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Should service firms introduce algorithmic advice to their existing customers? The moderating effect of service relationships

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Abstract

An increasing number of service firms are introducing algorithmic advice to their customers. In this research, we examine the introduction of such tools from a relational perspective and show that the type of relationship a customer has with a service firm moderates his or her response to algorithmic advice. Studies 1 and 2 find that customers in communal relationships are more reluctant to use algorithmic advice instead of human advice than customers in exchange relationships. Study 3 shows that offering customers algorithmic advice may harm communal relationships but not exchange relationships. Building on these findings, Studies 4, 5, and 6 examine how firms can mitigate the potentially negative relational consequences of algorithmic advice. While a fallback option that signals that customers can request additional human advice if needed is effective in preventing relational damages in communal relationships, this same intervention backfires in exchange relationships. These findings have important implications by showing that managers need to consider the relational consequences of introducing algorithmic advice to existing customers.

Keywords: Algorithmic advice; Robo-advisor; Service relationships; Professional services.

With artificial intelligence (AI) rapidly progressing, algorithms are increasingly able to match or outperform human experts such as financial consultants, lawyers, or doctors (e.g., Esteva et al. 2017; Uhl and Rohner 2018). Based on this development, professional services firms that have traditionally relied on highly trained specialists to provide advice have started to introduce algorithmic advice (Logg, Minson, and Moore 2019; Sampson 2021). One of the most prominent examples are "robo-advisors" in the financial services industry which provide investment advice without any human intervention (Hildebrand and Bergner 2021). Similarly, law firms have started investing in advice systems for automated legal expertise (Armour and Sako 2020). In healthcare, algorithmic advice applications are employed to diagnose diseases and recommend personalized treatments (Longoni, Bonezzi, and Morewedge 2019).

While algorithmic advice is gaining in popularity, research investigating the effects of algorithmic advice has led to contradictory results. On the one hand, research has found that consumers oppose algorithmic advice, a decision bias referred to as algorithm aversion (e.g., Dietvorst, Simmons and Massey., 2015; Longoni et al. 2019); on the other hand, other studies have called algorithm aversion into question (Logg et al., 2019) or have argued that algorithm aversion only extends to specific tasks (Castelo, Bos, and Lehmann 2019). While these studies have increased our understanding of how customers evaluate algorithmic advice, they have not considered that such evaluations are typically formed on the basis of an existing relational context. That is, although firms may attempt to reach new customers through launching algorithmic advice, in most cases these tools will be targeted at a firm's existing customer base. Hence, customers' responses to algorithmic advice may be affected by the norms and expectations that define their relationship with a firm (van Doorn et al., 2017). For example, a customer who maintains a personal, friendly relationship with her bank may have a different

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expectation of what constitutes appropriate advice than a customer who has a more impersonal, transactional relationship. These differing expectations may affect customers' responses to algorithmic advice as well as their perceptions of the firm.

In this research, we address this gap in the literature and examine how existing customers respond to the first-time introduction of algorithmic advice. Drawing on social relationship theory (Clark and Mills 1979, 1993) and research on advice (e.g., Dalal and Bonaccio 2010; Taylor, Welch, Kim, and Sherman 2007), we argue that customers respond differently to algorithmic advice depending on whether they have a communal relationship with a firm characterized by mutual concern or an exchange relationship that follows a transactional logic. Specifically, we suggest that communal customers are more reluctant to use algorithmic advice than exchange customers and that offering algorithmic advice will harm communal relationships more strongly than exchange relationships. Moreover, we propose that providing an option to request human advice if needed (i.e., a fallback option) can mitigate the negative effect of algorithmic advice in communal relationships but may backfire in exchange relationships. Six studies that investigate algorithmic advice in domains such as banking, insurance, and education provide converging evidence for these predictions.

By examining the impact of algorithmic advice in different service relationships, this research makes several contributions to the literature. First, we extend current theorizing on algorithmic advice by showing that the responses of existing customers are shaped by the relationship they have with a firm. That is, we demonstrate that algorithm aversion is more pronounced in communal relationships but attenuated in exchange relationships, an effect that materializes even when costs for algorithmic advice are lower than costs for human advice. Second, we extend the literature by investigating the relational consequences of algorithmic advice. While previous studies have mostly focused on the adoption of algorithmic advice (e.g., Logg et al. 2019; Longoni et al. 2019), our research shows that the introduction of algorithmic advice may harm important relationship outcomes such as customer loyalty or relationship quality. Third, there has been little research on practical interventions that firms can use to mitigate resistance to algorithmic advice (Castelo et al., 2019). In this respect, we show that including a human fallback option may be a double-edged sword. While this intervention is effective in mitigating the negative effects in communal relationships, it may backfire in exchange relationships.

Conceptual development

Algorithmic advice

Algorithmic advice refers to the automation of advice-giving (Logg et al. 2019). Instead of interacting with human professionals, customers using algorithmic advice interact with AI expert systems such as financial "robo-advisors" or health apps. Such systems use algorithms, machine learning, statistical modeling, and language processing technologies to emulate cognitive and conversational functions of a human expert (e.g., Hildebrand and Bergner 2021; Longoni et al. 2019). Typically, algorithmic advice tools ask customers about their preferences and make personalized recommendations based on this information (e.g., developing an investment strategy, finding the right insurance coverage).

Previous research on the acceptance of algorithmic advice has led to contradictory results. On the one hand, scholars have argued that people prefer human advice over algorithmic advice. For example, Dietvorst, Simmons, and Massey (2015) found that people chose inferior human advice to predict student performance after seeing an algorithm err. In the medical domain, studies have shown that patients do not trust algorithmic advice (Promberger and Baron 2006) as they fear the algorithm would neglect their unique circumstances (Longoni et al. 2019). On the other hand, Logg et al. (2019) demonstrated that people preferred algorithmic advice for a wide range of forecasting domains. Similarly, Castelo et al. (2019) and Longoni and Cian (2022) showed that people opposed algorithmic advice only for tasks that are believed to require intuition or that are hedonic in nature.

