* has a significant positive effect on *AT* (p = 0.022). Model 2 adds the main effects

(*EconomicSituation* and *BlamePotentialAdvisor*) and their corresponding interaction. The *EconomicSituation* has a significant negative effect on *AT* (p = 0.093). *BlamePotentialAdvisor* is nonsignificant, which means that advice utilization does not increase with a blamable advisor, as proposed by H.2. However, as proposed in H.3, there is a positive effect of the interaction between *EconomicSituation* and *BlamePotentialAdvisor* (p = 0.002). Advice utilization increases with a blamable advisor in an economic boom. Additionally, *ΔPerceivedRisk* now has a positive effect on *AT* (p = 0.020), which is plausible because the advisor recommended a riskier decision.

Model 3 implements additional independent variables (*ΔPerceived-OwnResponsibility*, *ΔPerceivedChanceAvoidingJustification*, *InvestmentDecision-WithoutAdvice*, and *PerceivedRiskWithoutAdvice*) to better understand the reasons for using advice. In contrast to H.2, there is now a significant negative effect of *BlamePotentialAdvisor* (p = 0.048) on *AT*. H.4a proposes a decrease in perceived own responsibility with an increase in advice utilization, whereas H.4b proposes an increase in the perceived chance of avoiding justification with an increase in advice utilization. *ΔPerceivedOwnResponsibility* (p < 0.001) and *InvestmentDecisionWithoutAdvice* (p = 0.008) have a negative effect on *AT*, whereas *ΔPerceivedChanceAvoiding-Justification* (p = 0.006) and *PerceivedRiskWithoutAdvice* (p < 0.001) have a positive effect on *AT*. These findings support H.4a and H.4b.

Model 4 adds the interaction between *EconomicSituation* and *ΔPerceivedChance-AvoidingJustification*, which results in a positive effect on *AT* (p = 0.057). Moreover, *ΔPerceivedChanceAvoidingJustification* no longer affects *AT*. The perceived chance of avoiding justification increases only in an economic boom. This finding partly confirms H.4b. Furthermore, *RiskPropensity* now has a significant negative influence on *AT* (p = 0.080).

Finally, using the results of Model 4, I demonstrate that overall advice utilization decreases with a blamable advisor. However, in an economic boom, advice utilization increases with a blamable advisor. Additionally, I find that managers' perceived responsibility for the investment decision decreases as *AT* increases. Furthermore, the perceived chance of avoiding justification increases in the economic boom as advice utilization increases. Overall, I can fully confirm H.3 and H.4a, partly confirm H.4b, and reject H.2.

5.4.4 Additional results

Additionally, I conduct the same multiple linear regression (see Table 11), without adjusting the data deviating from previous studies that have changed *AT* outliers to their maximum (minimum) theoretical values (i.e., *AT* > 1 are set to 1 and *AT* < 0 are set to 0) (Schultze et al., 2017; Soll & Larrick, 2009). Model 5 shows the results with the unmodified sample (see Table 11). My results overall continue to hold.[30]

5.5 Discussion and conclusion Study 1

5.5.1 Discussion of the results of the preliminary investment decision

In my experiment, the manager participants realized the riskiness of their preliminary investment decision. The riskier their preliminary investment decision was, the higher the risk the participants perceived (see Table 9). However, the participants perceived higher risk in the economic boom than in the economic crisis ($t(173) = -1.90$, $p = 0.059$) and they allocated their investment budget more defensively in the economic boom than in the economic crisis (10.70 vs. 11.32, see Table 9). These findings correspond to those of Sitkin & Weingart (1995) who show that decision makers who want to protect their existing resources or gains tend to perceive more risk and act more

[30] However, some minor effects lose their significance. Specifically, *ΔPerceivedRisk* and *AdvisorCompetence* are no longer significant.

defensively, whereas decision makers who want to avoid losses tend to perceive lower risk and act more riskily.

CPT explains managers' varying risk perceptions with loss aversion (Fennema & Wakker, 1997; Kahnemann & Tversky, 1979; Tversky & Kahneman, 1992). Managers try to reduce their losses in an economic crisis by making a riskier choice for their individual variable compensation and hope for a successful outcome. In an economic boom, managers try to avoid risk to achieve a safer and more stable gain. The results of Table 9 confirm H.1 and are in line with CPT.

5.5.2 Discussion of the advice-taking results

Research on BAT suggests that decision makers try to minimize their future blame potential. They can achieve this by delegating decisions to blame the advisor in the case of failure (Keil et al., 2007; Steffel et al., 2016). I study whether managerial blame avoiding advice-taking is influenced by the advisors' blame potential and the managers' risk perceptions as IPOm Individual-level factors. My study demonstrates that a blamable advisor increases *AT* only in an economic boom, which confirms H.3. Instead, a blamable advisor has a negative influence in an economic crisis (see Table 11). The reason for this behavior could be that managers perceive more risk in an economic boom than in an economic crisis (Sitkin & Weingart, 1995). In a boom situation, using a blamable advisor could be a simple solution for risk-averse managers to avoid being held responsible. This argumentation is supported by the significant effects of risk-related variables (e.g., *InvestmentDecisionWithoutAdvice*, *PerceivedRiskWithoutAdvice*, and *RiskPropensity* as an individual trait) on *AT*. *AT* increases when (1) managers made a defensive preliminary investment decision, (2) managers perceived more risk, and (3) they are more risk-averse as individual traits (see Table 11). This means that a blamable advisor who recommends an objectively riskier decision can resemble a safer decision for a blame avoiding manager. This adds to prior research (see chapters 2.1.2.2 and 3.2.2), as I show that sharing responsibility with advisors and passing the buck to them as scapegoats seem to be the main drivers of advice utilization for risk-averse decision makers.

My findings also indicate that the participants in the economic crisis condition did not perceive much risk and even became riskier. Nevertheless, 28% of the participants (nine of 32) adjusted their preliminary investment decision to be more financially defensive in the economic crisis with a blamable advisor, whereas only 8% (ten of 125) did so in the other groups. This indicates that the blamable advisor offers protection to the manager participants in the case of failure, but the blamable advisor thereby stresses the consequences of possible failures to the participants. Such a confrontation with possible failures could lead the participants to reevaluate the risk of their preliminary investment decision. The participants in the economic boom seem to be reaffirmed in their high-risk perception by the blamable advisor's warning and tend to use him to reduce their personal risk.

However, the participants in the economic crisis seem to be stimulated by the advisor's recommendation and therefore notice their risk increase for the preliminary investment decision and potentially begin to question their preliminary investment decision. I believe that this results in the participants being more financially defensive in their final investment decision. Based on a skewed risk perception, managers seem to worry more about justification in the economic boom and more about compensation in the economic crisis. In contrast to CPT (Fennema & Wakker, 1997; Kahnemann & Tversky, 1979; Tversky & Kahneman, 1992), my results indicate that managers' risk perceptions not only influence financial risk-taking but also seem to be the main driver for blaming a scapegoat. Risk-averse managers care only about avoiding a justification of their decision, independent of the recommended decision's financial riskiness.

I find that managers' perceived responsibility for their final investment decision decreases as *AT* increases. In all groups, the participants perceived less responsibility regardless of whether the advisor was introduced as a blamable advisor. However, the perceived chance of avoiding justification increases only in an economic boom with increasing *AT* (see Table 11). This is due to managers being more afraid of justification in an economic boom than in an economic crisis due to higher risk perceptions (Sitkin & Weingart, 1995). In contrast, managers in an economic crisis negatively adjust their preliminary investment decision and do not focus on avoiding justification.

In line with previous research, I find that *AdvisorCompetence* has a significant positive effect on *AT* (Bonaccio & Dalal, 2006; Harvey & Fischer, 1997). Similarly, the significant negative influence of the *EconomicSituation* on *AT* resembles an anchoring effect, which is usually stronger in negative settings due to emotionally distorted confirmatory hypotheses testing (Bodenhausen, Gabriel, & Lineberger, 2000; Englich & Soder, 2009).[31] In this study, I confirm these well-established findings and expand the literature with my findings concerning the use of scapegoats by managers.

5.5.3 Contribution, limitations, and future research

Overall, my contributions to the literature are twofold. I contribute to advice-taking literature and blame avoidance literature by studying whether managers use advice to blame advisors as scapegoats as an IPOm Output-Dimension factor and how this depends on their own risk perceptions and the advisors' blame potential as IPOm Individual-level factors (research questions 1 and 2) (see Table 1). I confirm and extend Harvey & Fischer's (1997) idea of an increase in advice use with higher risk perception. I demonstrate that the more risk managers perceive and the more they try to reduce their own responsibility, the more they pass the buck to advisors by using their advice and using them as scapegoats. Moreover, I extend BAT by highlighting the role of individual

[31] Confirmatory hypothesis testing in my setting suggests that managers with negative emotions (e.g., fear in an economic crisis) will think more intensely about the anchor, and therefore, they will find more arguments supporting it than their happy counterparts (Bodenhausen et al., 2000; Englich & Soder, 2009).

risk perceptions as an internal motive to use an advisor as a scapegoat. My findings concerning advisors' blame potential extend BAT by showing that advisors' blame potential and responsibility attribution are main factors for using the advisor as a scapegoat (see chapters 2.1.2.3 and 3.3).

I also contribute to literature on CPT. Prior research mainly describes how monetary problem framing – choosing between gains or losses – distorts a decision maker's risk perception and results in different decision preferences (Fennema & Wakker, 1997; Kahnemann & Tversky, 1979; Sitkin & Weingart, 1995; Tversky & Kahneman, 1992). However, the influence of nonfinancial gains and losses (e.g., change in reputation or threat of public blame) on individual risk perception and their interplay with financial gains or losses have scarcely been studied. Blame avoiding decision-making introduces a new nonfinancial threat for the decision maker – the threat of justification. I demonstrate that managers focus on avoiding nonfinancial losses by using a scapegoat in an economic boom, whereas they focus on avoiding financial losses by trying to make the best financial decision in an economic crisis. This provides novel findings concerning nonfinancial risk-taking to CPT literature (see chapters 2.1.2.3 and 3.3).

This study is also relevant for management practitioners by explaining why and under what circumstances managers tend to avoid blame and try to share responsibility with an advisor. When they must make difficult and high-risk decisions, such as investment decisions, managers likely seek blamable advisors in the form of external consultants who can be made responsible for possible future failures and protect managers from negative consequences. Companies should be aware of their managers' opportunistic motives when seeking advice.

Moreover, I contribute to prior advice-taking literature by relying on an experiment with experienced managers (rather than graduate students), which allows me to test for causal relationships in settings with great internal validity due to randomization and manipulation of the main variables of interest (advisors' blame potential and managers' risk perceptions as IPOm Individual-level factors) while simultaneously keeping the effect of other variables (e.g., magnitude of threat) constant. This typically comes at the cost of lower external validity due to the experiment's artificial setup and might lead to different behaviors in reality (Bryman & Bell, 2015). Despite the need to reduce complexity for my online experiment, I still aim to stay as close as possible to the real-world managerial work environment and exclusively rely on real managers as participants. Making investment decisions (e.g., investments in new product developments), being advised while doing so, and being evaluated based on the companies' economic success are everyday tasks for managers (Busenbark et al., 2017; Graham et al., 2015). Hence, I rely on a context-rich experiment (rather than more stylized game theoretical designs) to study for causal effects on managers' use of advice. As I include lower/middle managers as well as top managers in my study, I am confident that my findings can be transferred to the blame avoiding behavior of managers at different levels in corporate reality.

However, as with all experimental research, my setup comes with limitations (see chapter 4.1). Specifically, managers in my experiment interacted with advisors only in writing and they evaluated their competence based on written recommendations. Therefore, I cannot consider possible interpersonal effects (e.g., previous positive or negative experience with the consultant) that could influence managers' perception of advisors' competence in corporate reality. However, in business practice, managers also receive written decision templates and conduct competence evaluations based on written information.[32] Due to the experimental setup, which focuses on the role of few but

[32] Due to the experimental approach on which I relied, I had to keep these interpersonal factors constant. This eliminates possible behavioral effects associated with the advisor's personality and confidence.

important variables, I was not able to test a multitude of other factors. I encourage future qualitative or survey research to analyze the role of interpersonal effects and managers' previous experience with external consultants on managerial blame avoiding behavior.

Another possible limitation is the manipulation of the advisors' blame potential. Although personal performance evaluations are common in business practice, it is very difficult to simulate a threatening situation with severe consequences in a fictitious experimental setting. The threat of writing a justification of 200 characters is not comparable to the real threat of being blamed in corporate reality. Moreover, in business practice it is rarely the case that managers know in advance whether their superiors consider their advisors to be blamable.

Future research could concentrate on internal (e.g., personality traits, power, mood, fear of failure or perceived severity of the threat) and external (e.g., national and corporate culture or societal expectations) factors other than risk perception that influence a decision maker's tendency to use a scapegoat. Moreover, it would be interesting to determine whether different groups of decision makers (e.g., individuals in private life or employees, managers, and nonprofit decision makers in a business context) show different blame avoiding behavior. Additionally, possible attributes for the ideal scapegoat could be examined. Future survey or qualitative research could also analyze the attributes sought by decision makers when they consider using advisors as potential scapegoats (e.g., scapegoats' financial costs, communication style, credibility, visibility when having to justify, or perhaps even scapegoats' possibility of retribution and self-defense). Moreover, it would be interesting to know if and how different management leadership styles influence managerial blame avoiding decision behavior. In this study, I show that managers use consultants as scapegoats. However, the question remains whether consulting companies are aware of this managerial behavior. Future research could analyze whether actively offering a scapegoating role is – at least to some degree – part of the business models of consultancies.

6 Study 2: Selecting (non)human scapegoats – how advisors' social competence drives managers' algorithm aversion[33]

6.1 Introduction and motivation Study 2

Algorithmic decision aids – computers, algorithms, robots, and AI systems – are increasingly used to support decision-making in many settings (see chapter 2.2.1) (Burton et al., 2020; Prahl & van Swol, 2017). These settings range from doctors using clinical algorithmic decision aids to make better medical decisions, such as diagnoses (Esmaeilzadeh et al., 2015), to managers using algorithmic decision aids to make better business decisions, such as sales forecasts (Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011). The use of algorithmic decision aids as nonhuman advisors raises the question of to what extent algorithmic decision aids are made responsible for their recommendations (Burton et al., 2020; Floridi et al., 2018). Specifically, experts from academia, businesses, and governmental institutions have identified AI responsibility as a major challenge related to developing fair, trustworthy, and ethical nonhuman algorithmic decision aids (Robert et al., 2020).

