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RESEARCH ARTICLE

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Managerial advice-taking—Sharing responsibility with (non)human advisors trumps decision accuracy

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Abstract

Organizations are increasingly implementing algorithmic decision aids to advise managerial decision-making. We study managers' motives behind using advice (human and nonhuman), particularly sharing responsibility versus increasing decision accuracy motives. We conduct an online experiment with experienced managers in a sales forecasting setting and find that managers focus on increasing decision accuracy (sharing responsibility) when they are unable (able) to share responsibility with advisors. Moreover, managers prefer to share responsibility with blamable human advisors over nonhuman advisors unless they perceive algorithms as socially competent. Consequently, the results show that managers are not solely motivated to minimize forecast errors but also to reduce personal responsibility when taking advice. We contribute to the literature by highlighting the opportunistic motives of managers when taking (non)human advice. Our findings also bear important implications for practice. Specifically, firms should be aware of managers' opportunistic advice-taking motives when implementing algorithmic decision aids.

KEYWORDS

algorithm aversion, blame avoidance, experiment, forecasting, human judgment, judgmental adjustment

INTRODUCTION

Algorithmic decision aids—computers, algorithms, robots, and artificial intelligence (AI) systems—are increasingly used to support decision-making in many organizational settings (Burton et al., 2020). For example, algorithmic decision aids inform physicians about probable diagnoses and potential treatment options (Esmaeilzadeh et al., 2015) or advise managers to make better sales forecasts (Arvan et al., 2019; Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011). The implementation of algorithmic decision aids raises the question of why decision-makers use such advice. Prior research identifies two fundamental advice-taking motives: (1) increasing decision accuracy by considering advice or (2) sharing responsibility for the decision with the advisor to avoid personal responsibility in the case of a bad decision outcome (e.g., Bonaccio & Dalal, 2006). Indeed, experts from academia, businesses, and governmental institutions have identified AI responsibility and the question of sharing responsibility with algorithmic decision aids as a major challenge related to developing fair, trustworthy, and ethical nonhuman algorithmic decision aids (Burton et al., 2020; Robert et al., 2020). However, prior research on managers' use of algorithmic decision aids – especially extant research in the supply chain demand planning literature – has largely focused on how managers use these aids to increase forecast accuracy (e.g., Arvan et al., 2019; Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011).

Building on blame avoidance theory, we propose that managers generally try to share responsibility with advisors to avoid personal blame if these advisors are blamable; if they are not, managers focus on making the most accurate decision (Gangloff et al., 2014; Park et al., 2014; Steffel et al., 2016). We add to this literature 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., Ashrafian, 2015; Coeckelbergh, 2020), we study managers' willingness to share responsibility with human and nonhuman advisors. We propose that managers are more willing to share responsibility with human advisors than with algorithmic decision aids. However, we expect this preference to decrease when managers perceive algorithmic decision aids as socially competent.[1] We focus on responsibility attribution because an increasing level of technological sophistication (e.g., the implementation of AI-based algorithmic decision aids) potentially changes managers' perceptions of the possibilities of sharing responsibility with nonhuman advisors.

We test our propositions in a forecasting setting. Motives for engaging in blame-avoiding decision-making are expected to be highly relevant in managerial planning and decision-making, as large forecast errors have strong negative effects on corporate profits and competitiveness. Therefore, these contexts entail a high level of blame risk (Fildes et al., 2009; Salehzadeh et al., 2020). Today, managers in these settings are often supported by human advisors or algorithmic decision aids.

We conducted a fully anonymized and incentivized online experiment with managers using a 2 (unblamable advisor vs. blamable advisor) × 2 (expert as human advisor vs. AI as algorithmic decision aid) between-subject experiment in which participants made a sales forecasting decision after receiving forecast advice by a (un)blamable (non)human advisor. The results show that managers are not solely motivated to minimize forecast errors but also to reduce personal responsibility when taking advice. This supports prior findings in the blame avoidance theory literature (e.g., Artinger et al., 2019; Steffel et al., 2016). In line with our hypothesis, we further observe that managers share responsibility mostly with either human advisors or algorithmic decision aids they perceive to be socially competent.[2]

This paper contributes to the management literature and, in particular, the supply chain demand planning literature, by expanding our understanding of managerial advice-taking motives when making forecasting decisions (e.g., Arvan et al., 2019; Gönül et al., 2009; Lawrence et al., 2006; Leitner & Leopold-Wildburger, 2011). Our results suggest that striving to increase decision accuracy is not the sole motivation for managers when taking advice. Moreover, this study adds to prior literature on blame avoidance theory which has focused on if and why decision-makers share responsibility with human advisors (e.g., Artinger et al., 2019; Steffel et al., 2016). We add to this research by highlighting that such responsibility sharing can also occur for nonhuman advisors when the managers perceive these advice systems as both blamable *and* socially competent. Our findings also bear important implications for practice. The results highlight that firms need to be aware of managers' opportunistic advice-taking motives when implementing algorithmic decision aids.

THEORETICAL MODEL AND DEVELOPMENT OF HYPOTHESES

A growing body of research in the psychology and organizational behavior literature studies why and to what extent individuals incorporate advice in their decision-making. A consistent finding in that literature is that perceived advice quality increases advice utilization (Bailey et al., 2022). Prior studies also demonstrate that different biases (e.g., anchoring or egocentric bias) affect the perception of advice quality (e.g., Schultze et al., 2017; Yaniv & Choshen-Hillel, 2012). Moreover, Alon-Barkat & Busuioc (2022) find that advice is used to a greater extent when it confirms the decision-maker's prejudices. These biases are prevalent both when using human and nonhuman advice (e.g., Eroglu & Croxton, 2010; Theocharis & Harvey, 2016). We build on this research by studying the effect of blamability of (non)human advice in forecast settings.

Accurate demand forecasts based on historical data—which better identify sales opportunities, minimize operational costs through reduced inventories, optimize product distribution channels, increase customer satisfaction, and maximize corporate profits – are a decisive competitive advantage for firms (Salehzadeh et al., 2020). Consequently, algorithmic decision aids are increasingly used to support managers in making demand forecasts by providing forecast recommendations, typically combined with the managers' opportunity to adjust the recommendation (Arvan et al., 2019; Fildes & Goodwin, 2021). Prior forecasting literature identifies two main methods of integrating human judgment: (1) judgmentally adjusting a statistically recommended forecast and (2) combining the results of judgmental forecasting and a statistical forecast (Arvan et al., 2019). However research shows that these judgmental adjustments can be biased (such as through anchoring, overoptimism, or overreaction to randomness and noise) (e.g., Eroglu & Croxton, 2010; Fildes et al., 2009). Nonetheless, integrating human judgment into statistical forecasting systems is common in business practice. It enables managers to integrate domain-specific knowledge and contextual information in algorithmic forecasts (Arvan et al., 2019; Fildes & Goodwin, 2021).

We study managers' motives in accepting or adjusting (non)human advice. Specifically, we build on blame avoidance theory, which suggests that decision-makers try to pursue personal goals (e.g., promotions, avoiding

[1] Social competence describes the skill to handle interpersonal relationships in communication settings (Huang & Lin, 2018).