While algorithmic advice can outperform human advisors in terms of providing effective recommendations, it is limited in terms of another dimension of advice: social support. Social support refers to information from others that makes one feel that one is cared for and part of a social network of mutual assistance and obligations (Wills, 1991). Extant research has shown that social support is an integral and natural part of human advice (e.g., Dalal and Bonaccio 2010; Goldsmith and Fitch 1997) and comprises a wide range of experiences such as emotional support, affirmation, esteem support, alliance, or companionship (see Bavik, Shaw, and Wang 2020 for an overview). Although algorithmic advice may imitate social support to a certain extent by, for example, providing verbal acknowledgments and affirmations (Hildebrand and Bergner 2021), such imitations may not be considered true social support as they originate from machines to which people do not ascribe emotion-related abilities (e.g., Castelo et al., 2019; Haslam, Kashima, Loughnan, Shi, and Suitner 2008; Longoni and Cian 2022).

Arguably, these findings imply that the extent to which customers accept algorithmic advice depends on the extent to which they consider social support to be an integral part of the advice experience. Building on this idea, the following sections will develop a conceptual model that argues that the extent to which customers feel apprehensive about algorithmic advice is affected by the specific relationship they have developed with their service firm. Our model will first focus on settings where customers can choose between human advice and algorithmic advice and will then discuss settings where customers do not have this choice and are required to use algorithmic advice following its introduction. Fig. 1 summarizes our conceptual model.

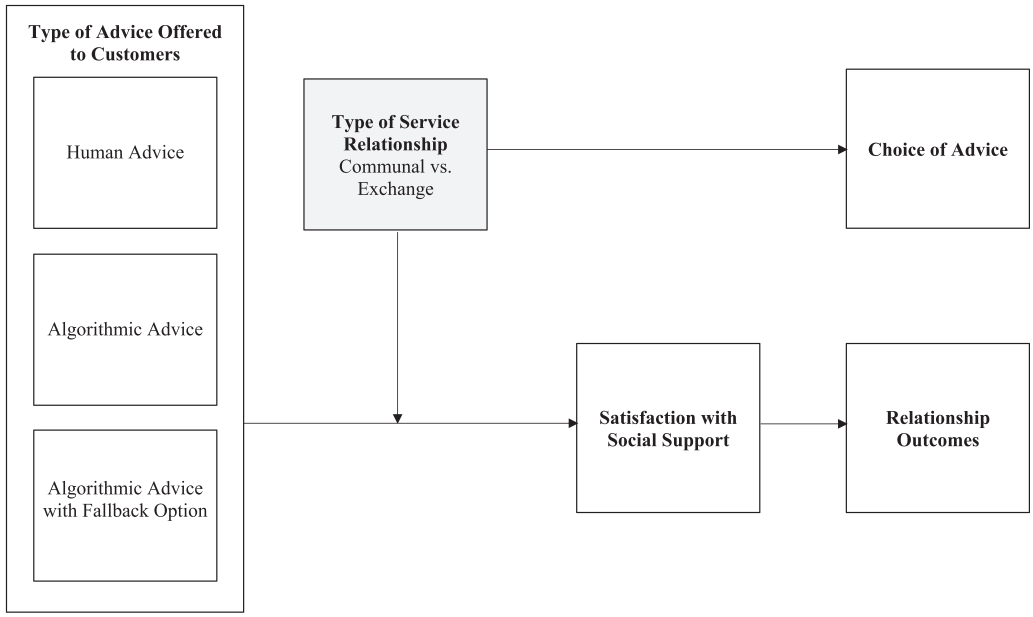

Fig. 1. Conceptual model.

The impact of different service relationships

One limitation of the current literature is that it has not considered that algorithmic advice is typically introduced into existing customer relationships. That is, in many cases the target audience of algorithmic advice will be a firm's existing customer base. This, in turn, implies that customers will not evaluate algorithmic advice against a "blank slate" but against the background of the norms and experiences that govern their relationship with the firm (van Doorn et al. 2017).

One of the most prominent distinctions of customer-firm relationships is the distinction between exchange and communal relationships (e.g., Aggarwal 2004; Wan, Hui, and Wyer 2011). According to social relationship theory (e.g., Clark and Mills, 1979 1993), exchange and communal relationships are governed by different norms that shape people's expectations of their relationship partners. In exchange relationships, partners follow a quid pro quo principle (Clark and Mills 1979). When a relationship partner gives a benefit to the other partner, she/he is expected to receive a comparable benefit in return. In contrast, in communal relationships, partners are expected to genuinely care about each other's welfare, to mutually support each other without prompt reciprocation, and to not seek maximization of their own interests (Clark and Mills 1979).

While service relationships (like all business relationships) are typically characterized by exchange norms, these relationships are often complemented by communal norms (e.g., Goodwin 1996; Rosenbaum 2009). For instance, in a relationship between a bank and a customer, exchange norms are salient because both partners are involved in commercial transactions. At the same time, however, many customers may perceive a certain level of communal norms as they have developed a friendly relationship with their bank. Importantly, research suggests that the extent to which customers perceive communal norms may vary considerably between customers (e.g., Aggarwal 2004; Wan et al. 2011). In other words, while both exchange and communal norms may be present within a single service relationship, one set of norms is typically dominant and determines the principal nature of the relationship.