In this study, I experimentally investigate whether and under what circumstances managers share responsibility with algorithmic decision aids. I focus on whether managers use identical advice differently and exhibit algorithm aversion by preferring human advisors to algorithmic decision aids (e.g., Burton et al., 2020). This is different from prior research, which generally focuses on investigating whether managers or algorithmic decision aids make better decisions (see chapter 2.2.2.2) (e.g., Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011). I study whether managers try to avoid personal blame by using advisors as scapegoats and how this depends on the advisors'

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blame potential (blamable advisors vs. unblamable advisors) and nature (human advisors vs. algorithmic decision aids) as IPOm Individual-level factors (see Figure 1).[34]

Building on BAT, I propose that managers try to avoid blame by delegating difficult decisions to advisors (Gangloff et al., 2014; Park et al., 2014; Steffel et al., 2016). Prior research identifies sharing of responsibility and avoiding blame as main reasons for taking advice (e.g., Bonaccio & Dalal, 2006). Bonaccio & Dalal (2006) also propose that "[m]otives such as sharing responsibility for the decision [...] become salient only in the case of human advisors" (p. 135). Prior literature has found that decision makers blame human advisors to avoid personal blame in different empirical contexts.[35] Specifically, I study the following research questions (see Table 1 as well as chapters 2.2.2.3, 2.3.2, and 3.3):

<u>Research question 3:</u> Do managers utilize nonhuman advice by blamable algorithmic decision aids to share responsibility?

<u>Research question 4:</u> Do managers exhibit algorithm aversion when utilizing blamable advice to share responsibility?

I extend this research by differentiating between advice given by human advisors and that given by algorithmic decision aids. Referring to philosophical discussions about responsibility attribution to algorithmic decision aids (e.g., Coeckelbergh, 2020; Ashrafian, 2015), I empirically investigate managers' responsibility attribution to human and nonhuman advisors in a managerial forecasting setting. I do this because an increasing level of technological sophistication (e.g., the implementation of AI-based algorithmic decision aids) might change managers' perceptions about sharing

[34] I refer to this behavior of blaming others to avoid personal blame as blame avoiding decision-making. Specifically, I argue that blamable advisors can be blamed and held responsible for their recommendations that result in bad decision outcomes, whereas unblamable advisors cannot be made responsible (see chapter 3.2.2).

[35] Public sector officials or politicians (e.g., James et al., 2016), students as proxies for private sector managers (e.g., Keil et al., 2007), and participants in dictator games (e.g., Bartling & Fischbacher, 2012) exhibit blame avoiding behavior with human advisors (see chapter 3.2.2 and Study 1 in chapter 5).

responsibility. Motives for engaging in blame avoiding decision-making are expected to be highly relevant in the contexts of managerial planning and decision-making, such as that of sales forecasting, because high forecast errors have strong negative effects on corporate profits and overall competitiveness. Therefore, these contexts entail a high level of blame risk (Fildes et al., 2009; Salehzadeh et al., 2020). Moreover, managers are typically supported either by human advisors (e.g., corporate experts) or by algorithmic decision aids, both of whom provide forecast information. Then, managers can usually subjectively adjust the recommendation (see chapter 2.2.2).[36]

In line with BAT, I propose that managers make smaller judgmental adjustments of forecasts recommended by blamable advisors than by unblamable advisors because managers want to be able to share responsibility and blame with blamable advisors in the case of a high forecast error and avoid own responsibility. Additionally, I propose that managers are more willing to share responsibility with human advisors than with algorithmic decision aids. This hypothesis is motivated by prior philosophical research that argues that a consciousness of one's own actions and the resulting consequences is the main precondition for assuming responsibility (Ashrafian, 2015; Coeckelbergh, 2020). I propose that this is also an important human-like precondition for others to share responsibility with someone or something. Moreover, I propose that managers reduce algorithm aversion in regard to scapegoat selection when they perceive a higher level of social competence of blamable algorithmic decision aids as a human-like criterion.

I conduct a fully anonymized and incentivized online experiment with managers using a 2 (unblamable advisor vs. blamable advisor) x 2 (expert as human advisor vs. AI as algorithmic decision aid) between-subject experimental design. Participants make a sales forecasting decision, which is a two-step process. First, participants were provided

[36] Fildes & Petropoulos (2015) find in a survey of forecasting practitioners that approximately 70% of the forecasts examined contain some kind of judgmental adjustment.

with a preliminary sales forecast, which was issued either by a human expert or an algorithmic decision aid. In a next step, participants had the opportunity to make an adjustment of the preliminary forecast. This adjustment is my main dependent variable (see chapter 2.2.2.1). Participants can avoid obligatory justification to the management board in the case of a large forecast error if they make no adjustments to blamable advisors' recommendations. Avoiding responsibility and blame for large forecast errors is not possible with unblamable advisors regardless of whether participants make forecast adjustments.

In line with my expectations and BAT, I find a main effect of the advisors' blame potential on adjustments. Managers make smaller adjustments of forecasts recommended by blamable advisors than of those recommended by unblamable advisors, as they are trying to avoid personal blame. Moreover, I find that managers exhibit algorithm aversion for blaming advisors and prefer to use human scapegoats. However, managers reduce this algorithm aversion when perceiving a higher level of social competence for blamable algorithmic decision aids. I show that perceived social competence (i.e., human-likeness) of algorithmic decision aids – in addition to their blame potential – is a main driver of managerial (non)human scapegoat selection.

This study contributes to BAT by expanding our understanding of the criteria used for scapegoat selection and demonstrating the existence of nonhuman scapegoats. Current literature on BAT exclusively focuses on the responsibility attribution to blamable human advisors (Artinger et al., 2019; James et al., 2016; Steffel et al., 2016). I demonstrate that managers prefer human scapegoats but also blame algorithmic decision aids and consider high social competence (i.e., human-likeness) important for nonhuman scapegoats. I identify advisors' nature and blame potential as important IPOm Individual-level factors influencing managerial advice-taking (see chapters 2.2.2.3, 2.3.2, and 3.3).

Furthermore, I contribute to research on algorithm aversion, which identifies a task-mismatch as a causal reason for this behavior (e.g., Burton et al., 2020; Lowens, 2020; Castelo et al., 2019). Specifically, I find that managers consider human-likeness in the form of blamable advisors' social competence as a task-specific requirement (i.e., IPOm Individual-level factor) for scapegoats. I demonstrate that socially competent blamable algorithmic decision aids reduce managers' algorithm aversion in regard to scapegoat selection (see chapters 2.3.2 and 3.3).

Additionally, this study contributes to literature studying the use of algorithmic decision aids in forecasting settings by transferring insights from BAT (e.g., Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011; Gönül et al., 2009). I provide additional explanations for why blame avoiding managers may want to avoid adjusting forecasts and how their blame avoiding behavior depends on their advisors' characteristics (e.g., blame potential, nature, and perceived social competence).

This study is also relevant for organizations and practitioners, as it explains managers' blame avoiding motives for not making forecast adjustments. Specifically, organizations need to be aware that managers exhibit algorithm aversion and make smaller adjustments to advice, as they prefer to share responsibility with human advisors and socially competent (i.e., human-like) algorithmic decision aids. Hence, companies that introduce algorithmic decision aids with human-like attributes to support managerial decision-making should be aware of this managerial blame avoiding behavior.

The remainder of this chapter is structured as follows. Next, the hypotheses are developed (see chapter 6.2). Subsequently, the experimental method used to gather the data is explained (see chapter 6.3). Finally, the results are shown and discussed (see chapters 6.4 and 6.5).

6.2 Theoretical background and hypothesis development Study 2

6.2.1 Influence of blamable advisors on managerial forecast adjustments

Building on BAT, this study analyzes managerial blame avoiding behavior in a forecasting setting depending on advisors' blame potential and nature as IPOm Individual-level factors. The use of algorithmic decision aids (e.g., AI) to support managerial decision-making by providing forecasts is often thought to increase forecast accuracy (Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011). It enables managers to integrate domain knowledge and contextual information (e.g., sales promotions) in statistical forecasts driven by existing data (see chapter 2.2.2.2) (Fildes et al., 2009; Goodwin, 2000).

Literature distinguishes between two main forms of AI: "Weak AI" and "strong AI". A "weak AI" is better than humans at performing a specific task (e.g., analyzing complex data for forecasting), whereas a "strong AI" functions in a way comparable to general human thinking and is at least equal to human intelligence in terms of a broad range of tasks (e.g., general artificial superhuman intelligence) (Fjelland, 2020; Russel & Norvig, 2016). In this study, I analyze the role of a "weak AI" that exclusively specializes in forecasting and does not possess general intelligence. I study "weak AI" because it is more prevalent than "strong AI" in current business practice and more closely represents the forecasting algorithmic decision aids that are described and used in the literature (Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011). In line with prior research, I am interested in a setting in which AI is used to advise managers regarding generating sales forecasts. However, in this study, I do not focus on forecast accuracy but on sharing responsibility as a motive for adjusting forecasts.

Building on BAT, I argue that decision makers try to pursue personal goals (e.g., promotions, avoiding layoffs) by avoiding responsibility and minimizing their future blame potential (e.g., internal reputational losses due to negative decision outcomes). To achieve these personal goals, managers need to avoid being held responsible for negative decision outcomes and having to justify their decisions (Artinger et al., 2019; Weaver, 1986). A strategy that can be used to avoid blame and share responsibility is PTB (Weaver, 1986). PTB entails delegating difficult decisions to third parties (e.g., advisors) who are used as scapegoats and assume responsibility for any negative consequences resulting from bad decision outcomes (e.g., major forecast errors) (see chapter 3.2.2). I examine PTB in a setting involving adjustments of sales forecasts within a firm that uses human advisors and algorithmic decision aids. Specifically, I argue that managers intentionally do not adjust forecasts to avoid blame and pursue personal goals by blaming advisors as scapegoats in cases where negative consequences result from major forecast errors.

This hypothesis is motivated by prior research that has found PTB behavior in different empirical contexts involving human advisors (see chapter 3.2.2 and Study 1 in chapter 5) (e.g., Bartling & Fischbacher, 2012; Artinger et al., 2019; James et al., 2016). For example, prior research identifies blame avoiding behavior in contexts where organizations blame and lay off managers after financial misconduct or events related to information technology-related weaknesses (e.g., data security breaches due to system deficiencies) (Banker & Feng, 2019; Gangloff et al., 2014; Haislip et al., 2016). Moreover, powerful managers blame weaker colleagues to avoid being laid off (Park et al., 2014).

In a similar vein, I argue that managers who perceive personal threats related to having to justify major forecast errors share responsibility with advisors by not making large forecast adjustments. Fildes & Goodwin (2007a) find that requiring forecasters to provide written explanations of their adjustments reduces the frequency and magnitude of such adjustments. I propose that the magnitude of these adjustments depends on the blame potential of the recommending advisor. In line with Keil et al. (2007), I differentiate between two different types of blame-shifting situations – those involving blamable advisors and those involving unblamable advisors.

Not making an adjustment of a blamable advisor's recommendation enables a manager to blame this advisor in the case of failure, whereas this is not possible with an unblamable advisor. In corporate reality, an advisor's blame potential is determined by the individual whose blame the manager is trying to avoid (e.g., the manager's superior). I argue that managers only use those advisors as scapegoats whose forecast recommendations they expect to be considered valuable by their superiors. In this way, managers can deflect their superiors' negative reactions to major forecast errors, shifting them to blamable advisors.

Therefore, I propose that managers try to avoid blame from their superiors by using only advisors who are held in high regard by their superiors as scapegoats (e.g., highly reputable marketing experts or highly sophisticated AIs with good historical track records). Advisors with very weak reputations are thought to be unblamable (e.g., inexperienced marketing trainees or simple, "old fashioned" statistical analyses with bad historical track records). Hence, I propose the following:

H.1: Managers make smaller adjustments of forecasts recommended by blamable advisors than of those recommended by unblamable advisors.

I also propose that the willingness to share responsibility with an advisor depends upon the advisors' nature (human advisor vs. algorithmic decision aid) as an IPOm Individual-level factor. There is a major debate on how national or supranational governmental institutions can determine responsibility for the consequences arising from AI implementation (Floridi et al., 2018; Robert et al., 2020). In my study, I do not focus on regulatory decisions but on managers' individual perceptions of whether algorithmic decision aids can bear responsibility for their judgments. Specifically, I expect that the advisors' nature influences managers' (subjective) perceptions of the advisors' blame potential.

In line with BAT, the main motive of PTB is to avoid blame and justification in cases of major forecast errors by delegating difficult forecasts to advisors and making no adjustments of their recommendations (Steffel et al., 2016; Weaver, 1986). I argue above that managers' perceptions of advisors' blame potential are based on their expectations of the degree to which their superiors will hold these advisors responsible for their forecast recommendations. Philosophical research shows that responsibility is a relational concept referring to someone (e.g., a manager) engaging in an action (e.g., making an adjustment), influencing someone else (e.g., the manager's company suffers a loss due to a major forecast error), and having to assume responsibility for the consequences (Brinkmann, 2009).

Can algorithmic decision aids in the form of AI advisors assume responsibility similarly to humans? Aristotle defines two conditions of responsibility that can be used to determine someone's expected responsibility attribution: (1) You are responsible if you do it and you have control over your actions and (2) you are aware of the consequences of your action (Coeckelbergh, 2020). In my setting, this means that (1) human advisors have a free will and consciously recommend forecasts and (2) know the possible consequences of potential major forecast errors. Because they are human beings, human advisors can be held responsible for their forecast recommendations (Ashrafian, 2015; Coeckelbergh, 2020).

In contrast, evaluating responsibility attribution to AI advisors is more difficult and largely depends on the technological sophistication of such advisors. An AI that is thought to have own consciousness, sentience, and intellectual abilities that are comparable to human intelligence ("strong AI") is supposed to make free and independent decisions. In contrast, a “weak AI” would not be able to make a decision without explicit human permission (Ashrafian, 2015; Fjelland, 2020; Russel & Norvig, 2016).

In business practice and in my experimental setting, managers rely on “weak AI” to provide forecasts (see Appendix B.1). Due to its lack of a consciousness, I expect that a “weak AI” is held less responsible for its recommendations than a human advisor (Ashrafian, 2015; Coeckelbergh, 2020). Similar to human advisors, human managers can be held responsible for their adjustments. Managers who try to avoid future blame and responsibility for their forecasting decisions are expected to focus on reducing their own responsibility by using advisors as scapegoats and by increasing such advisors’ responsibility. Therefore, I propose that managers expect their superiors to attribute responsibility for possible forecast errors in the following way: The manager and a human advisor will share responsibility for the final forecast depending on the manager’s adjustment. Palmeira et al. (2015) observe a higher responsibility attribution to the advisor with increasing advice-taking. Similar behavior has also been observed in forecasting settings. Managers perceive more own responsibility for the final forecast when they make larger adjustments (Gönül et al., 2009). Therefore, I argue that the more the final forecast is based on the advisor’s recommendation (the smaller the adjustment is), the more responsibility is attributed to that advisor. However, I assume that this is mainly the case for human advisors because managers face more difficulties in sharing responsibility with algorithmic decision aids, as they cannot be sure that superiors will attribute responsibility to algorithmic decision aids in the same way that they do to human advisors.