[2] We measure the managers' ease of interacting with a (non)human advisor as an equivalent of the managers' perception of the social competence of advisors. For brevity, we use the term "socially competent" for algorithmic decision aids as well as for human advisors.

layoffs) by avoiding responsibility and minimizing their 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). "Passing the buck" (PTB) is a strategy that can be used to avoid blame and share responsibility (Weaver, 1986). PTB entails delegating difficult decisions to third parties (e.g., advisors) who assume responsibility for any consequences resulting from negative decision outcomes (e.g., major forecast errors). We examine PTB in a setting involving adjustments to sales forecasts. Specifically, we argue that managers intentionally refrain from adjusting bad forecasts to avoid blame in future performance evaluation meetings and pursue personal goals by using advisors as scapegoats in cases where negative consequences may result from forecast errors. This assumption is motivated by prior research, which found PTB behavior in different contexts involving human and nonhuman advisors (e.g., Artinger et al., 2019; Aschauer et al., 2021; Bartling & Fischbacher, 2012; Stout et al., 2014).[3]

In a similar vein, we argue that managers share responsibility with advisors if they perceive personal threats related to having to justify forecast errors. However, in which demand forecasting situations are forecasters prone to engage in blame-avoiding opportunism? The two main factors driving this behavior are high perceived personal threats and expected direct personal accountability for the decision outcome. Specifically, we know that forecasters try to protect their reputation from the negative consequences of forecast errors by exhibiting a herding bias and adopting prevailing consensus to hide within a group of advisors (e.g., Hong et al., 2000; Huang et al., 2017). Additionally, Kirchgässner & Müller (2006) and Nordhaus (1987) demonstrate that forecasters are reluctant to admit mistakes and, therefore, only partially adjust prior forecasts after receiving new information. Moreover, Fildes & Goodwin (2007) find that requiring forecasters to provide written explanations of their adjustments reduces the frequency and magnitude of such adjustments. We add to this research by proposing that the magnitude of these adjustments depends on the blame potential of the advisor. In line with Keil et al. (2007), we differentiate between two types of blame-shifting situations: those involving blamable advisors and those involving unblamable advisors.

It is important to state that blaming others as well as trying to avoid personal blame is the same reciprocal intuitive cognitive process (Malle et al., 2014; Skarlicki et al., 2017). This behavior is grounded in human evolution which has enforced social forms of punishment or ostracism if individuals show socially undesirable behavior (Alicke, 2000; Chudek & Henrich, 2011; Cushman, 2013). Consequently, avoiding social punishment through shifting blame is an intuitive and adaptive strategy. This strategy should also apply to the corporate world.

In today's 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). Managers only use those advisors to share responsibility with whose forecast recommendations they expect to be considered valuable by their superiors. This way, managers can deflect their superiors' negative reactions to major forecast errors, shifting them to blamable advisors.

We propose that managers try to share responsibility and avoid personal blame by using advisors who are held in high regard by their superiors (e.g., highly reputable marketing experts or highly sophisticated AIs with good historical track records). Advisors with weak reputations (e.g., inexperienced marketing trainees or simple statistical analyzes with bad historical track records) are expected to be unblamable, which forces managers to focus instead on increasing decision accuracy to avoid any negative consequences.

> **H1.** Managers put more weight on advice given by blamable advisors than advice given by unblamable advisors.

Bonaccio & Dalal (2006) propose that "[m]otives such as sharing responsibility for the decision […] become salient only in the case of human advisors" (p. 135). We, however, study whether the willingness of managers to share responsibility with an advisor depends upon the nature of the advisor. There is a major debate on how national or supranational governmental institutions determine responsibility for the consequences arising from AI implementation (Robert et al., 2020). Our study does not focus on regulatory decisions but on managers' *individual perceptions* of whether algorithmic decision aids can bear responsibility for the judgments. We expect that the nature of the advisors influences the subjective perceptions of managers regarding the blame potential of advisors.

Philosophical literature highlights that responsibility is a relational concept referring to someone engaging in an action, influencing someone else, and having to assume responsibility for the consequences (Brinkmann, 2009). Due to their free will and awareness of the resulting consequences, human advisors can be held responsible for their advice (Ashrafian, 2015; Coeckelbergh, 2020). However, can algorithmic decision aids in the form of AI advisors assume responsibility similar to humans? Attributing responsibility to AI advisors is more difficult and largely depends on the technological sophistication of such advisors. The literature

[3]For example, research found blame-avoiding behavior in contexts where organizations blame and lay off managers after financial misconduct (Gangloff et al., 2014). Moreover, powerful managers blame weaker colleagues to avoid being laid off (Keil et al., 2007; Park et al., 2014). Additionally, Stout et al. (2014) demonstrate that individuals, who expect to justify their decisions, prefer to delegate travel arrangement decisions to automated software agents than deciding themselves.

distinguishes between two main forms of AI: "weak AI" and "strong AI." Weak AI typically performs specific tasks such as analyzing complex data for forecasting. In contrast, strong AI functions comparably to general human thinking and is at least equal to human intelligence in terms of a broad range of tasks (Fjelland, 2020). An AI that is thought to have consciousness, sentience, and intellectual abilities 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; Flemisch et al., 2012).

In this study, we analyze the role of a weak AI that exclusively specializes in forecasting and is commonly used in business practice today. Due to its lack of consciousness, we expect that a weak AI is held less responsible for its recommendations than a human advisor (Ashrafian, 2015; Coeckelbergh, 2020). However, as with human advisors, managers can be held responsible for their adjustments. Managers who try to avoid blame and responsibility for their forecasting decisions should thus focus on transferring responsibility to such advisors. We expect that the magnitude of this responsibility transfer depends on the managers' advice utilization. Specifically, Palmeira et al. (2015) observed a higher responsibility attribution to the advisor with increasing advice-taking.

Similar behavior has also been observed in forecasting settings. Managers perceive more responsibility for the final forecast when they make larger adjustments (Gönül et al., 2009). Therefore, we argue that the more the final forecast is based on the recommendation of the advisor, the more responsibility is attributed to that advisor. However, we assume this is primarily the case for human advisors because managers are less willing to share responsibility with algorithmic decision aids, as they cannot be certain that their superiors intuitively attribute responsibility to algorithmic decision aids. This argument is also informed by prior research, which suggests that individuals prefer human advice when they focus on increasing decision accuracy, as they tend to lose trust faster in algorithmic decision aids than human advisors when observing identical mistakes (e.g., Burton et al., 2020; Dietvorst et al., 2015; Dietvorst & Bharti, 2020; Önkal et al., 2009; Prahl & van Swol, 2017). Specifically, we expect that managers prefer to share responsibility with blamable human advisors more than with blamable AI advisors.

> **H2.** Managers put more weight on advice given by blamable human advisors than that given by blamable AI advisors.

Building on H2 and a possible algorithm aversion for blamable advice, we introduce the social competence of advisors as a possible moderating human-like criterion affecting managers' aversion to sharing responsibility with advisors. 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 tasks requiring subjective assessments. However, increasing the human-likeness of an algorithmic decision aid reduces algorithm aversion (Castelo et al., 2019; Lowens, 2020). We propose that managers' aversion to sharing responsibility with algorithmic decision aids decreases as their perception of the social competence of blamable algorithmic decision aids increases. Social competence is the ability to handle interpersonal relationships in communication settings (Huang & Lin, 2018). Huang & Lin (2018) defined 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 should generally help blamable advisors—irrespective of their nature—to justify their decisions to managers' superiors. In line with this, Garofalo & Rott (2018) demonstrated the importance of a blamed advisor's social competence in a blame-avoiding setting.

A prerequisite for managers to share responsibility with an algorithm is that the manager assumes that the algorithm can bear responsibility and defend managers from repercussions due to forecast errors. Consequently, nonhuman advisors that are not perceived as socially competent cannot be used as scapegoats. As previously mentioned, blaming others is typically an intuitive cognitive process causing individuals to make decisions about who and to what extent to blame others (Alicke, 2000; Chudek & Henrich, 2011; Cushman, 2013). We argue that managers expect their superiors to be more skeptical of attributing responsibility to nonhuman advisors compared to human advisors. However, we expect this effect to be reduced when managers perceive blamable advisors as socially competent. We assume that managers deem social competence an important attribute for blamable algorithmic decision aids.[4]

> **H3.** Managers' higher perceptions of the social competence of advisors reduce their aversion to sharing responsibility with blamable nonhuman advisors.