In the following, we are interested in understanding how customers in communal and exchange relationships respond to algorithmic advice. We propose that communal customers—assuming they have a choice—are more reluctant to choose algorithmic advice over human advice than exchange customers. In communal relationships, individuals expect their relationship partners to show genuine concern and to provide social support (Goodwin 1996; Lemay, Clark, and Feeney 2007). Algorithmic advice tools, however, may not be able to deliver such support effectively. Although such tools may provide social cues (Hildebrand and Bergner 2021), customers may not perceive that they are part of a social network of mutual assistance and obligations to the same extent as when they receive human advice (Haslam et al. 2008). Hence, they should show a strong preference for human advice over algorithmic advice.

In contrast, in exchange relationships, relationship partners follow a transactional logic and do not expect the other side to care about their well-being to the same extent as in communal relationships (Aggarwal 2004; Clark and Mills 1979). When communal norms are not salient in the first place, a lack of social support may not be at odds with customers' expectations. In fact, one may argue that algorithmic advice is congruent with exchange norms as customers are first and foremost concerned about how much they receive and may focus more strongly on concrete benefits. Thus, exchange customers may be more receptive to algorithmic advice.

H1. Customers in communal relationships are less likely to choose algorithmic advice over human advice than customers in exchange relationships.

While H1 assumes that customers have a choice between human and algorithmic advice, service firms often push their customers towards algorithmic advice by, for example, coupling certain products with algorithmic advice or by restricting access to human advice. For instance, insurance companies have started offering certain types of products exclusively to customers who use algorithmic advice (e.g., MassMutual offering its easy and affordable life insurance products "Haven Term" and "Haven Simple" to online customers only). Similarly, many banks restrict access to human investment advice to customers who are able to invest large amounts of money, whereas "robo" investment advisors are available to almost anybody. Hence, customers will often have no alternative to using algorithmic advice, raising the question of how they will respond in such situations. Specifically, we are interested in understanding how offering algorithmic advice only affects relational outcomes such as relationship quality (Palmatier, Dant, Grewal, and Evans 2006) and customer loyalty (Zeithaml, Berry, and Parasuraman 1996).

In this respect, we propose that offering algorithmic advice will be more harmful to relationship outcomes in communal relationships than in exchange relationships. As described above, algorithmic advice may not elicit perceptions of social support to the same extent as human advice (Haslam et al. 2008). Importantly, as social support is a constitutive element of communal relationships, the lack of such support represents a disconfirmation of relational norms. Put differently, communal customers may feel that the introduction of algorithmic advice implies that their service provider does not provide the level of support they would have expected. Consequently, they may evaluate their relationship more negatively and may be less loyal compared to customers who have been offered human advice. In contrast, a lower level of social support may not result in dissatisfaction in exchange relationships as being responsive to each other's emotional needs is not a salient relationship norm (Aggarwal 2004; Clark and Mills 1979). Hence, algorithmic advice should not have the same negative effect on relationship outcomes such as relationship quality and loyalty. Summarizing,

H2. Offering algorithmic advice instead of human advice will have a more negative effect on relationship outcomes in communal relationships than in exchange relationships.

Next, the underlying process is investigated. As the preceding arguments suggest, algorithmic advice is limited in terms of social support. To understand how this may affect relational outcomes, it is important to distinguish between the (perceived) quantity of social support and the subjective satisfaction with that support (Bavik et al. 2020). As such, satisfaction reflects the extent to which the quantity of support one has received matches one's desired or needed level (Doeglas et al. 1996). Of note, this sense of satisfaction may be particularly relevant in the current context. Specifically, after the introduction of algorithmic advice, communal customers may experience dissatisfaction with the amount of social support (or lack thereof) they receive from their service provider. This feeling, in turn, will have an adverse impact on downstream relationship variables. In contrast, exchange customers may not feel dissatisfied with the lack of social support as social support is not important to their relationship. Hence, the lesser amount of social support will not have a negative impact on their relational outcomes.

H3. The interactive effect of advice and relationship type will be mediated by satisfaction with social support. Specifically, relationship type (communal, exchange) will moderate the effect of advice (human, algorithmic) on satisfaction with social support, and satisfaction, in turn, will shape relationship outcomes.

Human fallback options as an intervention

If algorithmic advice adversely affects relational outcomes for communal customers, it seems important to explore approaches for making algorithmic advice more attractive. In this regard, one potentially effective strategy is to include a human fallback option when offering algorithmic advice. Service providers relying on this approach typically give their customers the option to ask for additional human guidance when interacting with algorithmic advice. For example, customers of the robo-advisor of Fidelity have access to additional financial coaching when they feel they need it. Hence, human advice is available to customers upon request but is not part of the standard advice process.

This approach may be an effective intervention to overcome algorithm aversion in communal relationships. As described earlier, customers may expect communal relationship partners to take care of each other by providing social support (Clark and Mills 1979; Goodwin 1996). Although customers who are offered a human fallback option may not make use of this option, they may nevertheless perceive that the firm is providing genuine social support. In this regard, research has found that merely knowing about the availability of communal relationship partners can make people believe that they have access to social support (Taylor et al. 2007). For example, simply telling people to think about a communal relationship partner (e.g., friends, family, one's team) can suffice to trigger perceptions of social support (e.g., Jiang, Drolet, and Kim 2018; Taylor et al. 2007). Hence, signaling to customers that human advice is there if needed may activate the feeling that social support is available. As a result, communal customers who are offered a human fallback option may evaluate the relationship with the firm more positively than communal customers who receive algorithmic advice without this option. Thus,

H4. In communal relationships, customers who receive algorithmic advice will evaluate their service relationship more positively when they are also offered a human fallback option relative to when they receive algorithmic advice only.