Accordingly, I propose managerial algorithm aversion in regard to scapegoat selection due to the expected variance in superiors’ responsibility attribution, which is dependent upon the advisors’ nature. Specifically, I expect managers to prefer using blamable human advisors as scapegoats rather than blamable AI advisors. Consequently, I formulate the following hypothesis:

H.2: Managers make larger adjustments of forecasts recommended by blamable AI advisors than of those recommended by blamable human advisors.

6.2.2 Influence of advisors' perceived social competence on algorithm aversion for scapegoat selection

I argue above that managers exhibit algorithm aversion for scapegoat selection due to their expectations that their superiors will attribute responsibility differently depending on the advisors' nature as an IPOm Individual-level factor. Next, I introduce advisors' social competence as a human-like criterion used for scapegoat selection. Lowens (2020) and Castelo et al. (2019) identify a possible task-mismatch as the main reason for algorithm aversion in different contexts. Specifically, decision makers exhibit algorithm aversion for subjective tasks (e.g., predicting whether a joke will be funny). However, increasing the human-likeness of an algorithmic decision aid reduces individuals' algorithm aversion (Castelo et al., 2019; Lowens, 2020; Yeomans et al., 2019). Therefore, I suggest that managers view scapegoats' social competence as a human-like attribute that is an important task-specific requirement. Specifically, I propose that managerial algorithm aversion decreases as managers' perceptions of the social competence of blamable algorithmic decision aids (i.e., the human-likeness of nonhuman scapegoats) increase.

Social competence is the personal ability to manage interpersonal relationships in communication settings (Huang & Lin, 2018; Rubin & Martin, 1994). Specifically, Huang & Lin (2018) define four core social competencies: (1) active listening; (2) empathy; (3) expressiveness, which is highly variable verbal and nonverbal communicative behavior; and (4) social relaxation, which is the ability to handle negative reactions and criticism. These skills represent human-like attributes and should help scapegoats justify their decisions to managers' superiors. In line with this, Garofalo & Rott (2018) demonstrate the importance of a scapegoat's social competence in a blame avoiding setting.

The main reason for using a blamable advisor as a scapegoat is that such an advisor can assume responsibility for a manager and defend him or her from repercussions due to major forecast errors in social communication settings with superiors (e.g., justifying errors to a superior in a performance evaluation meeting). Consequently, blamable advisors who are not perceived to be socially competent are not expected to be used as scapegoats by managers. I argue above that managers expect their superiors to be more skeptical of potential responsibility attribution to nonhuman scapegoats than they are of potential responsibility attribution to human scapegoats, resulting in managerial algorithm aversion (see H.2 in chapter 6.2.1). I expect this pattern to be reduced when managers perceive that blamable advisors have high levels of social competence. Therefore, I assume that managers view a high level of social competence as a human-like attribute that is especially important for blamable algorithmic decision aids.[37] I argue that blamable algorithmic decision aids to which managers ascribe high levels of social competence can prompt responsibility attribution similar to that attributed to human scapegoats.

Therefore, I propose that advisors' social competence is a main task-specific human-like criterion used for managerial scapegoat selection. Specifically, I expect lower levels of managerial algorithm aversion for blamable advisors with highly attributed social competence. Consequently, managers make smaller adjustments of forecasts recommended by blamable AI advisors with highly attributed social competence, as they

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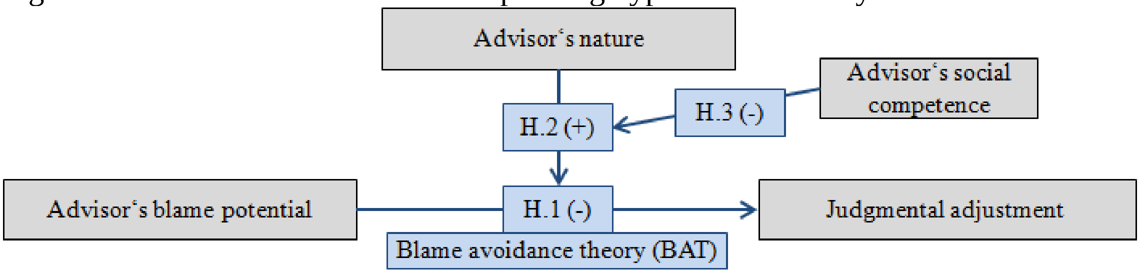
[37] The ability to socially interact with humans through verbal expressions does not necessarily require a "strong AI". Many algorithmic decision aids that are "weak AIs" are capable of processing oral commands and answering verbally (e.g., virtual voice assistants).

are more human-like than blamable AI advisors with lower attributed social competence. Hence, I propose the following:

H.3: Managers' higher perceptions of advisors' social competence reduces algorithm aversion for blamable (non)human advisors.

Figure 8 shows my overall theoretical model and the corresponding hypotheses.

Figure 8: Theoretical model and corresponding hypotheses in Study 2



Notes: This figure presents an overview of my hypotheses. Three independent IPOm Individual-level factors, namely advisors' blame potential, nature, and perceived social competence influence managers' forecast adjustments (H.1, H.2, and H.3). Specifically, H.1 proposes a decrease in adjustments of forecasts recommended by blamable advisors than of those recommended by unblamable advisors. H.2 theorizes an increase in adjustments of forecasts recommended by blamable AI advisors than of those recommended by blamable human advisors. H.3 proposes lower algorithm aversion in regard to scapegoat selection with higher levels of advisors' perceived social competence. This means that managers make smaller forecast adjustments for blamable AI advisors with high perceived social competence than for blamable AI advisors with low perceived social competence.

Sources: Author's interpretation.

6.3 Method Study 2

6.3.1 Experimental design

I conducted an online vignette experiment to study the influence of advisors' blame potential and nature as IPOm Individual-level factors (see chapter 4.1). I generally relied on prior related experimental settings, which provide statistical forecasts and subsequently allow forecasters to incorporate domain knowledge and subjectivity by adjusting the recommended forecasts (Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011). I use a 2x2 between-subjects experimental design (see Table 12). The between-subject factors are the advisor's nature (human marketing expert vs. algorithmic decision aid in the form of an AI) and the advisor's blame potential (unblamable advisor vs. blamable advisor) (see chapter 4.2). The manipulation of advisor's blame potential is in line with prior blame avoiding research (e.g., Keil et al. (2007)).

Table 12: 2x2 between-subject-factorial experimental design in Study 2

2x2 experimental design		Advisor's blame potential	
		Unblamable advisor	Blamable advisor
Advisor's nature	Human marketing expert	N = 43	N = 23
	AI advisor	N = 44	N = 33

Notes: This table shows the experimental design and the number of participants within each experimental group.

Sources: Author's interpretation.

6.3.2 Experimental task & procedure

The participants were asked to assume the role of a business unit manager in a highly competitive business environment. The business unit specialized in producing and selling medical walking aids (walkers). The business unit manager's main task was to produce only as many walkers as the sales division can sell in the upcoming year. The participants were supported by an advisor who forecasted the company's sales volume for the upcoming year and recommended a certain production volume. This advisor was either a human marketing expert or an algorithmic decision aid in the form of a "weak AI" (see Appendix B.1).

The participants received a fixed participation fee of 1.25€ and variable compensation of 0.000025% of the business unit's profit. There was no chance of negative variable compensation, even if a loss occurred for the business unit. The business unit's profit consisted of a 10€ profit margin per sold product and a 50€ loss per product deviating from the realized sales volume due to disposal costs associated with overproduction or increased production costs associated with underproduction. This created a possible individual compensation structure ranging from 1.25€ to 1.92€.[38]

Additionally, the management board expected the realized sales volume not to deviate from the forecast by more than 10%. In case of a missed forecast, the participants were informed that the management board would question their competence and suitability for the position of a business unit manager and expect them to provide a written justification of at least 200 characters explaining their missed forecast (see Appendix B.1 and Appendix B.2).

In line with previous research on sales forecasting, I artificially generated a sales time series consisting of six periods for all the participants (Goodwin, 2000; Goodwin et al., 2007). The sales time series was based on an exponential trend with an annual growth rate of 5% starting at 200.000 units and a normally distributed noise factor with a mean of 0 and a standard deviation of 20.000. The recommended forecast was created by using the forecast method "simple exponential smoothing" with a smoothing parameter of 0.7.[39]

First, the participants were shown the first five periods of the artificially generated sales time series, which represented historical data of the last five years. Additionally, the historical recommended forecasts of the advisor and the bandwidth of the acceptable forecast deviation were shown. Then, the participants were asked to express their trust in the advisor and evaluate the advisor's forecasting competence in an interposed questionnaire (see Appendix B.3).

Then, the participants were provided with the recommended forecast for the upcoming period and had the opportunity to adjust this forecast (see Appendix B.4). The participants with the blamable advisor were informed that if they did not adjust the

[38] The participants' median experimental duration was approximately 16 minutes (965 seconds) and their median compensation was 1.32€. This level of compensation for online experiments is in line with previous literature (e.g., Hunt & Scheetz, 2019).

[39] Simple exponential smoothing is a forecasting method that weights the actual realized value (A_{t-1}) and the original forecast (F_{t-1}) to calculate the forecast for the upcoming period (F_t). The smoothing parameter α is the weight of A_{t-1} (Ostertagová & Ostertag, 2012). It is calculated as follows: Equation 6: $F_t = \alpha A_{t-1} + (1-\alpha)F_{t-1}$.

recommended forecast, they would not have to write a justification independent of their forecast deviation (see Appendix B.5). This manipulation of the advisors' blame potential is similar to the experimental manipulation of different blame-shifting situations by Keil et al. (2007).

My goal was to create a trade-off scenario for the participants by providing a bad forecast that should be adjusted to reduce forecast errors. But my goal was also to provide an incentive not to adjust the bad forecast by allowing the participants to blame the advisor. Simple exponential smoothing is a suitable forecasting method for time series data without any trend (Ostertagová & Ostertag, 2012). Hence, I intentionally used this unsuitable forecasting method in a time series with a trend. I also manipulated the smoothing factor in such a way that there was a large deviation within each period due to an offset whipsaw pattern (see Appendix B.3).

After the participants had made their final forecast based on the historical data, they answered additional questions (on 7-point Likert scales) in the post-experimental questionnaire. I asked for their perceived responsibility, perceived forecast quality, and perceived advice satisfaction. Additionally, I asked for the participants' attitudes towards socially interacting with the advisor, which I used as a proxy for the advisors' social competence (see Appendix B.6). Finally, the participants were informed about the realized sales volume, their forecast deviation, if they had to write a justification, and their individual compensation (see Appendix B.7).

6.3.3 Experimental participants

The experiment was conducted online with a sample of managers that was provided by the research agency "Respondi". I received data from 225 participants, all of whom were managers from German-speaking countries. To ensure that the participants read the experimental instructions carefully, I included a series of test questions. As a consequence, the number of participants was reduced to 143 through comprehension screening (see Appendix B.2 and Appendix B.5).[40]

Of the remaining 143 participants, 95 were male. The average age was 47.72 (SD = 10.22 years). Fifteen (10%), 41 (29%), 48 (34%), and 39 (27%) participants reported working experience of less than 10 years, between 10 and 20 years, between 20 and 30 years, and more than 30 years, respectively. Furthermore, 80 (56%), 37 (26%), and 26 (18%) participants supervised fewer than 10 employees, between 10 and 30 employees, and more than 30 employees, respectively. The participants worked in different industry sectors (1% telecommunication, 6% consumer goods, 9% finance, 6% healthcare, 10% industrial, 6% craft industry, 2% real estate, 6% technology, 2% utilities, 13% public sector, 6% transportation, 4% travel & leisure, and 29% other).

6.3.4 Dependent variable

My study focuses on opportunistic reasons for adjusting the recommendations of advisors. The main dependent variable used to measure the managers' adjustments is *MAPA* – the *mean absolute percentage adjustment* (Fildes et al., 2009; Goodwin et al., 2007) – and is calculated as follows (see chapter 2.2.2.1 and Equation 3):

Equation 3: $$MAPA = mean(\left|\frac{Own\ Forecast - Recommended\ Forecast}{Recommended\ Forecast}\right| * 100)$$

6.3.5 Independent variables

NatureAdvisor. *NatureAdvisor* describes the different types of advisors examined, namely, a human marketing expert (dummy coded as 0) and an algorithmic decision aid in the form of a "weak AI" (dummy coded as 1) (see Appendix B.1).

BlamePotentialAdvisor. Each advisor who recommends a sales forecast is either

[40] There were two independent sets of comprehension questions. The comprehension questions were used to verify the participants' understanding of the forecasting situation across all the experimental groups. The participants were excluded from the analyses if they answered a test question incorrectly. Because I relied on an online experiment, which does not allow for participant monitoring, I had to use this strict rule to ensure that only the participants who understood the task were included in the analyses.

unblamable (dummy coded as 0) or blamable (dummy coded as 1) in the case of failure. Blamable advisors can be held responsible for forecast errors when their forecast recommendations are not adjusted (see Appendix B.5).

OwnResponsibility. *OwnResponsibility* measures the manager's subjective responsibility for the final forecast on a 7-point Likert scale (1 = no own responsibility, 7 = complete own responsibility) (see Appendix B.6).

AdvisorCompetence. *AdvisorCompetence* measures the manager's perception of advisor's general forecasting competence on a 7-point Likert scale (1 = not competent, 7 = very competent) using the performance expectancy instrument of the unified theory of acceptance and use of technology (UTAUT) model developed by Venkatesh, Morris, Davis, & David (2003) (Cronbach's alpha is 0.90) (see Appendix B.3).

ExpectedForecastQuality. *ExpectedForecastQuality* measures the manager's expected forecast accuracy of the final forecast after a possible adjustment on a 7-point Likert scale (1 = very bad forecast, 7 = very good forecast) (see Appendix B.6).

AdvisorSocialCompetence. *AdvisorSocialCompetence* measures the manager's perception of advisor's social competence by evaluating the manager's aversion to socially interact with the advisor. Specifically, I assess advisor's social competence by relying on the "negative attitude scale toward situations of interaction with robots" subscale of the "negative attitude toward robots" questionnaire developed by Nomura, Suzuki, Kanda, & Kato (2006).[41] *AdvisorSocialCompetence* is measured on a 7-point Likert scale (1 = low social competence, 7 = high social competence) (Cronbach's alpha is 0.87) (see Appendix B.6).