METHOD

Experimental design

We conducted an online experiment to study the influence of the blame potential and nature of advisors on managerial decision-making in a sales forecasting

[4]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).

TABLE 1 2 × 2 between-subject-factorial experimental design.[a]

2 × 2 experimental design		Advisor's blame potential: Unblamable advisor	blamable advisor
Advisor's nature	Human marketing expert	$N = 43$	$N = 23$
	AI advisor	$N = 44$	$N = 33$

[a]This table shows the experimental design and the number of participants within each experimental group.

TABLE 2 Participants' demographics.

Sex		Age		Working experience		Leadership span	
Male	95	<40 years old	32	<10 years' experience	15	<10 supervised employees	80
Female	48	≥40 and <50 years old	46	≥10 and <20 years' experience	41	≥10 and <30 supervised employees	37
		≥50 and <60 years old	44	≥20 years and <30 years' experience	48	≥30 supervised employees	26
		≥60 years old	21	≥30 years' experience	39		
143 participants							

setting.[5] We used a 2 × 2 between-subjects design, where we manipulated the nature of the advisor (human marketing expert vs. algorithmic decision aid in the form of an AI) and the blame potential of the advisor (unblamable advisor vs. blamable advisor) (see Table 1).

Participants

We received data from 225 managers from German-speaking countries. The market research agency Respondi recruited the sample and sent our experimental instruction online to managers from Germany, Austria, and Switzerland. To participate, managers needed to meet two criteria: (1) having budget responsibility and (2) supervising at least one employee. Moreover, we included a series of test questions to ensure that the participants read the experimental instructions carefully. Consequently, the number of participants was reduced to 143 through comprehension screening.[6] The participants' demographics are shown in Table 2.

Task and procedure

We based our design on prior experimental forecasting research (e.g., De Baets & Harvey, 2018). These experimental settings typically provide participants with fictitious data series (e.g., contextual information like seasonal patterns and promotional activities) and historical and future statistical forecast recommendations and ask participants to adjust these preliminary forecasts. In a similar vein, we asked participants 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 managers' 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 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.

The participants received a fixed participation fee of 1.25€ and a variable compensation of 0.000025% of the fictive business unit's profit. There was no negative variable compensation 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.[7] This created a possible individual compensation ranging from 1.25€ to 1.92€.[8]

Additionally, the management board expected the realized sales volume not to deviate from the forecast by

[5]Institutional IRB approval for conducting the experiment has been granted.

[6]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 we relied on an online experiment, which does not allow for the same level of participant monitoring as a laboratory experiment, we had to use this strict rule to ensure that only participants who understood the task were included in the analyses.

[7]The forecasting task in combination with a two-sided loss-function due to over- or underproduction is similar to the newsboy problem. Prior studies analyze different strategies to make forecasts in such circumstances like determining optimal marketing activities (e.g., Lee & Hsu, 2011), providing discounts for overproduced goods and substituting underproduced goods by upgrading to overproduced qualitatively higher goods (e.g., Moon et al., 2016; Zhang et al., 2020). However, due the symmetrical loss function and the existence of only a single product, our results should not be biased in line with what the newsboy problem suggests.

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

more than 10%. In case of a greater deviation, the participants were informed that the management board would question their competence and suitability for their current position and expect them to provide a written justification of at least 200 characters explaining their missed forecast.

In line with previous research on sales forecasting, we generated a sales time series consisting of six periods for all the participants (De Baets & Harvey, 2018; 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. All participants received identical data series and forecast recommendations. We generated the recommended forecast using simple exponential smoothing with a smoothing parameter of 0.7. However, this forecasting method is unsuitable for forecasting a trending data series like ours, as it 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} and is calculated as follows (Hyndman & Athanasopoulos, 2021): $F_t = \alpha A_{t-1} + (1-\alpha)F_{t-1}$. Consequently, the provided forecast recommendations were objectively bad.

In contrast to prior experiments, participants made a single forecast based on an identical time series instead of multiple forecasts with different statistical characteristics. This is important since we did not primarily examine the forecast accuracy of different statistical forecasts between experimental groups. Instead, we were interested in how the nature of the advisors affects advice utilization of identical advice.

First, the participants were shown five periods of the generated sales time series, which represented historical data for the last 5 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.

Next, the participants were provided with the recommended forecast for the upcoming period and had the opportunity to adjust this forecast. Such a two-step forecasting process is often used in business practice (e.g., Fildes & Goodwin, 2021). Specifically, the participants in the blamable advisor condition were informed that if they did not adjust the recommended forecast, they would not have to write a justification independent of the forecast accuracy. This manipulation of the advisors' blame potential is similar to the experimental manipulation of different blame-shifting settings as in Keil et al. (2007), Libby et al. (2004), Stout et al. (2014), and Maske et al. (2021), for example.

Our goal was to create a trade-off scenario for the participants by providing a bad forecast that should be adjusted to reduce forecast errors (i.e., focusing on increasing decision accuracy and individual remuneration). However, we also provided an incentive not to adjust the bad forecast by allowing the participants to blame the advisor (i.e., focusing on sharing responsibility and achieving the nonfinancial reward of avoiding justification). We intentionally used this unsuitable forecasting method in a time series with a trend and manipulated the smoothing factor in such a way that there was a large deviation within each period due to an offset whipsaw pattern which resulted in untypical negatively correlated forecast errors in a trending data series (see Appendix A).

After participants made their forecast decision, they answered additional questions in the post-experimental questionnaire. We asked for their perceptions of responsibility, forecast quality and advice satisfaction. Additionally, we polled participants' attitudes toward socially interacting with the advisor, which we used as a proxy for the advisors' social competence. Finally, the participants were informed about the realized sales volume, their forecast deviation, if they had to write a justification, and their remuneration.

Dependent variables

Our study focuses on managers' motives for adjusting the recommendations of advisors. The main dependent variable used to measure the participants' adjustments is *MAPA*—the *mean absolute percentage adjustment* (Fildes et al., 2009; Goodwin et al., 2007)—and is calculated as follows:

$$MAPA = \left| \frac{Own\ Forecast - Recommended\ Forecast}{Recommended\ Forecast} \right| * 100$$

Additionally, and in line with prior forecasting research (e.g., Fildes et al., 2009), we use the *mean absolute percentage error* (*MAPE*) to measure the effects of participants' advice utilization on decision accuracy (i.e., magnitude of forecast errors).

$$MAPE = \left| \frac{Realized\ Value - Forecast}{Realized\ Value} \right| * 100$$

By combining *MAPA* and *MAPE*, we identify whether managers use advice to (1) increase decision accuracy or (2) share responsibility with advisors.

Independent variables

NatureAdvisor

NatureAdvisor differentiates between a human marketing expert (dummy coded as 0) and an algorithmic decision aid as a "weak AI" (dummy coded as 1).

BlamePotentialAdvisor

Each advisor who recommends a sales forecast is either 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.

OwnResponsibility

OwnResponsibility measures the participant's perceived responsibility for the final forecast on a 7-point Likert scale (1 = *no own responsibility*, 7 = *complete own responsibility*).

AdvisorCompetence

AdvisorCompetence measures the participant's perception of the 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 et al. (2003) (Cronbach's alpha = 0.90).

ExpectedForecastQuality

ExpectedForecastQuality measures the participant'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*).