However, offering a fallback option may not have the same effect in exchange relationships. In fact, this intervention may backfire when a relationship is governed by exchange norms. Partners in exchange relationships follow a transactional, tit-for-tat logic that keeps track of each partner's inputs and outputs (Aggarwal 2004; Clark and Mills 1979). Specifically, people do not evaluate inputs and outputs separately but compute the net of total inputs and outputs (Aggarwal and Zhang 2006). When one partner feels that she/he receives less than expected, she/he may feel that she/he should also invest less in the relationship to maintain a balance. In contrast, when one partner feels that she/he gets more than expected, she/he may feel obligated to give more. Both patterns can be associated with negative feelings as one partner either feels deprived or indebted to the other partner (Aggarwal 2004; Buunk, Doosje, Jans, and Hopstaken 1993).

Against this background, we argue that offering a human fallback option may be regarded as a form of unsolicited social support by exchange customers, leading to an imbalance between inputs and outputs. That is, because they are offered additional support that goes beyond the standard advice solution, exchange customers may feel that they will need to increase their own input to maintain reciprocity in the relationship. As a result, they may not be satisfied with the amount of support they receive and may evaluate the relationship with their service provider more negatively when offered algorithmic advice with an additional human fallback option compared to when they receive algorithmic advice only. Thus,

H5. In exchange relationships, customers who receive algorithmic advice will evaluate their service relationship more negatively when they are also offered a human fallback option relative to when they receive algorithmic advice only.

Finally, the arguments laid out above suggest that satisfaction with social support will mediate the interactive effect of relationship type and advice type. That is, communal (exchange) customers will be more satisfied with the level of social support when they receive algorithmic advice with (without) a human fallback option, and this sense of satisfaction will subsequently shape their evaluations of the relationship with the service provider. Hence,

H6. The interactive effect of algorithmic advice and relationship type will be mediated by satisfaction with social support. Specifically, relationship type (communal, exchange) will moderate the effect of algorithmic advice (with, without fallback option) on satisfaction with social support, and satisfaction, in turn, will shape relationship outcomes.

Study 1

Design, procedure, and participants

The aim of Study 1 was to test H1. Seventy-one respondents (52.1% male, average age: 37.4 years) recruited through Amazon MTurk participated in the study. As Study 1 focused on real service relationships, participants were first asked to indicate the name of their main bank. Based on this information, we assessed their relationship type with their bank and several control measures. In the next part of the study, participants were told that their bank had started offering financial advice related to retirement planning and were asked to read a short description of a corresponding advice process (see Web Appendix). After reading the description, participants were asked to imagine that they were interested in a retirement plan and told that their bank offered a human advice option and an algorithmic advice option. Participants were then asked to indicate which option they would choose. To avoid any confounding effects, participants were also informed that, in the past, retirement plans from human financial advisors and digital financial advisors had been equally successful.

Measurement

Independent variable. To measure participants' relationship with their bank, we adapted six communal items (α = .76) and six exchange items (α = .83) from Clark and Aragón (2013). As suggested by previous research (Aggarwal 2004; Scott, Mende, and Bolton 2013), we formed a relationship index by averaging the communal and the reverse-coded exchange items. Hence, a higher value is indicative of a communal relationship, whereas a lower value reflects an exchange relationship. Unless stated otherwise, all items of this study and the other studies used 7-point scales labeled *strongly disagree (1)* and *strongly agree (7).*

Dependent variable. The choice measure served as the dependent variable (0 = personal advice, 1 = algorithmic advice).

Control variables. As our study focused on real service relationships, we controlled for participants' satisfaction with their bank's service quality and fees prior to their exposure to the stimulus materials (endpoints: *very dissatisfied = 1, very satisfied = 7*). Moreover, we asked participants how long they had been a customer of the bank and whether they had a permanently assigned personal advisor. At the end of the study, we also measured participants' performance expectancy of the type of advice they had selected with an item adapted from Venkatesh, Thong, and Xu (2012) ("Using this service would help me to plan my retirement more successfully") as well as demographic characteristics such as age, gender, and income.

Analyses and results

Control variable. None of the control variables emerged as a significant covariate. Thus, they were excluded from the analyses.

Hypothesis testing. We predicted choice of advice by using a logistic regression with service relationship as an independent variable. We found a marginally significant effect of service relationship (Wald $\chi^2(1) = 3.52$, $p = .06$). Following the recommendations of Osborne (2015), we z-standardized the independent variable and calculated predicted probabilities of adoption of algorithmic advice for participants in a communal relationship (+1 *SD*) and in an exchange relationship (−1 *SD*). As expected, communal customers were less likely to choose algorithmic advice (61.0%) than exchange customers (83.9%). These results support H1.

Discussion

Study 1 provides initial evidence that customers in communal relationships are more reluctant to choose algorithmic advice than customers in exchange relationships—despite the fact that they had been told that algorithmic advice tools were as effective in generating retirement plans as human advisors. However, to isolate the effects of different advice types, the descriptions in Study 1 did not refer to the costs associated with developing a retirement plan nor to any potential cost differences between human and algorithmic advice. Hence, communal participants may have felt they had little to lose by choosing the human advice option. In reality, however, algorithmic advice tools are frequently priced lower than human advice to provide customers with an incentive to make use of these tools. In Study 2, we wanted to test the robustness of the results revealed in Study 1 by testing if communal customers will still show a preference for human advice even when this option is associated with higher costs.

Study 2

Design, procedure, and participants

In Study 2, we aimed to test if the preference of communal customers for human advice would persist even when this kind of advice was costlier. We selected a different advice context, namely insurance advice. A total of 159 Amazon MTurk respondents participated in the study (58.5% male, average age: 44.3 years). Participants first indicated the name of their main insurance provider and were asked to assess the nature of their relationship. Next, they were informed that their main insurance provider offered advice on finding the right disability insurance and read a short description of the corresponding advice process (see Web Appendix). Participants were asked to imagine that they were interested in disability insurance and that their insurance provider offered a human advice option and an algorithmic advice option to find the right coverage. Importantly, half of the participants were told that the average annual price for a disability insurance was 2.0% of their annual salary when they used algorithmic advice but 2.2% of their annual salary when they used advice from a human insurance agent. In contrast, the other half of the participants were told that the average annual price was 2.2% of their annual salary regardless of type of advice. Participants then indicated which option they would choose.