NegativeAttiudeAdvisor. *NegativeAttiudeAdvisor* measures the manager's overall

[41] The scale by Nomura et al. (2006) was developed to assess individual preferences regarding social interactions between humans and algorithmic decision aids (e.g., blaming advisors and justifying decisions). Specifically, I use the reverse-coded items 1, 3, 5, and 6 of the subscale "negative attitude scale toward situations of interaction with robots" to measure *AdvisorSocialCompetence* (see Appendix B.6).

aversion against the advisor based on the "negative attitude scale toward situations of interaction with robots" subscale of the "negative attitude toward robots" questionnaire.[42] It is also measured on a 7-point Likert scale (1 = low aversion, 7 = high aversion) (Cronbach's alpha is 0.62) (see Appendix B.6).

6.3.6 Control variables

AdviceSatisfaction. *AdviceSatisfaction* measures the manager's subjective feeling of whether he or she was well-advised on a 7-point Likert scale (1 = badly advised, 7 = well-advised) (see Appendix B.6).

Trust. *Trust* measures the manager's trust in the advisor on a 7-point Likert scale (1 = low trust, 7 = high trust) (see Appendix B.3).

Additional control variables. Additional control variables are *Sex* (0 = male, 1 = female, and 2 = other), *Age* (measured in years), and *WorkingExperience* (1 = 0-5 years, 2 = 6-10 years, 3 = 11-15 years, 4 = 16-20 years, 5 = 21-25 years, 6 = 26-30 years, 7 = 31-35 years, and 8 = more than 36 years).[43]

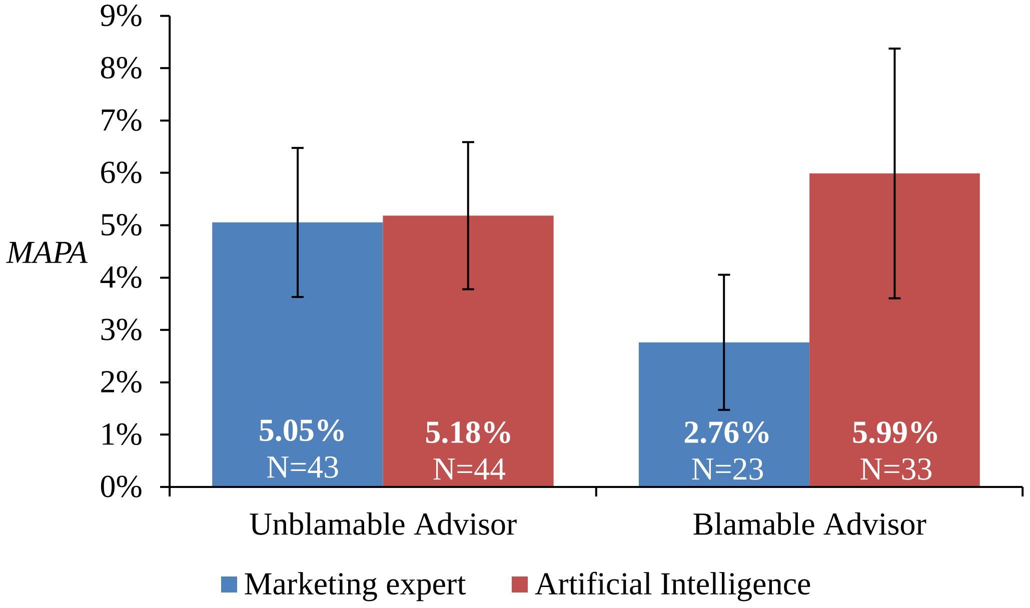
6.4 Results Study 2

In this study, I examine managerial blame avoiding behavior in a forecasting setting. Specifically, I propose that managers make smaller adjustments of forecasts recommended by blamable advisors to avoid personal blame and transfer responsibility than they do of those recommended by unblamable advisors (H.1). Moreover, I argue that this effect is stronger with blamable human advisors than blamable algorithmic decision aids in the form of "weak AI" (H.2). Third, I propose that managers' algorithm aversion when choosing scapegoats is reduced when they perceive that advisors have high levels of social competence (H.3). Figure 9 shows the *MAPA* of the recommended forecast

[42] Specifically, I use items 2 and 4 of the subscale "negative attitude scale toward situations of interaction with robots" to measure *NegativeAttitudeAdvisor* (see Appendix B.6).
[43] All nondichotomous independent and control variables are centered on their mean values (Aiken & West, 1991).

across the experimental conditions.

Figure 9: *Mean absolute percentage adjustment* (*MAPA*) of forecast recommendations in Study 2



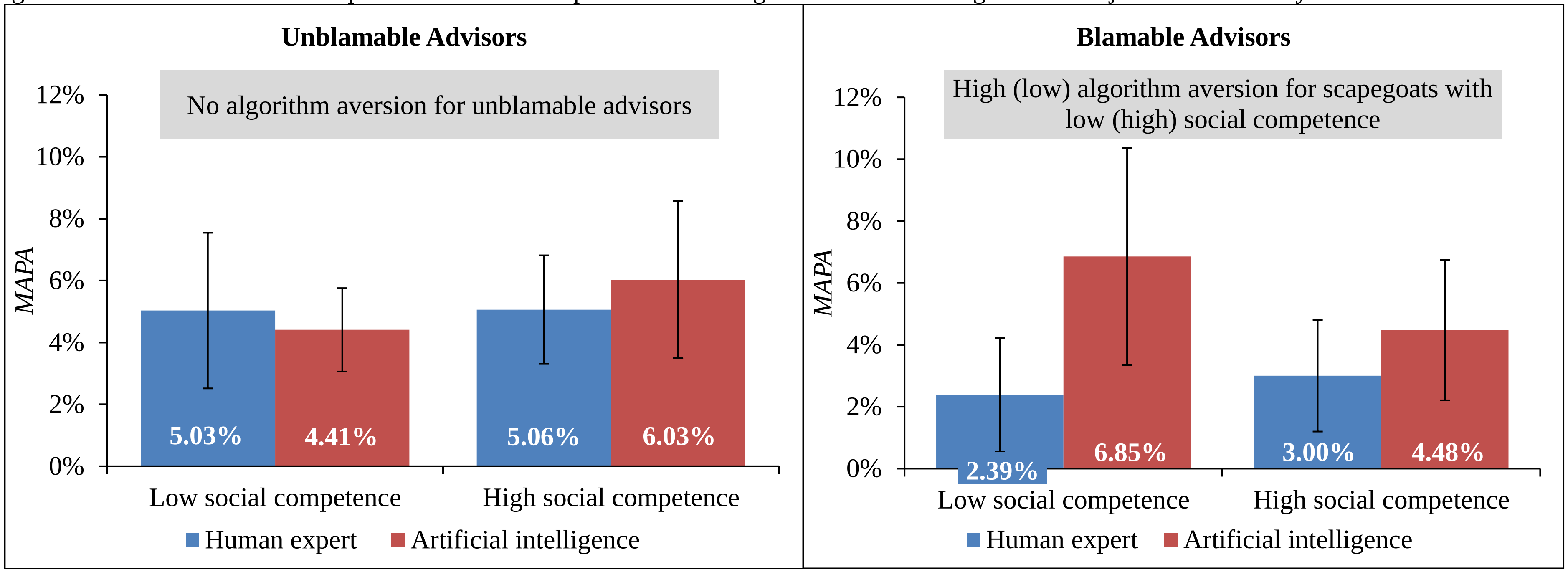
Notes: This figure shows the *mean average percentage adjustment* (*MAPA*) of the preliminary recommended forecast with 95% confidence intervals across all experimental conditions.

Sources: Author's interpretation.

The *MAPA* of the recommended forecast is 5.05% (2.76%) with an unblamable (blamable) marketing expert and 5.18% (5.99%) with an unblamable (blamable) AI. This suggests that managers try to avoid personal blame by reducing adjustments of forecasts recommended by blamable human advisors. Figure 10 illustrates the *MAPA* of the forecasts for perceived low (high) socially competent (non)human advisors separately for unblamable and blamable advisors.

Managers exhibit a high level of algorithm aversion for blamable advisors with low social competence (2.39% vs. 6.85%) but reduce this aversion for blamable advisors with high social competence (3.00% vs. 4.48%). Table 13 shows the descriptive statistics – mean and standard deviation – and the pairwise correlations of the independent and control variables. Next, I conduct a multiple linear regression to test my hypotheses; $F(19, 123) = 3.77$, $p < 0.001$, $R^2 = 0.279$ (see Table 14).

Figure 10: Influence of advisors' perceived social competence on managerial blame avoiding forecast adjustments in Study 2



Notes: This figure shows the *mean average percentage adjustment* (*MAPA*) of the preliminary recommended forecast with 95% confidence intervals depending on the advisors' nature and the perceived advisors' social competence (median-split) for unblamable and blamable advisors. Specifically, this figure illustrates the effect of the three-way interaction of *NatureAdvisor*, *BlamePotentialAdvisor*, and *AdvisorSocialCompetence*. Managers exhibit no algorithm aversion for unblamable advisors (N = 13 (30) for human expert with low (high) social competence and N = 23 (21) for AI with low (high) social competence). However, managers show high algorithm aversion for blamable advisors with low perceived social competence (N = 9 for human expert and N = 21 for AI) and low algorithm aversion for blamable advisors with high perceived social competence (N = 14 for human expert and N = 12 for AI).

Sources: Author's interpretation.

Table 13: Descriptive statistics and pairwise correlation matrix in Study 2

Variable	M	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. NatureAdvisor	0.54	0.50	1.00											
2. BlamePotentialAdvisor	0.39	0.49	0.08	1.00										
3. OwnResponsibility	0.00	1.80	0.01	-0.33 ***	1.00									
4. AdvisorCompetence	0.00	1.26	0.11	-0.05	-0.10	1.00								
5. ExpectedForecastQuality	0.00	1.06	-0.01	0.01	0.06	0.28 ***	1.00							
6. AdvisorSocialCompetence	0.00	1.42	-0.28 ***	-0.13	0.10	0.26 ***	0.13	1.00						
7. NegativeAttitudeAdvisor	0.00	1.50	0.05	0.08	0.08	-0.38 ***	-0.17 **	-0.73 ***	1.00					
8. AdviceSatisfaction	0.00	1.21	-0.03	-0.01	-0.03	0.63 ***	0.41 ***	0.29 ***	-0.38 ***	1.00				
9. Trust	0.00	1.50	-0.08	-0.05	-0.16*	0.69 ***	0.21 **	0.24 ***	-0.32 ***	0.54 ***	1.00			
10. Sex	0.34	0.49	-0.04	-0.12	-0.05	-0.08	-0.25 ***	-0.03	0.02	-0.08	-0.02	1.00		
11. Age	0.00	10.22	0.07	-0.05	0.19	-0.06	-0.01	-0.09	0.18 **	-0.00	-0.09	-0.23 ***	1.00	
12. WorkingExperience	0.00	1.93	0.08	0.02	0.11	-0.04	-0.02	-0.07	0.13	-0.06	-0.14*	-0.27 ***	0.86 ***	1.00

Notes: This table shows the mean (M), standard deviation (SD), and pairwise correlation for each independent variable and control variable for the 143 participants across all experimental groups. For more information on all the variables, see chapters 6.3.5 and 6.3.6. P values are reported in the following way: * $p < 0.10$ (two-tailed tests), ** $p < 0.05$, and *** $p < 0.01$.

Sources: Author’s interpretation.

Table 14: Results multiple linear regression – Scapegoat selection depending on advisors' blame potential, nature, and social competence in Study 2

Dependent Variable = *MAPA*	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
NatureAdvisor		-0.18(0.848)	-0.32(0.721)	-0.27(0.760)	-0.15(0.872)	-0.26(0.799)	-0.34(0.733)
BlamePotentialAdvisor		-2.90***(0.008)	-1.58(0.107)	-1.64*(0.096)	-1.66*(0.098)	-1.34(0.185)	-1.96*(0.050)
*NatureAdvisor * BlamePotentialAdvisor*		4.12*(0.059)	3.82*(0.068)	3.89*(0.076)	3.97*(0.075)	3.91*(0.098)	4.28*(0.068)
OwnResponsibility			0.86***(0.000)	0.81***(0.000)	0.79***(0.000)	0.80***(0.000)	0.81***(0.000)
AdvisorCompetence			0.50(0.215)	0.51(0.201)	0.48(0.251)	0.67(0.125)	0.59(0.162)
*OwnResponsibility * NatureAdvisor*				-0.01(0.979)	-0.01(0.967)	0.10(0.784)	-0.01(0.979)
*OwnResponsibility * AdvisorCompetence*				0.20*(0.079)	0.20*(0.081)	0.15(0.216)	0.22*(0.098)
ExpectedForecastQuality			0.75**(0.021)	0.81**(0.015)	0.82**(0.018)	0.74**(0.022)	0.78**(0.017)
AdvisorSocialCompetence					0.19(0.687)	0.66(0.326)	0.22(0.747)
*AdvisorSocialCompetence * NatureAdvisor*						-0.08(0.880)	0.69(0.356)
*AdvisorSocialCompetence * BlamePotentialAdvisor*						-1.01*(0.075)	0.39(0.589)
*AdvisorSocialCompetence * NatureAdvisor * BlamePotentialAdvisor*							-2.01*(0.071)
*AdvisorSocialCompetence * AdviceSatisfaction*						-0.65***(0.008)	-0.70***(0.006)
NegativeAttitudeAdvisor					0.05(0.929)	0.28(0.614)	0.37(0.515)
AdviceSatisfaction	-0.85**(0.040)	-0.96**(0.026)	-1.49***(0.004)	-1.47***(0.005)	-1.50***(0.006)	-1.41***(0.005)	-1.36***(0.006)
Trust	0.43(0.295)	0.65(0.169)	0.66(0.176)	0.60(0.211)	0.61(0.218)	0.71(0.147)	0.80*(0.099)
Sex	-1.63*(0.063)	-1.66*(0.071)	-1.01(0.270)	-1.09(0.246)	-1.09(0.246)	-1.30(0.140)	-1.32(0.128)
Age	0.03(0.639)	0.06(0.438)	0.03(0.636)	0.04(0.523)	0.05(0.477)	0.03(0.588)	0.02(0.682)
WorkingExperience	-0.29(0.449)	-0.46(0.274)	-0.38(0.335)	-0.43(0.271)	-0.44(0.256)	-0.50(0.196)	-0.46(0.224)
Constant	5.50***(0.000)	5.79***(0.000)	5.19***(0.000)	5.25***(0.000)	5.18***(0.000)	5.40***(0.000)	5.62***(0.000)
Observations	143	143	143	143	143	143	143
R-squared	0.047	0.100	0.203	0.211	0.213	0.267	0.279

This table shows the results of a multiple linear regression. The dependent variable is the mean absolute percentage adjustment (*MAPA*) of the recommended forecast (see chapter 6.3.4). The other variables used in the regression are explained in the chapters 6.3.5 and 6.3.6. Regression coefficients are reported in conjunction with p values in parentheses at the individual level; * $p < 0.10$ (two-tailed tests), ** $p < 0.05$, and *** $p < 0.01$.

Sources: Author's interpretation.