AdvisorSocialCompetence

AdvisorSocialCompetence measures the participant's perception of the advisor's social competence. Specifically, we capture the 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 et al. (2006). This scale allows us to measure how comfortable participants feel when interacting with algorithmic decision aids. Specifically, this assesses (1) participants' personal feelings during social interactions due to the social competence of algorithmic decision aids and (2) participants' overall personal aversion toward algorithmic decision aids.[9] *AdvisorSocialCompetence* is measured on a 7-point Likert scale (1 = *low social competence*, 7 = *high social competence*) (Cronbach's alpha = 0.87). Overall, participants show great heterogeneity regarding their perception of the social competence of advisors, indicating the subjectivity of this variable (see Table 3).

NegativeAttiudeAdvisor

NegativeAttiudeAdvisor measures the participant's aversion toward the advisor based on the "negative attitude scale toward situations of interaction with robots" subscale of the "negative attitude toward robots".[10] It is measured on a 7-point Likert scale (1 = *low aversion*, 7 = *high aversion*) (Cronbach's alpha = 0.62). Similar to *AdvisorSocialCompetence*, there is high heterogeneity regarding the aversion toward the advisor (see Table 3).

Control variables

AdviceSatisfaction

AdviceSatisfaction uses a 7-point Likert scale (1 = *badly advised*, 7 = *well-advised*) to measure the participants' subjective feeling of whether they were well-advised.

Trust

Trust uses a 7-point Likert scale (1 = *low trust*, 7 = *high trust*) to measure the participant's trust in the advisor.

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).[11]

RESULTS

We test three hypotheses. First, we expect managers to make smaller adjustments to forecasts recommended by blamable advisors relative to the advice given by unblamable advisors (H1). Moreover, we argue that this effect of sharing responsibility with blamable advisors is stronger with blamable human advisors than with blamable

[9]The scale by Nomura et al. (2006) was developed to assess individual attitudes toward robots (e.g., algorithmic decision aids). This main scale consists of three different subscales measuring different constructs: participants' attitude toward (1) situations of bilateral interaction with algorithmic decision aids, (2) societal influence of algorithmic decision aids, and (3) emotions in interactions with algorithmic decision aids. We only use the first subscale to measure how comfortable participants feel when interacting with algorithmic decision aids. We split this subscale into two variables: *AdvisorSocialCompetence* and *NegativeAttitudeAdvisor*. *AdvisorSocialCompetence* is measured by items 4, 8, 10, and 12 of the "Negative attitude toward robots scale" (see Appendix B).

[10]Specifically, we use items 7 and 9 of the subscale "negative attitude toward situations of interaction with robots" to measure *NegativeAttitudeAdvisor* (see Appendix B).

[11]All non-dichotomous independent and control variables are centered on their mean values (Aiken & West, 1991).

TABLE 3 Descriptive statistics.[a]

Variable	Mean	Median	Standard deviation	Min	Max
MAPA	4.94	3.74	5.17	0.00	30.84
MAPE	17.20	17.91	4.39	0.37	27.61
NatureAdvisor	0.54	1.00	0.50	0.00	1.00
BlamePotentialAdvisor	0.39	0.00	0.49	0.00	1.00
OwnResponsibility	5.50	6.00	1.80	1.00	7.00
AdvisorCompetence	4.48	4.50	1.26	1.00	7.00
ExpectedForecastQuality	4.91	5.00	1.06	2.00	7.00
AdvisorSocialCompetence	5.44	5.75	1.42	1.25	7.00
NegativeAttitudeAdvisor	2.79	2.50	1.50	1.00	7.00
AdviceSatisfaction	4.59	5.00	1.21	1.00	7.00
Trust	3.99	4.00	1.50	1.00	7.00

[a]This table shows the descriptive statistics for *MAPA* and *MAPE* as well as the independent variables used in the regression. To provide more detailed information, we display the descriptive statistics of the uncentred independent regression variables, although we centered all variables when conducting the regression analyses.

algorithmic decision aids (H2). Third, we propose that managers' aversion to sharing responsibility with blamable algorithmic decision aids is reduced when they attribute high levels of social competence to nonhuman advisors (H3).

The descriptive statistics support H1 and H2. Figure 1 shows the *MAPA* of the recommended forecasts and the *MAPE* of the adjusted forecasts across the experimental conditions.

The *MAPA* of the recommended forecasts is 5.05% (2.76%) with an unblamable (blamable) marketing expert and 5.18% (5.99%) with an unblamable (blamable) AI. Moreover, the *MAPE* of the adjusted forecasts is 16.98% (18.40%) with an unblamable (blamable) marketing expert and 16.96% (16.97%) with an unblamable (blamable) AI. This suggests that participants generally focus on increasing decision accuracy by making higher adjustments to bad unblamable advice resulting in lower forecast errors. Moreover, managers focus on sharing responsibility with blamable human advisors resulting in higher forecast errors, whereas they focus on increasing decision accuracy with blamable nonhuman advisors, resulting in lower forecast errors. Specifically, due to the advisors' bad forecast recommendation, participants with blamable human advisors have higher forecast errors than participants with unblamable human advisors ($t[64] = -1.36$, $p = 0.090$, one-tailed), whereas there is no negative effect on *MAPE* with (un)blamable nonhuman advisors ($t[75] = -0.010$, $p = 0.992$).

Figure 2 illustrates the *MAPA* of the forecast recommendations and the *MAPE* of the adjusted forecasts for perceived low (high) socially competent (non)human advisors separately for unblamable and blamable advisors. The descriptive statistics lend support to H3.

Participants exhibit an aversion to sharing responsibility with blamable nonhuman advisors with low social competence (*MAPA* human: $m = 2.39\%$ vs. nonhuman: $m = 6.85\%$). However, this aversion is less pronounced for blamable nonhuman advisors with high social competence (*MAPA* human: $m = 3.00\%$ vs. nonhuman: $m = 4.48\%$). Participants share responsibility (SR) with blamable human advisors and blamable nonhuman advisors with high social competence, resulting in lower decision accuracy (i.e., higher forecast errors: 18.24%, 18.50%, and 18.94%). However, they focus on increasing decision accuracy (DA) with blamable nonhuman advisors with low social competence (i.e., lower forecast errors: 15.85%).[12]

Next, we turn to the regression analyses. Table 3 shows the descriptive statistics—mean, median, standard deviation, minimum, and maximum value of the variables of interest—and Table 4 presents their pairwise correlations. We conduct a multiple linear regression to test our hypotheses (see Table 5).[13]

Model 1 consists of the control variables. Specifically, we summarized the demographic control variables *Sex*, *Age*, and *WorkingExperience* in the row "Controls." None of these variables materially affect the effects of the main variables of interest. The higher the *AdviceSatisfaction* of participants, the less they adjust the recommended forecast (*MAPA*) ($p = 0.040$). However, participants perceived no difference in *AdviceSatisfaction* ($t[141] = 0.31$,

[12]Participants reduce their aversion to sharing responsibility with blamable nonhuman advisors as the perceived social competence of advisors increases. Consequently, blameable nonhuman advisors with high social competence have a negative impact on *MAPE* compared to blameable nonhuman advisors with low social competence ($t(31) = -1.84$, $p = 0.076$).

[13]A visual check of the normal Q-Q plot shows no irregularity regarding the normal distribution of residuals, indicating that our results are valid despite uneven group sizes. Moreover, we did not find multicollinearity among the variables, as the VIF index is below 5 for all measures. However, we observed some signs of heteroscedasticity in the data. Consequently, we consistently used robust standard errors in all statistical models to increase the robustness of our model (Hayes & Cai, 2007). Moreover, the distribution of *MAPA* has some outliers and *MAPE* seems to be left-skewed (see Appendix C). Therefore, we confirmed the robustness of our results by conducting an 80% sampling split and a corresponding Chow test ($F = 0.76$, $p = 0.760$) (Lee, 2008). These findings support the robustness of our results.