Measurement

Independent variable. To measure type of relationship, we used the same scale as in Study 1 and formed a relationship index by averaging the communal items ($\alpha = .87$) and the reverse-coded exchange items ($\alpha = .91$).

Dependent measure. The choice measure served as the dependent variable (0 = personal advice, 1 = algorithmic advice).

Control variables. We used the same control variable as in Study 1 and adapted them to an insurance context.

Analyses and results

Control variables. Again, the control variables did not have a significant impact and were excluded from the analyses.

Hypothesis testing. We mean-centered the relationship score and estimated a model that predicted choice of advice by relationship, price, and the interaction between these variables. Again, relationship had a significant impact (Wald $\chi^2(1) = 13.17$, $p < .001$). However, the effects of price (Wald $\chi^2(1) = 1.22$, $p = .27$) and the relationship × price interaction (Wald $\chi^2(1) = .08$, $p = .77$) were not significant. Next, we z-standardized the independent variables and calculated predicted probabilities of adoption of algorithmic advice for participants across the two price conditions. In both conditions, customers with a communal relationship (+ 1 *SD*) were less likely to choose algorithmic advice (same price: 48.8%, lower price: 62.5%) than customers that had an exchange relationship (- 1 *SD*; same price: 85.2%, lower price: 88.6%).

Discussion

Study 2 provides renewed support for H1, showing that communal customers are less likely to choose algorithmic advice even when human advice is the costlier option. In the following studies, we will focus on settings where customers cannot choose between different types of advice and are only offered algorithmic advice by their service providers.

Study 3

Design, procedure, and participants

The aim of Study 3 was to test H2 and H3. A total of 171 participants (52.0% male, average age: 38.4 years) were recruited through Amazon MTurk. Similar to Study 1, we focused on pension planning. In the first part of the study, participants indicated the name of their main bank and rated their relationship with this bank. Next, they were asked to imagine that they wanted to develop a retirement plan and were offered a new service called RetirementPlus (see Web Appendix). They were informed that all customers interested in developing a retirement plan *had* to use this service and read a fictitious description of the service from the bank's website. In half of the conditions, the service was described as an algorithmic advice service, whereas in the other half the service was described as a human advice service. That is, participants were either informed that all steps of the advice process were carried out by a digital advisor or by a human client advisor. Finally, participants responded to the dependent measures.

Measurement

Independent variable. We used the same relationship scale as in the previous studies and formed a relationship index by averaging the communal items ($\alpha = .83$) and the reverse-coded exchange items ($\alpha = .85$).

Dependent measures. In this study, we wanted to examine how algorithmic advice affects relational outcomes. As customer loyalty is regarded as one of the most important relationship outcomes (Palmatier et al. 2006), we used the six-item customer loyalty scale from Homburg, Müller, and Klarmann (2011) as a dependent measure ($\alpha = .89$). This scale is based on Zeithaml, Berry, and Parasuraman (1996) definition of customer loyalty and includes items referring to customers' intentions to repurchase, to increase share of wallet, and to spread word of mouth. In addition, we assessed participants' switching intentions by asking them to rate the probability that they would go to another bank (three-item scale from Bansal and Taylor 1999; $\alpha = .70$).

Process measure. To investigate the underlying process, we measured satisfaction with social support. To this end, we adapted the five-item measure of daily emotional support from Doeglas et al. (1996) social support questionnaire ($\alpha = .81$). That is, we asked participants if they expected to receive as much social support as they would need when using this type of advice (e.g., "Do you expect your bank to demonstrate as much of the following behaviors as you like when using this type of advice?", "Sympathizing with me", "Lending me a friendly ear", etc.). Endpoints were labeled *much less than I like (1)* and *more than I like (7)*.

Control variables. We measured the same control variables as in Study 1.

Analyses and results

Control variables. Contrary to Studies 1 and 2, satisfaction with the bank's service quality and fees as well as performance expectancy emerged as significant covariates for both dependent variables ($p < .03$). From a theoretical perspective, it stands to reason that customers consider these aspects when evaluating their overall relationship with a service firm. Thus, we included these variables in the analyses.

Hypothesis testing. To test H2, we conducted OLS regression analyses. We mean-centered the relationship score and included it as a continuous predictor variable in our model. We also included advice (human advice = −1, algorithmic advice = 1), the interaction between advice and relationship, and the control variables in our model. We regressed customer loyalty and switching intentions on these variables (see Table 1). This analysis revealed a significant effect of the advice × relationship interaction (customer loyalty: $b = -.40$, $t(164) = -2.66$, $p < .01$; switching intentions: $b = -.38$, $t(164) = -2.73$, $p < .01$). To explore this interaction in more detail, we performed floodlight analyses using the Johnson-Neyman technique (Spiller, Fitzsimons, Lynch, and Mcclelland 2013). This analysis showed a significant negative effect of advice on loyalty for any participant whose mean-centered relationship score was greater than .05 ($b_{JN} = -.08$, SE = .04, $p = .05$) and on switching intentions for any participant whose mean-centered relationship score was greater than .09 ($b_{JN} = -.08$, SE = .04, $p = .05$), that is, for those participants that had a more communal relationship with their bank.[1] The Johnson-Neyman region of significance is indicated by the gray area in Fig. 2. These results provide support for H2.