Model 1 consists of the control variables.[44] The higher the participants' *AdviceSatisfaction*, the less they adjust the recommended forecast (*MAPA*) ($p = 0.040$).

Model 2 adds the main variables *NatureAdvisor* and *BlamePotentialAdvisor* as well as the corresponding interaction. I find a negative effect of *BlamePotentialAdvisor* on *MAPA* ($p = 0.008$). This means that the participants make smaller adjustments when advice is given by a blamable advisor. This supports H.1. Moreover, the positive effect of the interaction between *NatureAdvisor* and *BlamePotentialAdvisor* on *MAPA* ($p = 0.059$) suggests that blame avoiding behavior is more prevalent when advice is provided by a blamable human advisor than when it is provided by a blamable algorithmic decision aid. This supports H.2.

In the theory section, I argue that managers try to avoid assuming responsibility for forecast errors and blame their advisors for these forecast errors instead. Therefore, to provide additional insights into managerial blame avoiding behavior, I include the variables *OwnResponsibility*, *AdvisorCompetence*, and *ExpectedForecastQuality* in Model 3. I find a positive effect of *OwnResponsibility* ($p < 0.001$) and *ExpectedForecastQuality* on *MAPA* ($p = 0.021$). The managers' perceived responsibility decreases for final forecasts with smaller adjustments, but they also believe that the accuracy of their final forecasts increases when they make larger adjustments.

To better understand the role of responsibility attribution in scapegoat selection, I add two interactions between *OwnResponsibility* and *NatureAdvisor* as well as *OwnResponsibility* and *AdvisorCompetence* to Model 4. The latter interaction positively affects *MAPA* ($p = 0.079$). The managers are better able to blame and transfer responsibility to more competent advisors, whereas advisors' nature does not influence responsibility attribution ($p = 0.979$). Apparently, managers do not attribute

[44] Female managers make smaller forecast adjustments than male managers ($p = 0.063$). However, the gender variable does not materially change my results.

responsibility differently to human advisors and algorithmic decision aids.

Model 5 adds a (new) social dimension to determine why managers exhibit algorithm aversion in regard to blamable advisors. This dimension introduces two variables: managers' overall attitudes towards their advisors and advisors' perceived social competence. I find no influence of the managers' attitudes towards their advisors ($p = 0.929$) or the advisors' social competence ($p = 0.687$) on *MAPA*.

Model 6 implements three additional interactions between *AdvisorSocialCompetence* and *NatureAdvisor*, *BlamePotentialAdvisor*, and *Advice-Satisfaction*. I find that the greater advisors' perceived social competence is, the greater the influence of *AdviceSatisfaction* ($p = 0.008$). It is plausible that managers feel that they are well-advised by socially competent advisors and make smaller adjustments. Moreover, the influence of advisors' social competence does not depend on advisors' nature ($p = 0.880$) but instead affects the use of blamable advice. Managers make smaller adjustments of forecasts recommended by blamable advisors that are more socially competent ($p = 0.075$). Additionally, *BlamePotentialAdvisor* ($p = 0.185$) and the interaction between *OwnResponsibility* and *AdvisorCompetence* are no longer significant ($p = 0.216$). Apparently, managers only want to use blamable advisors as scapegoats when they perceive that advisors have a high level of social competence. Specifically, managers perceive that human advisors have higher levels of social competence than AI advisors ($t(141) = 3.44$, $p < 0.001$). Social competence seems to be an important factor for explaining managers' algorithm aversion in regard to scapegoat selection.

Therefore, Model 7 introduces a three-way interaction between *NatureAdvisor*, *BlamePotentialAdvisor*, and *AdvisorSocialCompetence*. This three-way interaction negatively affects *MAPA* ($p = 0.071$). Moreover, after the integration of this three-way interaction, the main effect of *BlamePotentialAdvisor* is significant again ($p = 0.050$), whereas the interaction between *BlamePotentialAdvisor* and *AdvisorSocialCompetence* is nonsignificant ($p = 0.589$). Managers try to use blamable advisors as scapegoats but do not generally increase their use of scapegoats with an increase in advisors' social competence. Instead, managers reduce their algorithm aversion with an increase in the perceived social competence of blamable algorithmic decision aids.[45] This supports H.3.

Overall, managers make smaller adjustments of forecasts recommended by blamable advisors than of those recommended by unblamable advisors and exhibit algorithm aversion by preferring blamable human advisors to blamable algorithmic decision aids. This supports H.1 and H.2. Moreover, managers reduce their algorithm aversion in regard to scapegoat selection as advisors' perceived social competence increases. This confirms H.3.

6.5 Discussion and conclusion Study 2

6.5.1 Discussion of the results of forecast adjustments

I find managerial blame avoiding behavior and a negative effect of advisors' blame potential on the magnitude of advice adjustments made by managers. This indicates that managers try to reduce their own responsibility when they have the chance to do so. When managers are advised by a blamable advisor, then their adjustment decreases because they want to blame the advisor as a scapegoat in the case of a major forecast error. The more managers want to reduce their own responsibility for the forecast, the less they adjust the preliminary forecast recommendation. The more competent the managers perceive the advisor to be, the stronger this effect is. This is also plausible because it should be easier to avoid responsibility by following an expert's advice than by following a novice's recommendation. Moreover, I find that managers do not differ in terms of their responsibility attribution depending on the advisors' nature. This means

[45] After integrating the three-way interaction, I find that managers transfer more responsibility to experts than to novices ($p = 0.098$). Moreover, managers' trust in the advisor positively affects their forecast adjustments ($p = 0.099$).

that blame avoiding managers prefer to delegate forecasting decisions with high blame risk to competent blamable advisors.

I find that managers try to avoid blame by making no adjustments when they believe that a preliminary forecast carries a high level of risk for a major forecast error. In my experiment, the participants believed to make better forecasting decisions, the larger the adjustment of the preliminary forecast was. Indeed, managers seem to consider their personal blame avoidance to be more important than making a good forecast. Concentrating on avoiding responsibility and blame - irrespective of the perceived quality of advisors' forecast recommendations - can have major negative consequences for companies.

Additionally, I find no general algorithm aversion for unblamable advisors; rather, I find this only in regard to scapegoat selection. In line with prior blame avoidance literature (e.g., Bonaccio & Dalal, 2006; Steffel et al., 2016), I argue that the reason for this is that managers expect their superiors to attribute more responsibility to blamable human advisors than blamable AI advisors. Consequently, managers only use blamable advisors when they think they have a high chance of avoiding personal blame. It is plausible that managers can convince their superiors of the responsibility of a human scapegoat more easily than they can convince them of the responsibility of a blamable algorithmic decision aid. Nonetheless, I find no difference in terms of managerial responsibility attribution based on advisors' nature; rather, I find only an overall effect of *OwnResponsibility*. This indicates that the managers completely aligned their scapegoat selection to their superiors' expected reactions in this justification setting by exhibiting algorithm aversion.

BAT describes the ideal scapegoat predominantly in relation to responsibility attribution (e.g., Steffel et al., 2016; Artinger et al., 2019). In contrast, I examine *AdvisorSocialCompetence* as an additional criterion that influences managers' algorithm aversion in regard to scapegoat selection. Specifically, I find that the three-way interaction of *NatureAdvisor*, *BlamePotentialAdvisor*, and *AdvisorSocialCompetence* has a negative effect on *MAPA*. It is interesting that when blamable advisors have a higher level of social competence, managers' algorithm aversion in regard to scapegoat selection decreases. I believe that the reason for this behavior is that managers try to choose optimal scapegoats whom they believe to have the greatest chances of convincing their superiors of their responsibility. Specifically, I think that managers consider blamable advisors' human-likeness in the form of a high level of social competence to be a central task-specific requirement for scapegoats.

In my experimental setting, the participating managers perceived that human advisors had a higher level of social competence than AI advisors. Therefore, I find that managers view a high level of social competence as a human-like criterion and perceive that blamable AI advisors with higher social competence have greater human-likeness. Managers believe they can more easily convince their superiors of the responsibility of perceived socially competent (i.e., human-like) nonhuman scapegoats, causing superiors to attribute responsibility to them similarly to the way that responsibility is attributed to human scapegoats. In contrast, managers dislike using blamable algorithmic decision aids with low social competence due to their expectation of decreased responsibility attribution by their superiors.

This argumentation is also supported by prior research on algorithm aversion. Lowens (2020) and Castelo et al. (2019) argue that decision makers exhibit algorithm aversion only when they perceive a specific task-mismatch. In my setting, this would correspond to the suitability of a scapegoat in the form of high social competence resembling advisor's human-likeness. Managers exhibit no algorithm aversion for unblamable advisors. However, when the possibility of blame avoidance in the form of blamable advisors exists, managers perceive human advisors to be more suitable scapegoats than algorithmic decision aids. Nonetheless, managers reduce their algorithm aversion for perceived socially competent (i.e., human-like) blamable algorithmic decision aids. This is speculative but would imply that managers prefer to use human scapegoats and blamable algorithmic decision aids with human-like attributes such as the ability to speak (e.g., those that verbally communicate forecast recommendations, such as virtual voice assistants) rather than blamable algorithmic decision aids with no human-like attributes (e.g., those that display forecast recommendations on a monitor).

6.5.2 Contribution, limitations, and future research

The contributions of my study are threefold. First, I contribute to BAT by demonstrating that managers not only use human scapegoats but also blame algorithmic decision aids to avoid personal blame as an IPOm Output-Dimension factor. Existing blame avoidance literature (Artinger et al., 2019; Steffel et al., 2016) proposes that advisor's potential responsibility attribution is the main relevant criterion for a scapegoat and implies that this is applicable to human scapegoats. In this study, I demonstrate that managers prefer to blame human advisors but also use algorithmic decision aids as scapegoats if necessary, especially when they are perceived to be socially competent (research questions 3 and 4) (see Table 1). Specifically, I identify advisors' nature and blame potential as important IPOm Individual-level factors influencing managerial advice-taking (see Figure 1 as well as chapters 2.2.2.3, 2.3.2, and 3.3).

Second, I expand research on algorithm aversion. In line with prior research (e.g., Burton et al., 2020; Lowens, 2020; Castelo et al., 2019), I identify a task-mismatch as the main reason for algorithm aversion. I demonstrate that managers do not exhibit general algorithm aversion in a forecasting setting. However, when choosing a potential scapegoat, managers exhibit algorithm aversion due to a perceived lack of social competence. Specifically, I propose that human-likeness in the form of high social competence is a central task-specific criterion for nonhuman scapegoats (i.e., IPOm

Individual-level factor) because managers can relatively easily convince their superiors of the responsibility of socially competent human-like algorithmic decision aids (see chapters 2.3.2 and 3.3).

Third, I contribute to advice-taking research specialized in forecasting settings by introducing managerial blame avoiding motives for adjustments of recommended forecasts as an IPOm Output-Dimension factor (e.g., Leitner & Leopold-Wildburger, 2011; Lawrence et al., 2006; Gönül et al., 2009). I demonstrate that managers make smaller adjustments of forecasts to avoid future blame potential, and I introduce this as a novel blame avoiding strategy. Moreover, I highlight the influence of the perceived social competence (i.e., human-likeness) of algorithmic decision aids on managerial adjustments of forecast recommendations (see chapter 2.2.2).

My study is also important for business practice because I explain how individual blame avoiding behavior impacts forecast adjustments, which may lead to negative firm outcomes (e.g., managers consciously making bad forecasts to pursue their own goals). Specifically, I demonstrate that managers prefer to use human scapegoats and blamable algorithmic decision aids with high perceived social competence. Companies should be aware of this when providing human advice or implementing algorithmic decision aids with human-like attributes.

However, I also acknowledge that my study, like all experiments, has some limitations in regard to external validity (see Aguinis & Bradley (2014)). In particular, the experimental operationalization of the manager's threat is very difficult to simulate in a fictitious setting. The threat of writing a justification of 200 characters is not comparable to a threat in real life (e.g., losing one's job). Additionally, in business practice managers usually do not know in advance whether their superiors consider their advisors to be blamable and have to make subjective assumptions. Moreover, simulating an AI advisor purely through a verbal description is challenging. Managers might react differently if a real AI interacts with them or maybe even had a real physical presence. These factors might influence managers' perceptions – especially those regarding human-likeness in the form of high social competence – and cause different results. Nonetheless, I believe that my results are transferable to business practice because human blame avoiding intentions should be even higher in real life than they are in a fictitious setting.

Future research should focus on studying the influence of social competence of blamable algorithmic decision aids (i.e., human-likeness) on their use as scapegoats and what sub-skills of social competence drive their perceived blame avoiding potential (e.g., the expressiveness of virtual voice assistants). Moreover, it would be interesting to study whether there are varying levels of technological sophistication of AI advisors (e.g., "weak AI" or "strong AI") that have higher levels of social competence and are perceived differently in regard to their blame potential. There might even be a tipping-point after which AI advisors are perceived to be better scapegoats than human advisors.

7 Conclusion of the thesis

Advice-taking is important and highly relevant for manager practitioners (Macdonald, 2006; Niewiem & Richter, 2006). This thesis provides a consolidated and structured literature review of important advice-taking studies along the IPOm framework (see chapter 2). Moreover, I review research on managerial blame avoidance literature and possible blame avoiding strategies. Specifically, I connect the blame avoiding strategy PTB with the advice-taking motive sharing responsibility (see chapter 3) and thereby identify four research questions (see Table 1 as well as chapters 2.1.2.3, 2.2.2.3, 2.3.2, and 3.3). In the empirical part of this thesis, I conducted two experimental studies which focus on analyzing potential IPOm Individual-level factors (i.e., managers' risk perceptions as well as advisors' blame potential, nature, and perceived social competence) influencing managerial blame avoiding behavior in regard to advice utilization (see chapters 5 and 6). In the following, I discuss my theoretical contributions, practical implications, and possible limitations. Additionally, I suggest ideas for future research.

7.1 Theoretical contributions

This thesis contributes to advice-taking literature and blame avoidance literature in three ways. First, general identified findings based on the review of corresponding literature are discussed. Specifically, I provide a holistic overview of research on blame avoiding behavior in advice-taking settings. Second, my theoretical contributions resulting from Study 1 and Study 2 are explained. Third, I summarize and integrate the overall theoretical implications of my empirical research results in the current literature on advice-taking with blame avoiding intentions.

Managerial advice-taking is a broad research field with many different influencing factors and possible fields of application. This causes prior advice-taking literature to often specialize on concrete advice-taking settings. I connect different specialized advice-taking literature streams focused on advice-taking in forecasting settings with algorithmic decision aids (e.g., Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011) and judges exhibiting algorithm aversion (e.g., Burton et al., 2020) to general advice-taking literature mostly analyzing psychological phenomena (e.g., Bonaccio & Dalal, 2006). Specifically, this thesis suggests how new technological advisors – algorithmic decision aids – can be integrated in general human advice-taking literature. Moreover, I show many similarities and the transferability of the IPOm framework to these specialized literature streams and especially algorithmic decision aids (see Figure 2).