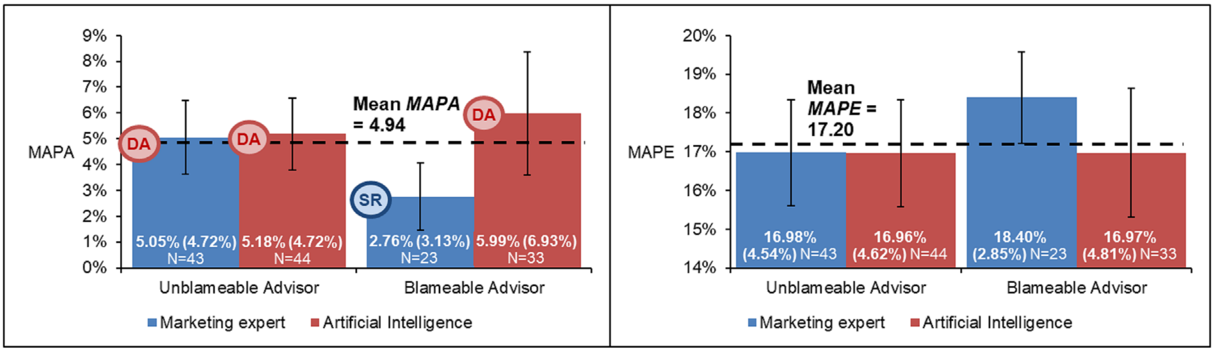

FIGURE 1 This figure shows the *mean average percentage adjustment* (*MAPA*) to the preliminary recommended forecasts and the *mean absolute percentage error (MAPE)* of the adjusted forecasts across all experimental conditions with 95% confidence intervals. The standard deviation for each cell is shown in parentheses. Abbreviations indicate participants' advice-taking motive—increasing decision accuracy (DA) or sharing responsibility (SR)—for each cell.

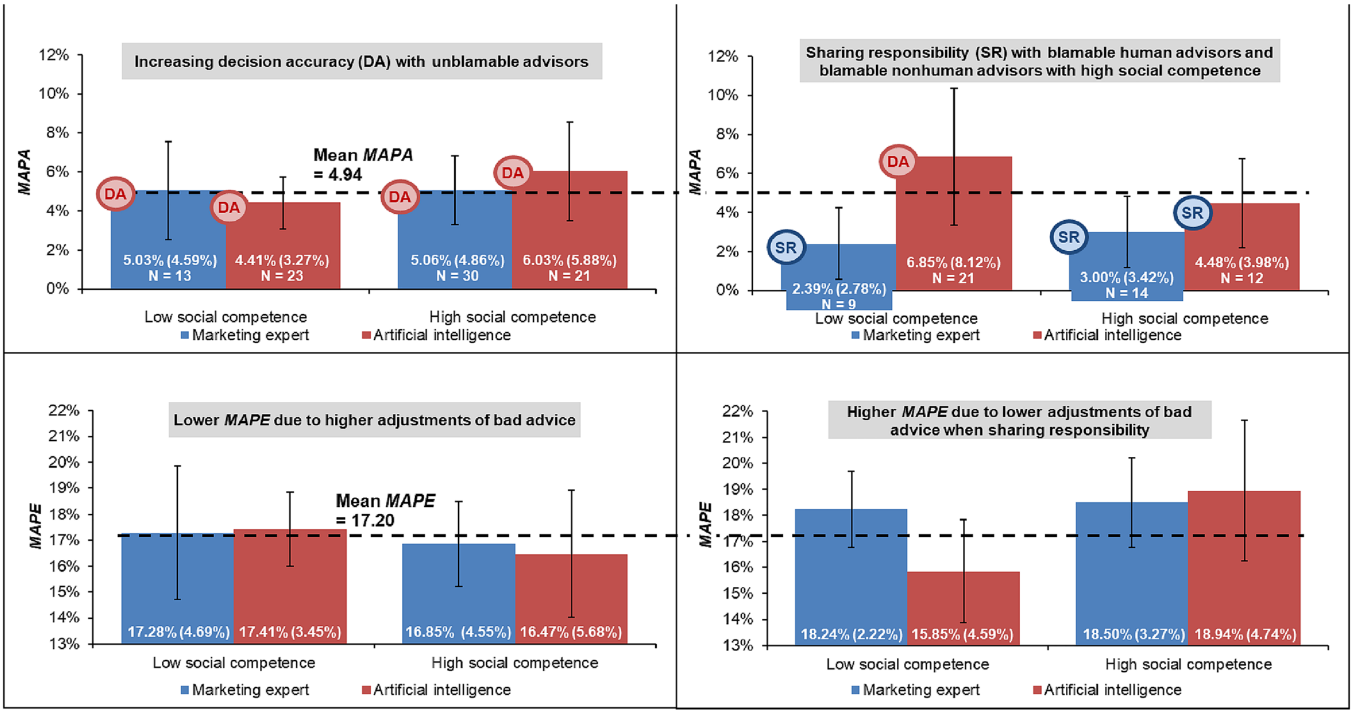

FIGURE 2 This figure shows the *mean average percentage adjustment* (*MAPA*) to the preliminary recommended forecasts and the *mean absolute percentage error (MAPE)* of the adjusted forecasts depending on the nature and the perceived social competence of the advisors (median-split) for unblamable and blamable advisors with 95% confidence intervals. The standard deviation for each cell is shown in parentheses. Specifically, this figure illustrates the effect of the three-way interaction of *NatureAdvisor*, *BlamePotentialAdvisor*, and *AdvisorSocialCompetence*. Abbreviations indicate the advice-taking motive of participants—increasing decision accuracy (DA) or sharing responsibility (SR)—for each cell.

$p = 0.758$) and *Trust* depending on the advisors' nature ($t[141] = 0.95$, $p = 0.345$).

Model 2 adds the main variables *NatureAdvisor* and *BlamePotentialAdvisor* and their interaction. We find a negative effect of *BlamePotentialAdvisor* on *MAPA* ($p = 0.008$), that is, participants make smaller adjustments when advice is given by a blamable advisor. This finding supports H1. Moreover, the positive effect of the interaction between *NatureAdvisor* and *BlamePotentialAdvisor* on *MAPA* ($p = 0.059$) suggests that participants make smaller adjustments when advice is provided by a blamable human advisor than when it is provided by a blamable algorithmic decision aid. This finding supports H2.