Process analysis. To examine if satisfaction with social support mediated the link between advice, relationship type, and the dependent variables, we ran a mediation analysis with the above-mentioned variables and the control variables as covariates (Hayes 2018; model 8). Using the bootstrapping method (5000 resamples), we compared the impact of advice via satisfaction with social support on loyalty and switching intentions when a customer had a communal relationship (i.e., one standard deviation above the mean) and an exchange relationship (i.e., one standard deviation below the mean). In line with our theoretical reasoning, this analysis revealed a significant indirect effect of advice on the dependent variables via satisfaction with social support for customers in a communal relationship (customer loyalty: −.04, 95% CI = −.0761, −.0033; switching intentions: −.05, 95% CI = −.0966, −.0145) but not for customers in an exchange relationship (customer loyalty: .02, 95% CI = −.0030, .0604; switching intentions: .03, 95% CI = −.0043, .0792). The confidence interval for the index of moderated mediation did not include zero (customer loyalty: −.11, 95% CI = −.2404, −.0128; switching intentions: −.17, 95% CI = −.3109, −.0470), indicating that the mediation is moderated.

Discussion

Study 3 provides support for our notion that the introduction of algorithmic advice has a more harmful effect on relational outcomes in communal than in exchange relationships. Study 3 also provides insights into the underlying process and the role of social support. That is, unlike customers in exchange relationships, customers in communal relationships feel that they do not receive sufficient social support

[1] The analyses also revealed significant positive effects of advice for customers with relationship scores below −.71 and −.53 (loyalty: $b_{JN} = .22$, SE = .11, p = .05; switching intentions: $b_{JN} = .16$, SE = .08, p = .05). That is, customers high in exchange orientation responded more *positively* to algorithmic advice than human advice. Although not formally hypothesized, these results align with our arguments that exchange-oriented customers may prefer advice tools that are not associated with (perceived) social obligations. At the same time, it is important to note that this effect was not very strong as only .6% and 3.5% of participants had relationship scores below these points.

Table 1
Study 3: Regression results for customer loyalty and switching intentions.

	Customer loyalty			Switching intentions		
	b	*t*	*p*	*b*	*t*	*p*
(Constant)	5.40	140.97	.00	6.11	170.06	.00
Advice	−.06	−1.53	.13	−.04	−1.10	.27
Service relationship	.07	.47	.64	−.29	−2.04	.04
Advice × service relationship	−.40	−2.66	.01	−.38	−2.73	.01
Satisfaction with fees	.21	4.29	.00	.10	2.23	.03
Satisfaction with service quality	.32	6.45	.00	.23	4.92	.00
Performance expectancy	.27	5.24	.00	.21	4.28	.00
R^2	.67			.51		

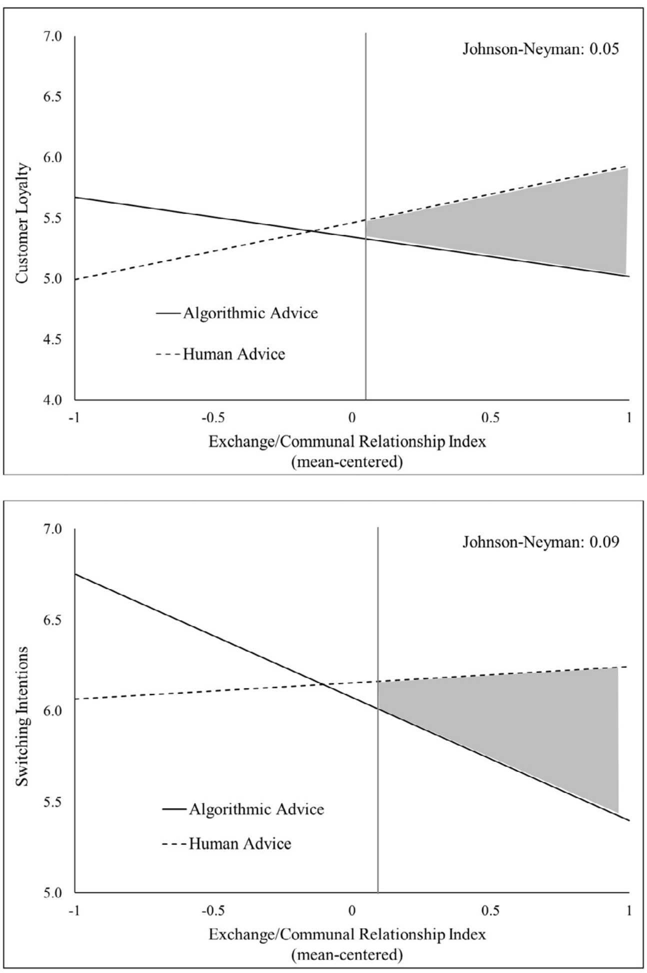

Fig. 2. Study 3: Relationship type moderates the effect of advice on loyalty and switching intentions.

when they have been offered algorithmic advice and therefore question their relationship more strongly. As firms often prefer their customers to use algorithmic advice instead of human advice, the following studies will investigate how firms can alleviate the potentially negative effects of offering only algorithmic advice to existing customers.

Study 4

Design, procedure, and participants

The aim of Study 4 was to test H4, H5, and H6 and to examine the impact of providing a human fallback option. Similar to Studies 1 and 3, we focused on pension planning. However, in this study, we manipulated type of relationship rather than measuring it. We used a two-stage 2 × 2 between-subjects design and assigned participants randomly to different relationship conditions (i.e., communal and exchange) and different algorithmic advice conditions (i.e., with and without a human fallback option). A total of 156 consumers recruited through the panel of Prolific participated in the study (52.6% male, average age: 37.7 years).

The study consisted of two parts conducted at different points in time. In the first part, participants experienced different customer touchpoints of an allegedly newly established bank called Investera (see Web Appendix for all stimulus materials). First, they were asked to browse the main screen of the bank's website. Next, they read a customer testimonial published on the company's website and watched a social media video from another customer who talked about the bank's services. Finally, they were asked to read two online reviews that included a star rating. Importantly, all stimuli featured either communal norms (i.e., mutual care and concern) or exchange norms (i.e., keeping track of each other's inputs and outputs). We considered these stimuli as a realistic way to manipulate relational orientations as companies will rely on very similar touchpoints to build service relationships. At the end of the first part, participants responded to a relationship measure that served as a manipulation check.