Additionally, I identify a lack of research on the advice-taking motive sharing responsibility despite its general relevance across different advice-taking settings (see chapter 2) (e.g., Harvey & Fischer, 1997; Gönül et al., 2009). Specifically, I connect advice-taking literature and blame avoidance literature by showing the parallels of the advice-taking motive sharing responsibility and the blame avoiding strategy PTB (see chapter 3) (e.g., Hood, 2011; Mitchell, 2014; Weaver, 1986). Both literature streams propose the use of blamable advisors or delegees to avoid own responsibility. The consolidated literature on managerial advice-taking and blame avoidance provides a holistic view and is a good starting point for scholars interested in identifying potential interdependencies between specialized advice-taking settings and managerial blame avoiding behavior in combination with the advice-taking motive sharing responsibility. Following, I stress the empirical relevance of the blame avoiding strategy PTB for managers and explain the results of my two studies directly analyzing this behavior.

Study 1 analyzes whether managers use blamable advisors for the blame avoiding strategy PTB (see research question 1) and how their individual risk perceptions influence their blame avoiding behavior (see research question 2). Results of Study 1 demonstrate that managers generally want to shift blame to blamable advisors but individual risk perceptions are a main driver for the adoption of the blame avoiding strategy PTB. In line with CPT, monetary decision framing influences managers' risk perceptions and affects their blame avoiding behavior. Risk-averse managers – due to a gain framed decision context (i.e. choosing between gains) – focus on avoiding blame by utilizing blamable advisors for PTB, whereas risk-seeking managers – due to a loss framed decision context (i.e., choosing between losses) – focus on increasing their financial results and individual compensation by ignoring personal threats. These results theoretically contribute to advice-taking literature and blame avoidance literature by showing the relevance of the advice-taking motive sharing responsibility as an IPOm Output-Dimension factor in a management context. Moreover, I analyze and explain the influence of advisors' blame potential and managers' individual risk perceptions as IPOm Individual-level factors on managerial blame avoiding behavior. Additionally, these results contribute to literature on decision-making under risk by showing the relevance of nonfinancial risk – the threat of personal blame – in addition to traditional monetary problem framing (see chapter 5) (e.g., Kahnemann & Tversky, 1979; Tversky & Kahneman, 1992; Fennema & Wakker, 1997; Sitkin & Weingart, 1995).

Study 2 examines whether managers use blamable algorithmic decision aids for the blame avoiding strategy PTB (see research question 3) and whether they exhibit algorithm aversion (see research question 4). I demonstrate that managers also use algorithmic decision aids as scapegoats but exhibit algorithm aversion and prefer to use human scapegoats due to their perceptions of a lack of human-likeness in the form of lower social competence. Expanding prior research on algorithm aversion in other settings (e.g., Lowens, 2020; Castelo et al., 2019), I explain that managers consider a high level of social competence (i.e., human-likeness) as a task-specific requirement for scapegoats. Specifically, I demonstrate that managers reduce their algorithm aversion in regard to scapegoat selection when perceiving a higher level of human-likeness in the form of higher social competence of blamable algorithmic decision aids. This study contributes to advice-taking literature and blame avoidance literature by studying the relevance of sharing responsibility and PTB with nonhuman advisors (i.e., algorithmic decision aids) as an IPOm Output-Dimension factor. I identify advisors' blame potential, nature, and perceived social competence as IPOm Individual-level factors influencing managerial blame avoiding behavior (see chapter 6).

Overall, this doctoral thesis provides a theoretical perspective for understanding managerial advice-taking by studying blame avoiding decision-making. My empirical findings (see Study 1 and Study 2) stress the relevance of managerial blame avoidance, analyze potential influencing factors, and fit into existing theoretical advice-taking models. Specifically, the IPOm used to structure advice-taking research is a suitable framework to cluster my main findings (see Figure 1).

Building on the IPOm framework, managerial advice-taking is influenced by IPOm Input-Dimension and IPOm Process-Dimension factors when managers focus on sharing responsibility and avoiding blame as an IPOm Output-Dimension factor (e.g., Hogan, 2014; Bonaccio & Dalal, 2006).

This thesis analyzes the IPOm Input-Dimension in the form of possible IPOm Individual-level factors (i.e., manager's and advisor's characteristics) influencing managerial advice-taking with a blame avoiding intention. Specifically, I demonstrate that individual manager's risk perception, advisor's blame potential, nature, and perceived social competence affect advice utilization focused on sharing responsibility.

Interestingly, all identified IPOm Individual-level factors – except advisor's nature – are based on individual perceptions. Depending on whether managers perceive high risk, consider their advisors to be socially competent, and expect their superiors to view their advisors to be blamable, this has an impact on managerial advice utilization and possible blame avoiding intentions.[46] Consequently, two managers can behave differently in the exact same situation. One manager may perceive IPOm Individual-level factors promoting blame avoiding behavior (e.g. high risk perceptions), whereas another manager may not (e.g. low risk perceptions).

Nonetheless, the identified IPOm Individual-level factors help us to understand what criteria managers are evaluating when considering blame avoiding decision-making. This evaluation of blame avoiding criteria is triggered by an evolutionary ingrained cognitive and intuitive human process which should guarantee personal survival by avoiding social ostracism (Chudek & Henrich, 2011; Cushman, 2013). Once this intuitive blame avoiding reflex is triggered, managers intuitively use blame avoiding decision-making strategies like PTB to transfer own responsibility and blame risk (i.e., representing social risk of ostracism) to advisors.

Finally, by studying relevant blame avoiding criteria (i.e. IPOm Individual-level factors promoting blame avoidance), we can better understand why in some circumstances this protective cognitive process is more likely to be triggered than in other situations. Moreover, sharing responsibility and blame avoidance are a central part of individual decision-making and need to be equally considered in addition to other decision-making motives like increasing decision accuracy. This is pivotal when studying individual decision-making as I find that under certain circumstances managers consider their personal blame avoidance to be more important than overall decision accuracy (see chapter 6.5.1).[47] The next chapter discusses the practical implications of my results.

[46] In both studies the experimental manipulation of advisor's blame potential was explicit and not subjective (i.e., managers were informed that their superiors considered the advisor to be blamable). However, in reality this should rarely be the case. Consequently, in practice managers have to rely on their subjective expectations of advisor's blame potential (see chapter 7.3).

[47] In Study 2 participants consciously accepted a lower expected forecast accuracy to avoid personal blame (i.e. *ExpectedForecastQuality*).

7.2 Practical implications

This thesis demonstrates that managers do not always focus on increasing decision accuracy but sometimes utilize blamable advisors to avoid personal threats. The more managers perceive that personal blame is threatened, the more they try to protect themselves which can lead to worse economic decisions causing financial harm to their companies. This helps to understand why managers tend to hire advisors as scapegoats for high-risk decisions. Consequently, costly advisors with high expertise are not necessarily used to increase decision accuracy but only paid to assume responsibility. Therefore, companies should try to reduce perceived personal threats, so that managers can concentrate on increasing decision accuracy and do not have to worry about sharing responsibility in the form of using the blame avoiding strategy PTB. Organizations should be aware of managers' potential opportunistic motives in hiring expensive blamable advisors.

Moreover, managers exhibit algorithm aversion and prefer to use blamable human advisors as scapegoats because they believe it is easier to convince others of a human scapegoat than a nonhuman scapegoat. However, and in contrast to common prior assumptions, this thesis demonstrates that managers do not exclusively blame human advisors as scapegoats. Specifically, I demonstrate that managers increasingly blame algorithmic decision aids with a perceived higher level of social competence (i.e., higher level of human-likeness) to reduce own responsibility for bad decision outcomes. Consequently, organizations need to be aware of the existence of nonhuman scapegoats and possible criteria for managerial (non)human scapegoat selection (e.g., human-likeness in the form of social competence). This is important to know for organizations introducing and implementing human-like algorithmic decision aids supporting managerial decision-making.

7.3 Limitations and concluding remarks

Like all experiments, my empirical research has some limitations (see chapters 4.1, 5.5.3, and 6.5.2). As discussed in the previous chapters, Study 1 and Study 2 have high internal validity at the cost of lower external validity. I identify causal factors influencing managerial blame avoiding behavior by randomizing participants across different experimental groups and manipulating different variables of interest while eliminating potential noise. However, due to the need to use a drastically simplified fictitious setting for an online experiment, external validity decreases and I do not know if managers would act identically in real-world settings (Aguinis & Bradley, 2014; James et al., 2017a; Shadish et al., 2002; Tanner, 2002; Tepe & Prokop, 2017). Nonetheless, I tried to stay as closely as possible to typical managerial tasks (e.g., making investment decisions and sales forecasts). Busenbark et al. (2017) argue that investment decisions are a main task for managers, whereas Salehzadeh et al. (2020) stress the importance of managerial forecasts. For both tasks, managers are usually supported by human advisors (e.g., Bonaccio & Dalal, 2006) or algorithmic decision aids (e.g., Lawrence et al., 2006). Moreover, and as recommended by Aguinis & Bradley (2014), I specifically use context-rich vignette experiments to increase external validity. Additionally, I explicitly use real-world managers as experimental participants because Kirchler et al. (2018) find different economic decision-making behavior between students and managers.

Nonetheless, a general problem of experimental research in blame avoidance literature is the fact that it is very difficult, if not impossible, to simulate a real personal threatening situation (e.g., Bartling & Fischbacher, 2012; Keil et al., 2007; Lindermüller et al., 2021). Despite the fact that personal evaluation talks with superiors and providing personal justifications for past decisions are common in business practice, managers may behave differently in real life when their job or career is on the line than when they are threatened to write a fictitious justification of 200 characters in an experiment. Moreover, in business practice managers usually do not explicitly know their advisors' blame potential. Consequently, managers have to make subjective assumptions about their advisors' blame potential and anticipate their superiors' reactions in regard to responsibility attribution to the blamed advisors.

Despite these limitations, I am confident that my results hold and can be transferred to managers because the experimental tasks are very close to everyday managerial tasks and managerial blame avoiding behavior should be even stronger in reality.

Additionally, my findings provide suggestions for future research endeavors concerning IPOm Individual-level factors on managerial blame avoiding behavior with advisors. In addition to individual risk perceptions, managers' other individual characteristics may also influence their blame avoiding behavior (e.g., perceived threat of personal blame, management leadership style, power within the organization, mood, or personality traits). Moreover, the blamable advisors' characteristics should probably also influence managerial blame avoiding decision-making. There may be other relevant characteristics of an ideal scapegoat apart from being able to assume responsibility and having human-like attributes like a perceived high level of social competence (e.g., the inability to retribute after being unwillingly utilized as a scapegoat). Moreover, it would be interesting to study what sub-skills of social competence drive the perceived scapegoating competence of blamable algorithmic decision aids. This is especially relevant with increasing managerial adoption of algorithmic decision aids. Future algorithmic decision aids may one day resemble a "strong AI" which would be comparable to general human intelligence and may have a perceived higher level of social competence than nowadays (non)human advisors. Then, highly sophisticated future algorithmic decision aids might be even better scapegoats than human experts (see chapters 5.5.3 and 6.5.2).

Blame avoiding decision-making is an important factor influencing managerial advice-taking. Nonetheless, current literature on managerial advice-taking not focused on increasing decision accuracy but on sharing responsibility is scarce. This thesis contributes to our theoretical and practical understanding of managerial advice-taking with a blame avoiding intention. Specifically, I call for more research on the managerial blame avoiding strategy PTB which should gain even more future relevance with increasing adoption and implementation of more sophisticated and human-like algorithmic decision aids as nonhuman advisors.

8 References

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Appendix A Experimental instrument Study 1[48]

A.1 Case description and manipulation of the economic situation

Initial situation[49]

Now please imagine that you are the divisional business unit manager of a large, established industrial company. You manage two business units in this company, each business unit produces and sells its own products. As a divisional business unit manager, you have the task of maximizing the profits of your two business units and thus the company value.

You have been a divisional business unit manager for many years and so far have successfully guided two divisions through good and bad economic phases. Your two divisions are currently in ***a severe economic crisis (an economically prosperous situation)****. Very* ***poor (good)*** *future sales opportunities and increasing* ***losses (profits)*** *are expected. Due to the* ***poor (good)*** *economic development,* ***job layoffs (the creation of new jobs) are (is)*** *planned.*[50]

Presentation of possible investment plans

To successfully cope with this difficult economic situation (In order for your business units to continue to be successful in the future)*, you have to make the right investment decisions. Your employees have drawn up two different investment plans in order to optimally use the limited financial resources available to the company.*

[48] Following, the used experimental instrument is presented. Text in italics is part of the experimental instrument and was identically shown to the participants. The experiment was conducted in German. Therefore, all following descriptions have been translated.

[49] Before reading the experimental description, participants answered demographic questions concerning sex, age, working experience, number of supervising employees, own budget responsibility, and industry sector. Due to the specific target group (i.e., managers), participants who did not supervise employees or had no own budget responsibility were screened out.

[50] Words in bold are the manipulation of the economic situation causing distorted risk perceptions. Manipulations in bold frame a bad (good) economic situation.

- *The investment plan "Stable Solutions" is aimed at increasing sales of already established products in both business units.*
- *The investment plan "New Technology" exclusively focuses on the introduction of what is probably a very profitable new product. However, the success of the new product is uncertain.*

You have a limited investment budget which you can distribute to the two investment plans in increments of 5%. A simultaneous partial implementation of both investment plans is therefore possible. In order to be able to make the investment decision, two possible future scenarios (future states) are considered. Both states (state 1 and state 2) are equally likely and each occur with a probability of 50%. Depending on the state, the two investment plans have different outcomes.

Due to the ***severe crisis (good economic situation)*** *in which both business units are, predominantly* ***negative (positive)*** *investment results can be expected in any condition. The complete distribution of the investment budget is* ***still mandatory (imperative)*** *in order to be able to assert oneself in the current competition.*

The possible investment results of the two investment plans, each with a 10% share of the investment budget, are shown below:

Investment result for each investment plan	*Investment result in state 1*	*Investment result in state 2*
Investment plan „Stable Solutions“ each 10% share of the investment budget	***-1,250,000€ (1,250,000€)***	***-1,250,000€ (1,250,000€)***
Investment plan „New Technology“ each 10% share of the investment budget	***-2,375,000€ (125,000€)***	***0€ (2,500,000€)***

Remuneration

In your role as divisional business unit manager, you receive a basic performance-unrelated remuneration of ***250,000€ (125,000€)*** *and additionally 0.5% of your investment result as a variable remuneration. A* ***negative (positive)*** *investment result* *leads to* ***negative (positive)*** *variable remuneration, which is* ***deducted from (added to)*** *your basic remuneration. Your remuneration is therefore calculated as follows:*

$$\begin{aligned}&Total\ remuneration\\&\qquad = basic\ remuneration\ \big(\mathbf{250{,}000€}\ (\mathbf{125{,}000€})\big)\\&\qquad +\ 0.5\%\ of\ the\ investment\ result\end{aligned}$$

Following the study, a random number generator determines whether state 1 (50%) or state 2 (50%) occurs. The respective status occurs simultaneously for both investment plans and is only determined once for the entire investment decision.