To provide additional insights into the blame-avoiding behavior of managers, we include the variables *OwnResponsibility*, *AdvisorCompetence*, and *ExpectedForecastQuality* in Model 3. Moreover, we analyze managers' responsibility attribution depending on advisors' nature and perceived competence. Overall, we find a

TABLE 4 Pairwise correlation matrix.[a]

Variable	1	2	3	4	5	6	7	8	9	10	11
1. MAPA	1.00										
2 MAPE	−0.76***	1.00									
3. NatureAdvisor	0.13	−0.09	1.00								
4. BlamePotentialAdvisor	−0.09	0.06	0.08	1.00							
5. OwnResponsibility	0.29***	−0.21**	−0.01	−0.29***	1.00						
6. AdvisorCompetence	−0.02	0.07	0.12	−0.04	−0.07	1.00					
7. ExpectedForecastQuality	0.13	−0.10	−0.05	−0.01	0.03	0.30***	1.00				
8. AdvisorSocialCompetence	−0.03	0.11	−0.26***	−0.10	0.22***	0.32***	0.13	1.00			
9. NegativeAttitudeAdvisor	0.00	−0.09	0.02	0.06	−0.04	−0.39***	−0.14 *	−0.72***	1.00		
10. AdviceSatisfaction	−0.14	0.19**	−0.01	−0.01	0.05	0.65***	0.43***	0.32***	0.31***	1.00	
11. Trust	−0.08	0.11	−0.07	−0.04	−0.13	0.71***	0.23***	0.26***	−0.32***	0.54***	1.00

[a]This table shows the pairwise correlation for each variable for the 143 participants across all experimental groups. For more information on all variables, see subsections "Dependent Variables," "Independent Variables," and "Control Variables."
*$p < 0.10$ (two-tailed tests).
**$p < 0.05$.
***$p < 0.01$.

positive effect of *OwnResponsibility* ($p < 0.001$) and *ExpectedForecastQuality* on *MAPA* ($p = 0.015$). The participants' 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. Additionally, participants are better able to transfer responsibility to more competent advisors ($p = 0.079$), whereas the nature of the advisors does not influence responsibility attribution ($p = 0.979$). Apparently, participants do not attribute responsibility differently to human advisors and algorithmic decision aids. Specifically, participants perceived less own responsibility with blamable human ($t[64] = 3.35$, $p = 0.001$) and blamable nonhuman advisors ($t[75] = 2.65$, $p = 0.010$) than with unblamable human and nonhuman advisors. Moreover, participants considered both advisors (i.e., human marketing expert and AI) to be equally competent ($t[141] = -1.36$, $p = 0.175$).

Model 4 adds participants' overall attitudes toward their advisors and their perceived social competence to the regression. We find no influence of the participants' attitudes toward their advisors ($p = 0.747$) or their social competence ($p = 0.515$) on *MAPA*. However, advisors' perceived social competence affects managerial blame-avoiding behavior. Specifically, a three-way interaction between *NatureAdvisor*, *BlamePotentialAdvisor*, and *AdvisorSocialCompetence* negatively affects *MAPA* ($p = 0.071$). Participants share responsibility with blamable advisors but do not generally increase their advice utilization with an increase in advisors' social competence. Instead, participants reduce their aversion to sharing responsibility with nonhuman advisors with an increase in the perceived social competence of blamable algorithmic decision aids. This finding supports H3. Finally, participants perceived human advisors to have higher levels of social competence than AI advisors ($t[141] = 3.44$, $p < 0.001$). Consequently, social competence seems important in explaining participants' aversion to sharing responsibility with blamable algorithmic decision aids.[14]

DISCUSSION OF THE ROBUSTNESS OF THE RESULTS

We first discuss potential alternative explanations for the observed behavior in our experiment and explain why we are confident in the interpretation of our results. It may be argued that participants in the experiment did not exhibit blame-avoiding behavior but just wanted to avoid the unpleasant, tedious task of writing a justification. However, if that were the case, we would not expect different managerial behavior with blamable human and nonhuman advisors. Instead, our data show differences between the groups. We further inspected the written justifications the participants provided and observed two

[14]Advisors' social competence increases the influence of *AdviceSatisfaction* ($p = 0.006$). It is plausible that participants feel well advised by socially competent advisors and hence make smaller adjustments.

TABLE 5 Multiple linear regression results.[a]

Dependent variable = *MAPA*	Model 1	Model 2	Model 3	Model 4
NatureAdvisor		−0.18(0.848)	−0.27(0.760)	−0.34(0.733)
BlamePotentialAdvisor		−2.90***(0.008)	−1.64*(0.096)	−1.96*(0.050)
*NatureAdvisor*BlamePotentialAdvisor*		4.12*(0.059)	3.89*(0.076)	4.28*(0.068)
OwnResponsibility			0.81***(0.000)	0.81***(0.000)
AdvisorCompetence			0.51(0.201)	0.59(0.162)
*OwnResponsibility*NatureAdvisor*			−0.01(0.979)	−0.01(0.979)
*OwnResponsibility*AdvisorCompetence*			0.20*(0.079)	0.22*(0.098)
ExpectedForecastQuality			0.81**(0.015)	0.78**(0.017)
AdvisorSocialCompetence				0.22(0.747)
*AdvisorSocialCompetence*NatureAdvisor*				0.69(0.356)
*AdvisorSocialCompetence*BlamePotentialAdvisor*				0.39(0.589)
*AdvisorSocialCompetence*NatureAdvisor*BlamePotentialAdvisor*				−2.01*(0.071)
*AdvisorSocialCompetence*AdviceSatisfaction*				−0.70***(0.006)
NegativeAttitudeAdvisor				0.37(0.515)
AdviceSatisfaction	−0.85**(0.040)	−0.96**(0.026)	−1.47***(0.005)	−1.36***(0.006)
Trust	0.43(0.295)	0.65(0.169)	0.60(0.211)	0.80*(0.099)
Controls	Yes	Yes	Yes	Yes
Constant	5.50***(0.000)	5.79***(0.000)	5.25***(0.000)	5.62***(0.000)
Observations	143	143	143	143
Adjusted R-squared	0.012	0.047	0.132	0.167

[a]This table shows the results of a multiple linear regression. The dependent variable is the *mean absolute percentage adjustment* (*MAPA*) to the recommended forecast. The other variables used in the regression are explained in the subsections "Independent Variables" and "Control Variables." All demographic variables have no significant impact in our final regression model 4. However, due to the absence of important explanatory variables, *Sex* is significant for model 1 and model 2. Specifically, female participants make smaller forecast adjustments than male participants ($p = 0.063$). The regression coefficients are reported in conjunction with the p-values in parentheses at the individual level.
*$p < 0.10$ (two-tailed).
**$p < 0.05$.
***$p < 0.01$.

major justification themes: (1) Participants directly addressed the bad forecast quality and stated that they tried to correct the bad forecast recommendation (but did so insufficiently) and (2) argued regarding why they made the right decision or could not make a better decision (e.g., needed more data). These justification reports show that participants who had to justify their forecasts focused on increasing decision accuracy, as they were not able to avoid blame (i.e., personal justification) due to an unblamable advisor. Therefore, we are confident that we successfully manipulated advisors' blame potential.

Additionally, it could be argued that participants exhibited a general algorithm aversion and preferred human advice independent of their advice-taking motive. In our setting, the participants correctly recognized the bad advice quality (i.e., *ExpectedForecastQuality*). However, they did not consider the human advisors more competent (i.e., *AdvisorCompetence*), did not trust them more (i.e., *Trust*), and did not feel they were better advised (i.e., *AdviceSatisfaction*). Additionally, the experimental instructions explicitly mentioned that (non) human advisors had domain-specific knowledge. Hence, we have no evidence to suggest that participants preferred human or nonhuman advisors out of any motive other than the advisor's blame potential. Specifically, we see no different advice-taking behavior for unblamable advisors, indicating that participants exhibit no general algorithm aversion in our setting. However, algorithm aversion emerges for blamable advisors perceived as socially incompetent.

DISCUSSION AND CONTRIBUTION

General discussion of the results of forecast adjustments and forecast errors

We find managerial blame-avoiding behavior and a negative effect of the blame potential of advisors on the magnitude of advice adjustments made by managers. When managers are advised by a blamable advisor, their adjustment decreases because they want to blame the advisor in the case of a major forecast error. Moreover, the more competent the managers perceive the advisor to be, the stronger this effect, which is also plausible because it should be easier to avoid responsibility by following an expert's advice than following a novice's recommendation. High perceived competence of advisors (e.g., highly respected expert or sophisticated forecasting tool) seems to be an important factor driving advisors' blame potential, as it represents organizational support and leniency when punishing forecasting errors.