One day after completing the first part, participants were contacted again and had a one-week window for completing the second part of the study (average time period between first and second part: 1.4 days). In the second part, participants first experienced two of the previous touchpoints (website, testimonial) again to confirm their relationship type. Following this, they were exposed to the advice manipulation. Participants were informed that Investera had launched a new algorithmic advice service that all customers interested in pension planning should use. Next, they were asked to read a description of the new service on the bank's website which was similar to the description of algorithmic advice in Study 3. Hence, participants responded to the algorithmic advice manipulation based on their previously formed relationship type. In the condition *with* a human fallback option, participants were told that they could request additional advice from a human advisor when interacting with the algorithmic advice tool. Therefore, the website included a setting that allowed customers to contact a human advisor. In the condition *without* a human fallback option, participants were told that they would receive algorithmic advice only. Hence, the website did not include an additional setting. After reviewing the advice description, participants responded to the dependent measures.

Measurement

Dependent measure. Building on the results of Study 3, this study sought to address the impact of algorithmic advice on relationship quality, that is, the *overall strength* of participants' relationship with their bank. To effectively capture the strength of a service relationship, one must not only assess customers' *satisfaction* with the relationship but also their *trust* in the relationship partner as well as their *commitment* to continue the relationship (e.g., De Wulf, Odekerken-Schroeder, and Iacobucci 2001; Palmatier et al., 2006). Hence, to measure relationship quality, we drew on a nine-item scale from Mende, Bolton, and Bitner (2013) that conceptualizes relationship quality as a higher-order construct consisting of satisfaction, trust, and commitment. As recommended by the authors, the items were merged into a single construct ($\alpha = .97$, see Appendix).

Process measure. We measured satisfaction with social support with the same scale as in Study 3 ($\alpha = .94$).

Manipulation check. To confirm that the relationship manipulation was successful, we asked participants to characterize the nature of their relationship using the relationship scale from the previous studies. Again, we formed a relationship index by averaging the communal items ($\alpha = .88$) and the reverse-coded exchange items ($\alpha = .89$).

Control variable. Similar to the previous studies, we included performance expectancy and demographic characteristics as controls. As we focused on a newly developed relationship, previous satisfaction with service quality, previous satisfaction with fees, and previous access to a client advisor were not included.

Analyses and results

Manipulation check. Participants in the communal conditions believed more strongly that their relationship with the bank was shaped by communal norms than participants in the exchange conditions ($M_{\text{communal}} = 4.47$, $M_{\text{exchange}} = 3.40$, $F(1, 154) = 57.60$, $p < .001$).

Control variables. As in the previous study, performance expectancy emerged as a significant covariate ($p < .001$). Hence, this variable was included in the analyses.

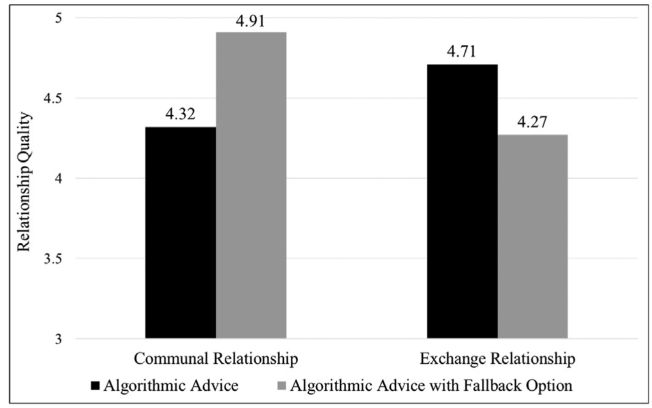

Fig. 3. Study 4: Relationship type moderates the effect of advice on relationship quality.

Hypotheses testing. An ANCOVA revealed insignificant effects for advice ($F(1, 151) = .26$, $p = .61$) and relationship ($F(1, 151) = .66$, $p = .42$). Importantly, the interaction between advice and relationship was significant ($F(1, 151) = 11.50$, $p < .01$). As Fig. 3 shows, participants in the communal condition experienced a higher relationship quality when learning that algorithmic advice included a human fallback option ($M_{\text{without\_human\_fallback}} = 4.32$, $M_{\text{with\_human\_fallback}} = 4.91$, $F(1, 151) = 7.05$, $p = .01$). In contrast, participants in the exchange condition responded less favorably to algorithmic advice with a human fallback option than to algorithmic advice without a human fallback option ($M_{\text{without\_human\_fallback}} = 4.71$, $M_{\text{with\_human\_fallback}} = 4.27$, $F(1, 151) = 4.43$, $p = .04$). These results support H4 and H5.

Process analysis. We ran a mediation analysis with the independent variables, their interaction, performance expectancy, and satisfaction with social support as mediator (Hayes 2018; model 8). We coded algorithmic advice as −1 when no human fallback option was offered and as 1 when a human fallback option was offered. Using the bootstrapping method (5000 resamples), this analysis revealed a significant indirect, positive effect of algorithmic advice on relationship quality via satisfaction with social support when participants had a communal relationship (.12, 95% CI = .0016, .2384). In contrast, there was a significant indirect, negative effect of algorithmic advice on relationship quality via satisfaction when participants had an exchange relationship (−.12, 95% CI = −.2514, −.0026). The confidence interval for the index of moderated mediation did not include zero (.2348, 95% CI = .0714, .4178), indicating that the mediation is moderated. These findings provide support for H6.