As the divisional business unit manager, you now have the task of deciding which share of the investment budget the individual investment plans should receive. The total investment result is the sum of the individual investment results of the investment plans "Stable Solutions" and "New Technology" depending on the respective share of the investment budget. Regardless of the investment result, there is no risk of bankruptcy for the company.

Additional information

The management board of your company expects that the investment ***loss (result)*** *should not be* ***greater (less)*** *than* ***-10,000,000€ (15,000,000€)****. If the* ***loss (profit)*** *of your investment decision is* ***higher (lower)****, you must justify yourself for your failure by writing an explanation (you will write a written justification after the study with a minimum length of 200 characters). It can be expected that if you have to justify, your internal standing will be damaged and this will have a negative impact on your future career.*[51]

[51] This paragraph creates personal blame potential to trigger individual blame avoiding decision-making behavior.

A.2 Comprehension questions I

<u>The following is a brief summary of the previous explanations</u>[52]

You are in a ***bad (good)*** *economic situation and should make an investment decision. You can invest in both investment plans ("Stable Solutions" and "New Technology") at the same time. One of the two possible states (state 1 and state 2) is equally likely to occur when making the investment decision. You will receive a basic remuneration independent of results and an additional 0.5% of the investment result as variable remuneration. If you miss the by the management board expected investment* ***loss (result)*** *of* ***-10,000,000€ (15,000,000€)****, you must justify yourself in writing for not achieving it.*[53]

Before you make your investment decision, please answer the questions below. If your answers are incorrect, you will be returned to the initial situation.[54]

Comprehension questions I
1. Can you invest in both investment plans at the same time?
2. Are state 1 and state 2 equally likely?
3. Do you receive a basic remuneration that is independent of the investment result?
4. Do you receive a variable remuneration depending on the investment result?
5. Can you receive a negative variable remuneration which is deducted from your basic remuneration?[55]
6. Is there any investment ***loss (result)*** *expected by the management board?*

[52] Following the description of the initial situation (see Appendix A.1) and before answering the comprehension questions, a detailed example was shown to all participants.
[53] Words in bold slightly adjust the text depending on the manipulation of a bad (good) economic situation.
[54] Participants had to answer all comprehension questions (Yes/No) correctly to continue the study. This guaranteed that all participants fully understood the study. If they answered a comprehension question wrongly, they were redirected to the beginning of the case description and could read the instructions again.
[55] Question 5 was only asked in experimental groups with the economic crisis manipulation.

A.3 Investment decision with and without advice

Investment decision[56]

The following is an overview of the possible investment results depending on the allocation of the investment budget. Please indicate your desired capital allocation for the two investment plans. Please keep in mind that the management board expects an investment ***loss (result)*** *of* ***-10,000,000€ (15,000,000€)*** *or* ***lower (higher)***.[57] *State 1 and state 2 are equally probable and each has a 50% probability. Either state 1 or state 2 can occur.*

Share of the investment plan "Stable Solutions"	*Share of the investment plan „New Technology"*	*Investment result in state 1*	*Investment result in state 2*
100%	*0%*	***-12,500,000€ (12,500,000€)***	***-12,500,000€ (12,500,000€)***
95%	*5%*	***-13,062,500€ (11,937,500€)***	***-11,875,000€ (13,125,000€)***
90%	*10%*	***-13,625,000€ (11,375,000€)***	***-11,250,000€ (13,750,000€)***
85%	*15%*	***-14,187,500€ (10,812,500€)***	***-10,625,000€ (14,375,000€)***
80%	*20%*	***-14,750,000€ (10,250,000€)***	***-10,000,000€ (15,000,000€)***
75%	*25%*	***-15,312,500€ (9,687,500€)***	***-9,375,000€ (15,625,000€)***
70%	*30%*	***-15,875,000€ (9,125,000€)***	***-8,750,000€ (16,250,000€)***
65%	*35%*	***-16,437,500€ (8,562,500€)***	***-8,125,000€ (16,875,000€)***
60%	*40%*	***-17,000,000€ (8,000,000€)***	***-7,500,000€ (17,500,000€)***
55%	*45%*	***-17,562,500€ (7,437,500€)***	***-6,875,000€ (18,125,000€)***
50%	*50%*	***-18,125,000€ (6,875,000€)***	***-6,250,000€ (18,750,000€)***
45%	*55%*	***-18,687,500€ (6,312,500€)***	***-5,625,000€ (19,375,000€)***
40%	*60%*	***-19,250,000€ (5,750,000€)***	***-5,000,000€ (20,000,000€)***
35%	*65%*	***-19,812,500€ (5,187,500€)***	***-4,375,000€ (20,625,000€)***
30%	*70%*	***-20,375,000€ (4,625,000€)***	***-3,750,000€ (21,250,000€)***
25%	*75%*	***-20,937,500€ (4,062,500€)***	***-3,125,000€ (21,875,000€)***
20%	*80%*	***-21,500,000€ (3,500,000€)***	***-2,500,000€ (22,500,000€)***
15%	*85%*	***-22,062,500€ (2,937,500€)***	***-1,875,000€ (23,125,000€)***
10%	*90%*	***-22,625,000€ (2,375,000€)***	***-1,250,000€ (23,750,000€)***
5%	*95%*	***-23,187,500€ (1,812,500€)***	***-625,000€ (24,375,000€)***
0%	*100%*	***-23,750,000€ (1,250,000€)***	***0€ (25,000,000€)***

[56] After correctly answering the comprehension questions (see Appendix A.2), participants initially made this decision without advice. Then, they could adjust their preliminary decision after receiving advice (see Appendix A.4) and answering the interposed experimental questionnaire (see Appendix A.5).
[57] Words in bold differ depending on the manipulation of a bad (good) economic situation.

A.4 Case manipulation of advisor’s blame potential and comprehension questions II

<u>Support from an internal employee</u>[58]

It is common in your company that important decisions are discussed transparently and openly. An employee of one of your two business units came to you informally and would like to share his / her thoughts on the upcoming investment decision. The employee is an in-house expert and was also involved in the preparation of the two investment plans "Stable Solutions" and "New Technology". She / He has familiarized herself / himself with the upcoming investment decision and would like to give you the following recommendation.

<u>(Support from an external consultant</u>

Due to increasing economic complexity and the associated increasing environmental uncertainty as well as higher competitive pressure, the management board has decided that each divisional business unit manager should make use of an external consultant when making important decisions. In response to this corporate policy, you hired a very experienced external consultant from a market-leading strategy consulting firm.)

After an intensive analysis of the future prospects of the already existing products as well as the new product to be launched, the **internal expert (external consultant)** *comes to the conclusion that it would not make sense to invest the limited internal funds predominantly in the existing products. Instead, the* **employee (external consultant)**

[58] After having made the investment decision without advice (see Appendix A.3), the participants were either supported by an internal employee (unblamable advisor) or an external consultant (blamable advisor). Words in bold are the manipulation of the advisor’s blame potential and represent an unblamable advisor (blamable advisor).

suggests that the company should focus more on the introduction of the new product. The ***employee (external consultant)*** *recommends the following investment decision.*[59]

- [-20% relative to preliminary investment decision] *of the investment budget in the investment plan "Stable Solutions"*
- [+20% relative to preliminary investment decision] *of the investment budget in the investment plan "New Technology"*

You can now adjust your preliminary investment decision based on the ***employee's (consultant's)*** *recommendation. But you do not have to do this.*

<u>(If you follow the advice of the external consultant</u> (+/- 5% deviation is still considered to follow the advice), the management board <u>waives a written justification if the expected investment result is not achieved</u>. The management board believes that you do not have to explain your faulty trust in an external expert and his / her poor performance.)[60]

Before you can adjust your initial investment decision, please answer the questions below. If the answer is incorrect, you will be returned to the explanation of the new starting situation.[61]

<u>**Comprehension questions II**</u>
1. Do you have to adjust your original decision?
2. Can you adjust your original decision?
3. Is there a way to safely avoid the justification to the management board irrespective of the investment ***loss (result)****?*[62]

[59] The advisor's recommendation was linked to the participants' own preliminary decision. The advisor recommended to invest 20% more investment budget in the risky investment plan "New Technology". If the participant invested more than 80% in the risky investment plan on his or her own, then the advisor recommended 100% in the risky investment plan.
[60] This paragraph also represents the manipulation of the advisor's blame potential and was only shown to participants with blamable advisors.
[61] Participants had to answer all comprehension questions (Yes/No) correctly to continue the study. This guaranteed that all participants fully understood the study. If they answered a comprehension question wrongly, they were redirected to the beginning of the case description introducing the advisor and could read the instructions again.
[62] Question 3 was only asked in experimental groups with the blamable advisor manipulation.

A.5 Interposed and post-experimental questionnaire

When answering the following questions, please always refer to your previous investment decision.[63]

1. What was your goal of the investment decision you just made? **(Perceived risk without advice/with advice for ΔPerceivedRisk)**								
Making a defensive decision with a maximal stable result for the company	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Making a risky decision with a maximal result for the company*
2. How responsible do you see yourself for the result of the investment decision you just made? **(Perceived own responsibility without advice/after the investment result for ΔPerceivedOwnResponsibility)**[64]								
Not at all	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Completely*
3. How sure are you that you made the right decision from a company perspective? **(Confidence)**								
Very insecure	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very secure*
4. How sure are you that you made the right decision for you personally?								
Very insecure	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very secure*
5. How much have you tried to avoid the written justification to the management board?								
Not at all	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very much*
6. How high do you rate your chances of not having to write a justification to the management board? **(Perceived chances avoiding justification without/with advice for ΔPerceivedChanceAvoidingJustification)**								
Very low	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very high*
7. How strongly did you allow yourself to be influenced by the recommendation of the advisor when making your decision?[65]								
Not at all	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Completely*
8. How competent do you consider the advisor to be?[66] **(AdvisorCompetence)**								
Not very competent	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very competent*

[63] Participants answered the items on 7-point Likert scales after making the investment decision without advice and with advice (see Appendix A.3). Bold text in items refers to the corresponding variables used in Study 1 and was not shown to participants.
[64] Item 2 was also asked after the participants were informed about their realized investment result (see Appendix A.7).
[65] Item 7 was only asked after receiving advice.
[66] Item 8 was only asked after receiving advice.

A.6 Manipulation checks and risk propensity scale

General questions[67]

Please assess the risk of the two investment plans. Please do this regardless of the ***employee's (external consultant's)*** *recommendation and the expected investment* ***loss (result)***.[68]

1. How risky do you think the investment plan "Stable Solutions" is?								
Not risky	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very risky*
2. How risky do you think the investment plan "New Technology" is?								
Not risky	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very risky*
3. How do you assess the current economic situation in your two business units?								
Very bad	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very good*

Please indicate the extent to which you personally agree or disagree with the following statements (no longer in your role as divisional business unit manager). Please respond intuitively, i.e., without thinking about a single statement any longer.[69]

1. Safety first.								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
2. I do not take risks with my health.								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
3. I prefer to avoid risks.								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
4. I take risks regularly.								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
5. I really dislike not knowing what is going to happen.								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
6. I usually view risks as a challenge.								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
7. I view myself as a ...								
Risk avoider	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Risk seeker*

[67] Following the post-experimental questionnaire (see Appendix A.5), I use these questions on 7-point Likert scales as a manipulation check (in addition to the comprehension questions – see Appendix A.2 and Appendix A.4) for the economic situation and whether participants recognized the safe and risky investment plan.

[68] Words in bold differ depending on the manipulation of a bad (good) economic situation and advisor's blame potential.

[69] Items 1-7 on 7-point Likert scales represent the risk propensity scale by Meertens & Lion (2008). Items, 1, 2, 3, and 5 are to be reverse-coded.

A.7 Realized investment result and justification

In the end, the participants were informed about the realized investment state, their corresponding investment result/loss, and their remuneration. Furthermore, the participants were informed if they had to write a justification to the management board. If that was the case, then the participant wrote the justification. Additionally, all participants – independent of their investment result – were asked again who they considered to be responsible (see Appendix A.5).

Appendix B Experimental instrument Study 2[70]

B.1 Case description and manipulation of advisor's nature

<u>*Initial situation*</u>[71]

Please imagine the following situation: You are a business unit manager of a company in a highly competitive environment. Your business unit specializes in the manufacture and sale of medical walking aids (walkers). Your main task is to produce as many walkers as your sales department can sell in the upcoming year. However, the sales volume for the upcoming year is uncertain and can only be estimated.

<u>*Remuneration*</u>

In your function as a business unit manager, you receive a performance-independent basic annual salary of 125,000€ and an additional 2.5% of the realized annual business unit's profit as variable remuneration. In the event of a negative business unit's profit, you will receive 0€ as variable remuneration.

The business unit's profit is made up of a profit margin of 10€ per product sold and the costs for plan deviation. The more your production volume deviates from the realized sales volume, the more the business unit's profit and thus your variable remuneration are reduced. The plan deviation can occur as follows:

- *"Overproduction": Exceeding the sales volume (production volume > sales volume) leads to unsalable overcapacities that have to be costly disposed of.*
- *"Underproduction": Falling below the sales volume (production volume < sales volume) leads to increased costs for "express productions".*

---

[70] Following, the used experimental instrument is presented. Text in italics is part of the experimental instrument and was identically shown to the participants. The experiment was conducted in German. Therefore, all following descriptions have been translated.

[71] Before reading the experimental description, participants answered demographic questions concerning sex, age, working experience, number of supervising employees, own budget responsibility, and industry sector. Due to the specific target group (i.e., managers), participants who did not supervise employees or had no own budget responsibility were screened out.

You know from the past that for every plan deviation, additional costs of 50€ per product arise. The business unit's profit can thus be described as follows:

$$Business\ unit's\ profit = 10€ * sales\ volume - 50€\ number\ of\ too\ many\ (less)\ produced\ products$$

<u>Support from your company's self-learning artificial intelligence application (Support from an internal marketing expert)</u>

A self-learning algorithm ("Artificial Intelligence Application") (An internal marketing expert) *of your company supports your sales forecasting decision. The* ***algorithm (internal expert)*** *evaluates all available internal data (e.g., historical sales volume, advertising campaigns, etc.) and external data (e.g., from social networks, from research institutes on the development of consumer sentiment and the global economy, etc.)* ***in real time***.[72] *You can adjust the production volume recommended by the* ***Artificial Intelligence Application (marketing expert)****, but you do not need to.*[73]

<u>Justification</u>

The central corporate requirement is that the realized sales volume must not deviate by more than 10% from the planned production volume. It is to be expected that in the event of a deviation of more than 10%, your competence and your suitability for the position of a business unit manager will be questioned. In this case, you must justify your incorrect decision to the company's management board by providing a written justification of at least 200 characters.[74]

[72] There was no reference to the timeliness of human advisor's analysis.
[73] This paragraph manipulates the advisor's nature. Words in bold refer to the different manipulation and introduce an artificial intelligence advisor (human advisor).
[74] This paragraph creates personal blame potential to trigger individual blame avoiding decision-making behavior.