Additionally, sharing responsibility with blamable advisors to avoid own responsibility in the form of justifications and blaming the advisors for providing poor advice is similar to the phenomenon of scapegoating (e.g., Gangloff et al., 2014; Park et al., 2014). In our experiment, the participants made better forecasting decisions resulting in lower forecast errors when they made larger adjustments to the preliminary forecast. This means managers correctly identified the low quality of the provided advice. However, managers seemed to consider their personal blame avoidance more important than making a good forecast. Concentrating on avoiding responsibility and blame—irrespective of the perceived quality of the forecast recommendations of advisors—can have major negative consequences for companies.

We also find that participants considered the human advisor and the algorithmic decision aid equally competent (i.e., the experimental description stated that both advisors possess additional contextual information). Specifically, we observe no general aversion to using identical advice from unblamable algorithmic decision aids when managers focus on increasing decision accuracy; rather, we find this only when managers try to share responsibility. In line with prior blame avoidance literature (e.g., Bonaccio & Dalal, 2006; Steffel et al., 2016), we argue that the reason for this behavior is that managers expect their superiors to intuitively attribute more responsibility to blamable human advisors than blamable AI advisors. It is plausible that managers can convince their superiors of the responsibility of a blamable human advisor more easily than they can convince them of the responsibility of a blamable algorithmic decision aid. Nonetheless, we find no difference in terms of managerial responsibility attribution based on the nature of the advisors; rather, we only find an overall effect of *OwnResponsibility*.

Blame avoidance theory describes the ideal scapegoat predominantly in relation to responsibility attribution (e.g., Artinger et al., 2019; Steffel et al., 2016). In contrast, we examine *AdvisorSocialCompetence* as an additional criterion that influences managers' aversion to sharing responsibility with nonhuman advisors. Specifically, we find that the three-way interaction between *NatureAdvisor*, *BlamePotentialAdvisor*, and *AdvisorSocialCompetence* has a negative effect on *MAPA*. Interestingly, when blamable advisors have a higher level of social competence, managers' willingness to share responsibility with algorithmic decision aids increases. We believe this behavior occurs because managers try to choose blamable advisors they believe to have the greatest chances of convincing their superiors of their responsibility. Specifically, we believe managers consider blamable advisors' social competence a central task-specific requirement for blamable advisors (i.e., scapegoats). The existence of this three-way interaction is also very logical, as it is the direct conclusion of managers' algorithm aversion to blamable (non)human advice. The more socially competent the algorithmic decision aid, the weaker the managers' aversion to using the algorithm as a scapegoat.

Moreover, we emphasize that we use the forecasting task with judgmental adjustment in this study mainly as a prototypical management decision under uncertainty. We specifically chose this setting, as algorithms are established and highly used in this specific field of application. However, we consider the forecasting task as one experimental operationalization. Automations or algorithms are also utilized in nonindustrial companies like financial or medical institutions (i.e., providing financial investment advice or suggestions for suitable medical treatment) (Esmaeilzadeh et al., 2015; Xidonas et al., 2011). Specifically, we suggest that if managers want to increase the operative adoption of supposedly beneficial algorithms for all kinds of tasks, the algorithms should be perceived to be highly socially competent. This suggestion is speculative but would imply that managers prefer to share responsibility with 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).

Contributions, limitations, and future research

The contributions of our study are twofold. First, we contribute to management literature, particularly the supply chain demand planning literature, by showing that the advice-taking motives of managers depend on the blame potential, nature, and perceived social competence of the advisors. Specifically, we highlight that managers make smaller adjustments to bad forecast recommendations to avoid future blame potential, and we introduce this as a novel blame-avoiding strategy. Prior blame avoidance literature (e.g., Artinger et al., 2019; Steffel et al., 2016) proposes that the potential responsibility attribution of advisors is the main relevant criterion for a blamable advisor (i.e., scapegoat) and implies that this is only applicable to humans. In this study, we demonstrate that managers prefer to share responsibility with blamable human advisors but also use blamable algorithmic decision aids if necessary, especially when algorithmic decision aids are perceived to be socially competent.

Second, we expand research on algorithm aversion. In line with prior research (e.g., Burton et al., 2020; Castelo et al., 2019; Lowens, 2020), we identify a task mismatch as the main reason for managers' aversion to sharing responsibility with algorithmic decision aids. We demonstrate that managers do not exhibit a general aversion to using unblamable advice from algorithmic decision aids in a forecasting setting when focusing on increasing decision accuracy. However, when focusing on sharing responsibility with blamable advisors, managers exhibit an aversion to blame algorithmic decision aids due to a perceived lack of social competence. Specifically, we propose that social competence is pivotal when individuals intuitively assess the blamability of nonhuman advisors.

Our study is also important for business practice. First, we explain how individual blame-avoiding behavior impacts forecast adjustments, which may lead to negative firm outcomes (e.g., managers intentionally making bad forecasts to pursue their own goals). Second, whether or not socially competent algorithmic decision aids have a positive or negative impact on managers' judgment depends on the advice quality. Specifically, we find that if algorithmic decision aids provide beneficial advice, then blaming the advisors should be financially beneficial to the company. However, if the nonhuman advisor provides bad advice, then a higher level of social competence of the algorithmic decision aid should increase the likelihood to not adjust bad forecasts that would be detrimental to the firms. This suggests that as socially competent algorithmic decision aids become increasingly common in business practice, understanding social collaboration between human and nonhuman colleagues gains importance. Hence, companies should be aware of possible human-nonhuman social interactions such as managerial blame-avoiding behavior when implementing algorithmic decision aids with a high level of perceived social competence (e.g., Bankins & Formosa, 2020).

We also acknowledge that our study, like all experiments, has some limitations. First, the experimental operationalization of the manager's threat is difficult to simulate in an experiment. The threat of writing a justification of 200 characters is not comparable to a threat in real life (e.g., losing personal reputation), though an approach similar to ours has been extensively used and rigorously tested by prior research on blame avoidance theory (e.g., Keil et al., 2007; Libby et al., 2004; Maske et al., 2021). Second, in business practice, managers usually do not know in advance whether their superiors consider their advisors blamable. Specifically, persisting low advice-quality as in our experimental setting might reduce advisor's blame potential over time or completely negate it as superiors become increasingly aware of the advisors' poor advice quality. This should in the long run lead to a replacement of the poor advisors and thus create new blame opportunities for managers. In contrast, superiors might also force managers to utilize algorithmic decision aids with a perceived lower level of social competence (i.e., company-wide imposed forecasting systems), resulting in perceived high blame potential. Third, simulating an AI advisor purely through a verbal description is challenging. Managers might react differently if a real AI interacted with them or had a physical presence. These factors might influence the perceptions of managers - especially regarding the AI's social competence. Fourth, in reality, managers can try to blame the individuals programming the algorithmic decision aid. However, we could not control for possible bilateral social connections between the managers and the human advisors. Consequently, individuals might also be hesitant to blame friendly colleagues. Fifth, in business practice, managers may generally prefer human advisors to algorithmic decision aids due to higher domain-specific knowledge.

Nonetheless, we focused on staying as close as possible to real-world managerial business practice and exclusively asked manager practitioners to participate. Making sales forecasts with judgmental adjustments, incorporating advice from human experts or algorithmic decision aids, and justifying forecasts are common tasks for managers (Arvan et al., 2019; Lawrence et al., 2006). Specifically, managers must often justify their decisions to others and are blamed and penalized when they are unable to credibly explain their decisions (Gangloff et al., 2014; Park et al., 2014). Additionally, our setting reflects reality because—due to information asymmetry—it is indubitably more difficult for superiors to determine the advice quality compared to the manager who works with the advisor. Hence, our setting speaks to many business situations in which the degree of managers' advice utilization depends on their expectation of their superiors' perception of advice quality.

We use the forecasting setting as a suitable decision-making context to analyze general managerial behavior when managers perceive personal threats in combination with blamable (non)human advice. However, our results should also be transferrable to other typical management decision scenarios, such as performance evaluation, capital investing, or budgeting. Future research should examine whether our findings also hold in other settings. Future research should also study the influence of the social competence of blamable algorithmic decision aids (i.e., human-likeness) on their use as blamable advisors (i.e., scapegoats) and what sub-skills of social competence drive their perceived blame-avoiding potential (e.g., the voice expressiveness of virtual assistants). Additionally, future studies should analyze whether advice quality influences the advisors' perceived blame potential depending on the advisors' nature. Moreover, it would be interesting to study whether varying levels of technological sophistication of AI advisors (e.g., "weak AI" or "strong AI") have higher levels of social competence and are perceived differently regarding their blame potential. Finally, research could analyze how the social ties between the manager and the (non)human scapegoat affect blame-avoiding behavior.

AUTHOR CONTRIBUTIONS

All authors contributed equally to the development of this article.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest to declare relating to this work.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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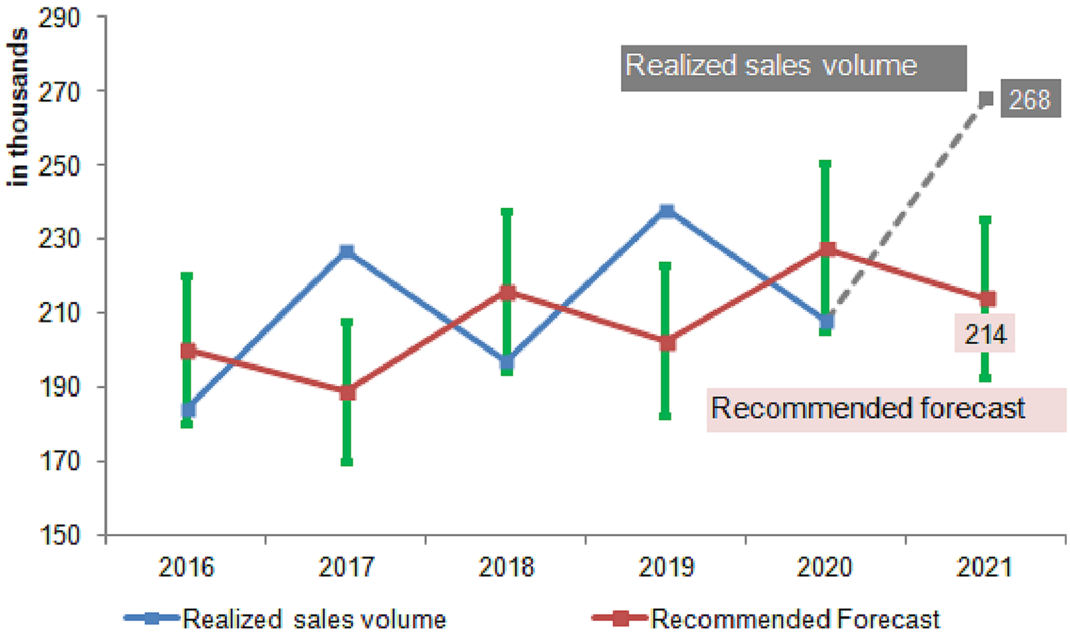
APPENDIX A: HISTORICALLY REALIZED AND FORECASTED SALES VOLUME WITH FORECAST FOR THE UPCOMING PERIOD

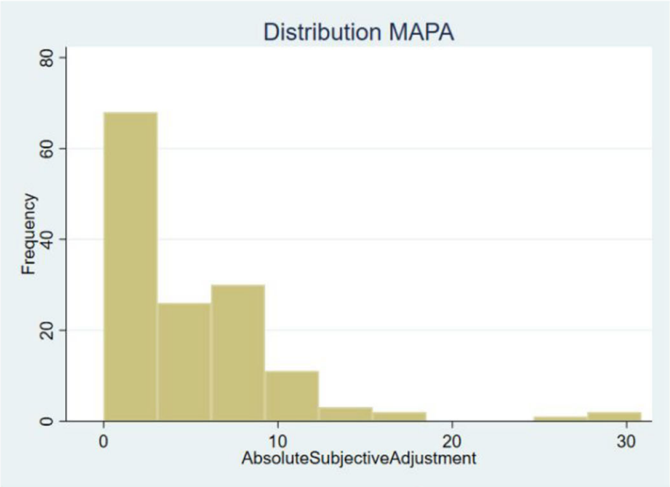


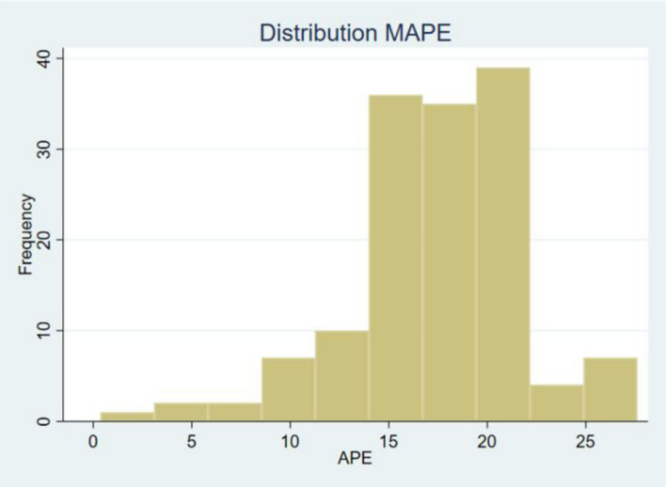
The participants were shown this figure, which shows the historically realized sales volumes (blue line) compared to the historically recommended forecasts by the advisor (red line). The acceptable forecast deviation is represented by the green bandwidth. Moreover, the recommended forecast for the upcoming period is shown. The gray dot represents the (future) realized sales volume, which was not shown to the participants before they made their final adjustment.

APPENDIX B: NEGATIVE ATTITUDE TOWARD ROBOTS SCALE BY Nomura et al. (2006)

Item	Questionnaire items by Nomura et al. (2006)	Subscale
1	I would feel uneasy if robots really had emotions.	S2
2	Something bad might happen if robots developed into living beings.	S2
3	I would feel relaxed talking with robots. (reverse-item)	S3
4	I would feel uneasy if I was given a job where I had to use robots.	S1
5	If robots had emotions, I would be able to make friends with them. (reverse-item)	S3
6	I feel comforted being with robots that have emotions. (reverse-item)	S3
7	The word “robot” means nothing to me.	S1
8	I would feel nervous operating a robot in front of other people.	S1
9	I would hate the idea that robots or artificial intelligence were making judgments about things.	S1
10	I would feel very nervous just standing in front of a robot.	S1
11	I feel that if I depend on robots too much, something bad might happen.	S2
12	I would feel paranoid talking with a robot.	S1
13	I am concerned that robots would be a bad influence on children.	S2
14	I feel that in the future, society will be dominated by robots.	S2

APPENDIX C: DISTRIBUTION GRAPHS OF *MAPA* AND *MAPE*





The distribution of *MAPA* is skewed to 0, as most participants only slightly adjusted the recommended forecast. Moreover, since *MAPA* is an absolute measure, there are only positive values for an upward or a downward forecast adjustment. However, there are also some outliers resulting from major forecast adjustments. *MAPE* is not perfectly normally distributed.