B.2 Comprehension questions I

Summary of the initial situation[75]

Your job as a business unit manager is to estimate the future sales volume of walkers as precisely as possible and produce accordingly. To support you, you receive a sales forecast recommendation from an ***artificial intelligence application (internal marketing expert)****. You can still adjust this recommendation, but you do not have to do so. The management board expects you to have a maximum deviation of 10% between the forecasted and the realized sales volume. The smaller the deviation between the forecasted and the realized sales volume, the higher the business unit's profit and thus your variable remuneration, which is dependent on the business unit's profit. Regardless of this, you will receive a basic remuneration that is independent of the business unit's profit.*

Please answer the following comprehension questions.[76]

Comprehension questions I
1. Can you adjust the sales forecast recommended by the ***artificial intelligence application (internal marketing expert)****?*
2. Do you have to adjust the sales forecast recommended by the ***artificial intelligence application (internal marketing expert)****?*
3. Is there a maximum tolerated deviation between the forecasted and the realized sales volume?
4. Is the business unit's profit higher, the less the sales forecast deviates from the realized sales volume?
5. Do you receive a basic remuneration that is independent of the business unit's profit?
6. Do you receive variable remuneration depending on the business unit's profit?

[75] Following the description of the initial situation (see Appendix B.1) and before answering the comprehension questions, a detailed example was shown to all participants.

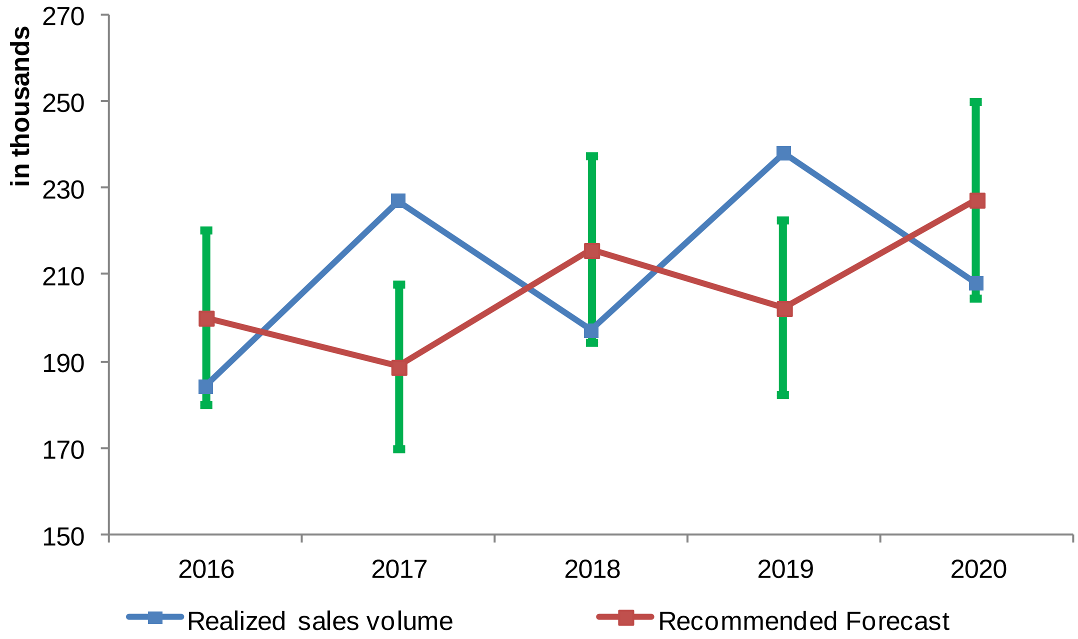
[76] Words in bold slightly adjust the description and comprehension questions depending on the manipulation of the advisor's nature. Participants had to answer all comprehension questions (Yes/No) correctly to continue the study. This guaranteed that all participants fully understood the study. The screenout was very strict due to the simplicity of the comprehension questions and the fact that the solution for the questions was shown on the same page to the participants.

B.3 Evaluating advisor’s forecasting ability

Assessment of the forecasting ability of the ***artificial intelligence application (marketing expert)***[77]

In order to be able to assess the forecasting ability of the ***artificial intelligence application (marketing expert)****, you can see below the realized sales volume (blue) and the forecasted sales volume by the* ***artificial intelligence application (marketing expert)*** *(red) in the last 5 years. The range (green) of the acceptable 10% deviation is shown around the forecasted sales volume:*

Historically realized and forecasted sales volume



The figure shows the following:

- *In 3 out of 5 years the realized sales volume was within the specified 10% range.*

[77] After answering the comprehension questions correctly (see Appendix B.2), participants evaluated advisor’s competence based on historical data. Words in bold slightly adjust the description depending on the manipulation of the advisor’s nature.

- *In 2 out of 5 years the realized sales volume was outside the specified 10% range.*
- *The* ***artificial intelligence application (marketing expert)*** *remains within the tolerated range of forecast deviation in 60% of the observed periods.*

Please answer the following questions based on this information:[78]

1. I rate the predictive ability of the ***artificial intelligence application (marketing expert)*** *as very good.*								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
2. I would find the ***artificial intelligence application (marketing expert)*** *useful for my decision.*[79] **(AdvisorCompetence)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
3. Using the ***artificial intelligence application (marketing expert)*** *enables me to accomplish my task more quickly.* **(AdvisorCompetence)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
4. Using the ***artificial intelligence application (marketing expert)*** *increases my productivity.* **(AdvisorCompetence)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
5. If I use the recommendation of the ***artificial intelligence application (marketing expert)****, I will increase my chances of getting a higher variable remuneration.* **(AdvisorCompetence)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
6. I trust the ***artificial intelligence application (marketing expert)****.* **(Trust)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*

[78] Participants answered items on 7-point Likert scales to evaluate advisor's competence. Words in bold and italic differ depending on the advisor's nature. Words only in bold allocate the measured variables of Study 2 to the corresponding items or scales and were not shown to participants.

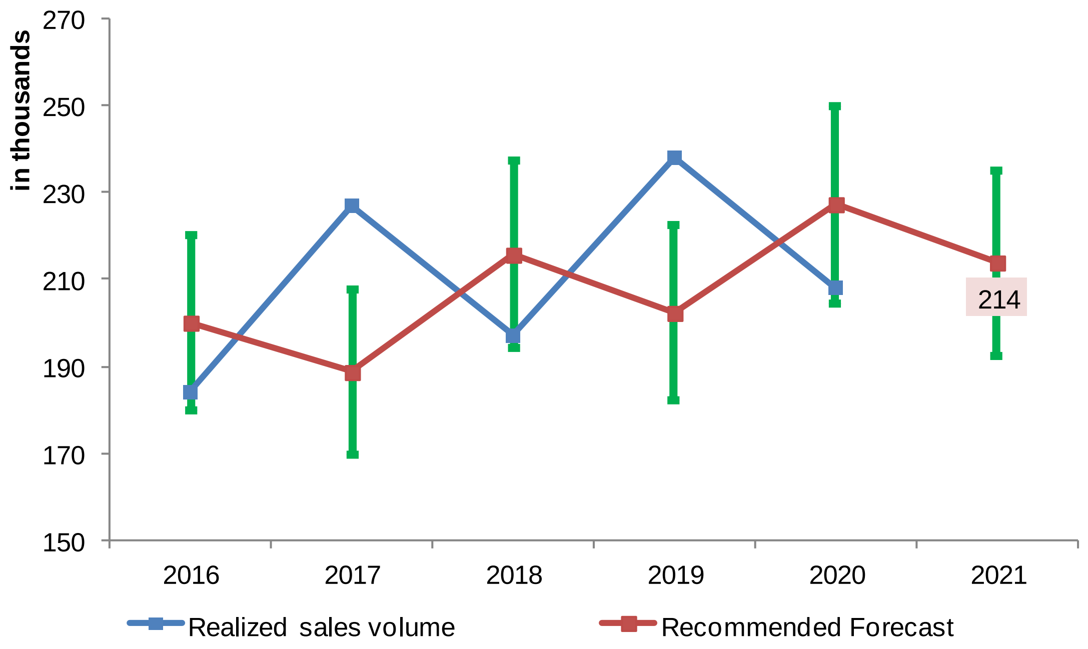
[79] Items 2, 3, 4, and 5 are the contextualized performance expectancy scale of the UTAUT model by Venkatesh et al. (2003) used to measure the variable *AdvisorCompetence* in Study 2.

B.4 Making forecasting decision with judgmental adjustment

Determination of the production volume for the upcoming year[80]

You now have the task of determining the production quantity for the upcoming year with the support of the ***artificial intelligence application (marketing expert)****.*

Historically realized and forecasted sales volume with forecast for the upcoming period[81]



The ***artificial intelligence application (marketing expert)*** *recommends a forecasted sales volume of 214,000 walkers for the upcoming year. You can now adjust this forecast.*

Please bear in mind that the management board expects a maximum deviation of 10% between the realized and the forecast sales volume.[82]

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[80] After evaluating advisor's competence (see Appendix B.3), participants were presented with the forecast for the upcoming period. Words in bold slightly adjust the description depending on the manipulation of the advisor's nature.

[81] The realized sales volume of the upcoming period for determining participants' compensation and deciding whether participants had to justify was 268 (thousand) walkers.

[82] Subsequently, participants made the forecasting decision by determining their judgmental adjustment. However, participants in the experimental groups with the blamable advisor manipulation were first informed about the potential scapegoat (see Appendix B.5).

B.5 Case manipulation of advisor's blame potential and comprehension questions II

However, the management board has pointed out to you in advance that it will not hold you responsible for errors that you cannot influence. Who the management board blames for an incorrect forecast depends on how the forecast was decided.[83]

- *<u>Adjustment of the preliminary forecast</u>: If you have adjusted the preliminary forecast recommended by the* ***artificial intelligence application (marketing expert)****, you are fully responsible for it. This is true regardless of how much you adjusted the forecast and how good or bad the preliminary forecast was. In the event of an incorrect forecast (deviation > 10%), you must provide a written justification to the management board.*
- *<u>No adjustment of the preliminary forecast</u>: If you have not adjusted the preliminary forecast recommended by the* ***artificial intelligence application (marketing expert)****, the management board will not hold you responsible for it. However, the preliminary forecast you have accepted will be used to calculate your remuneration. In the event of an incorrect forecast (deviation > 10%) recommended by the* ***artificial intelligence application (marketing expert)****, the management board* ***will request a technical review of the artificial intelligence application by IT specialists (expects a written justification from the marketing expert)****.*

Please answer the following comprehension question.[84]

<u>Comprehension questions II</u>
1. Do you have to justify yourself for any forecast deviation (> 10%) if you have <u>not</u> adjusted the preliminary forecast?

[83] After being informed about the recommended sales forecast (see Appendix B.4), the participants were either supported by a blamable advisor or an unblamable advisor. Participants in the experimental groups with the blamable advisor manipulation were informed about the potential blame avoidance for non-adjusted forecasts. Words in bold slightly adjust the description depending on the manipulation of the advisor's nature.

[84] Participants in the experimental groups with the blamable advisor had to answer this comprehension question (Yes/No) correctly to continue the study. This guaranteed that all participants fully understood the potential scapegoat before making their forecasting decision (see Appendix B.4).

B.6 Post-experimental questionnaire

When answering the following questions, please always refer to the decision you made on the previous page.[85]

1. Did you feel that you were well-advised? **(AdviceSatisfaction)**								
Not at all	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Completely*
2. How confident are you that you made the right decision to maximize your business unit's profit? **(ExpectedForecastQuality)**								
Very unsure	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very sure*
3. How sure are you that you have made the right decision to maximize your personal success (career as a division leader, justification, compensation)?								
Very unsure	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very sure*
4. How difficult do you think it is to forecast the sales volume?								
Very easy	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very difficult*
5. How much have you tried to avoid the written justification to the management board?								
Not at all	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very much*
6. How high do you rate your chances of not having to provide a written justification to the management board?								
Very low	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Very high*
7. Who is responsible for any plan deviation between the forecasted and the realized sales volumes? (for the decision just made) **(OwnResponsibility)**								
The ***artificial intelligence application (marketing expert)*** *is completely responsible*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*I am completely responsible*

[85] Participants answered the items on 7-point Likert scales after making the forecasting decision with advice (see Appendix B.4). Words in bold and italic adjust the items depending on the advisor's nature. Bold text in items refers to the corresponding variables used in Study 2 and was not shown to participants. Additionally, participants answered the items of the risk propensity scale by Meertens & Lion (2008) (see Appendix A.6).

*In the following, you will be presented with six statements that describe your attitude towards **artificial intelligence applications (advisors)**. Please rate these sentences on a scale from "totally agree" to "totally disagree". There is no right or wrong answer, please answer spontaneously based on your first impression.*[86]

*1. I would feel uneasy if I was given a job where I had to use an **artificial intelligence (advisor)***. **(AdvisorSocialCompetence)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
*2. The word **"artificial intelligence" ("advisor")** means nothing to me.* **(NegativeAttitudeAdvisor)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
*3. I would feel nervous using an **artificial intelligence (advisor)** in front of other people.* **(AdvisorSocialCompetence)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
*4. I would hate the idea that an **artificial intelligence (advisor)** was making judgments about things.* **(NegativeAttitudeAdvisor)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
*5. I would feel very nervous interacting with an **artificial intelligence (advisor)***. **(AdvisorSocialCompetence)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*
*6. I would feel paranoid talking with an **artificial intelligence (advisor)***. **(AdvisorSocialCompetence)**								
Totally disagree	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*Totally agree*

[86] These contextualized items on 7-point Likert scales represent the "negative attitude scale toward situations of interaction with robots" subscale of the "negative attitude toward robots" questionnaire by Nomura et al. (2006). Words in bold and italic adjust the items depending on the advisor's nature. Bold text in items refers to the corresponding variables used in Study 2 and was not shown to participants. Items 1, 3, 5, and 6 measure *AdvisorSocialCompetence*, whereas items 2 and 4 measure *NegativeAttitudeAdvisor*.

B.7 Realized sales volume, forecast accuracy, and justification

In the end, the participants were informed about the realized sales volume, the forecast deviation, and their remuneration. Furthermore, the participants were informed if they had to write a justification to the management board. If that was the case, then the participant wrote the justification.