Discussion

Study 4 finds that offering algorithmic advice with a human fallback option may be an effective measure to avoid negative responses to algorithmic advice in communal relationships. Customers in communal relationships who received algorithmic advice with an additional human fallback option demonstrated a higher level of relationship quality than customers who received algorithmic advice without this option. As expected, a different pattern of results emerged for customers in an exchange relationship. In these cases, relationship quality was lower when algorithmic advice was coupled with an additional human advice option.

One limitation of Study 4, however, is that participants evaluated a description of an algorithmic advice tool. Hence, participants did not actually experience algorithmic advice and had to imagine how this would affect their relationship with the bank. In Studies 5 and 6, we sought to address this limitation by designing a setting where participants *actually* received algorithmic advice in response to a real decision problem and by examining how this affected their relationship with the organization providing the advice.

Study 5

Design, procedure, and participants

The aim of Study 5 was to replicate H4 and H5 in a different advice domain, namely, student counseling. Student counseling is provided by universities and ranges from psychological counseling over financing advice to academic guidance. In our research, we focused on academic advice about thesis writing. In general, research has found that writing a thesis is a very challenging task for students associated with high levels of (human) advice (e.g., Ylijoki 2001). Hence, we considered thesis advice as a suitable context for our research. A total of 120 business students (60.0% male, average age: 22.9 years) who had not started their thesis at the time of the study were recruited through the subject pool of a large German university. As in Study 4, participants were randomly assigned to a condition *without* a human fallback option or to a condition *with* a fallback option.

In the first part of the study, participants were asked to characterize their relationship with the university. Next, they were told that the university had developed a new digital tool to provide advice on finding the right type of thesis and that they had been selected to test the tool before its official launch. Specifically, participants were informed that the tool would ask them to self-assess a range of abilities that were relevant for writing different kinds of theses and that this self-assessment would be used to derive a recommendation on the kind of thesis that was best suited to their abilities. Moreover, they were told that the analysis and recommendation process were completely automated and that the recommendation would be sent to their email address once the analysis had been completed.

After receiving this information, students were directed to the algorithmic advice system and started the self-assessment. The self-assessment consisted of several item batteries derived from the literature to measure different kinds of abilities such as creativity, statistical skills, analytical thinking, practical intelligence, and communicative skills. In addition, participants were asked to read short descriptions of five types of "thesis writers" (e.g., "Qualitative thesis: I am very empathetic, have good listening skills, and can respond to the feelings and moods of other people. I am a diligent worker and can handle extensive tasks") and to rank these descriptions according to the extent to which they matched their abilities.

Once participants had completed this self-assessment, they were told that they would receive an email with their personalized recommendation within 24 hours (see Web Appendix for an example). Specifically, participants' scores were matched against five different types of theses (i.e., conceptual thesis, qualitative thesis, quantitative thesis, experimental thesis, applied thesis). These types reflect the range of theses that business students at the university in question can typically choose from and require different kinds of skills (e.g., a quantitative thesis requires strong statistical skills, whereas an experimental thesis requires strong creative and analytical skills). Each participant received a recommendation that focused on the thesis type that best matched her or his specific skills. The recommendation did not only include a detailed description of the best-suited thesis type but also featured three specific tips on the challenges that students typically faced when writing this type of thesis and how best to overcome these challenges. Importantly, all participants were told that the recommendations had been derived automatically by a matching algorithm.[2]

The key manipulation focused on the extent of human support linked with the automated thesis advice. As the recommendations were sent directly to participants' email addresses, all recommendations included an introductory and a closing statement by a (fictitious) student advisor. In addition, half of the participants were offered a human fallback option ("If you want to discuss your recommendation, you can contact me at any time"), whereas the other half did not receive this offer. Participants were instructed to read their recommendations thoroughly. Finally, they were instructed to take part in a survey about the new algorithmic advice tool. Participants responded to the dependent measures and were thoroughly debriefed.

Measurement

Independent variable. We used the same items as in previous studies to measure type of relationship and formed a relationship index (communal items: $\alpha = .67$, exchange items: $\alpha = .65$).[3]

Dependent measure. As in the previous study, we relied on relationship quality as a dependent variable and measured it with the same nine-item scale ($\alpha = .93$).

Control variables. We adapted the control variables from Study 1 to a university context except for the client advisor variable which did not apply to this context. For example, we asked students to indicate their general satisfaction with the lectures and the support of faculty members (endpoints:

[2] In fact, the matching was done manually by the researchers as this could be achieved more efficiently than developing, training, and implementing a matching algorithm.

[3] One item exhibited low reliability (i.e., the sixth exchange item in the Appendix). Note that the results would be similar if this item was excluded.

Table 2
Study 5: Regression results for relationship quality.

	Relationship quality		
	b	*t*	*p*
(Constant)	4.84	59.17	.00
Advice	−.01	−.16	.87
Service relationship	.21	1.38	.17
Advice × service relationship	.40	2.73	.01
Satisfaction with lectures and faculty	.22	3.95	.00
Performance expectancy	.27	4.10	.00
R^2	.35		

very dissatisfied = 1, *very satisfied* = 7). Finally, we asked participants to evaluate the perceived quality of the recommendation to rule out a competing explanation for our effects ("How do evaluate your recommendation?" *very negative (1) – very positive (7)*). As such, participants that evaluate their recommendation more (less) positively may also feel more (less) attached to the entity providing the recommendation—irrespective of whether they can contact a human advisor or not.

Analyses and results

Control variables. Performance expectancy and satisfaction with the lectures and support of faculty members emerged as significant covariates and were included in the analyses ($p < .05$). Importantly, the recommendations were generally considered very positively ($M = 5.54$ on a 7-point scale), and these evaluations did not differ between the two experimental conditions ($M_{\text{with_}}$human_fallback = 5.57, $M_{\text{without_}}$human_fallback = 5.52, $F(1, 119) < 1$).

Hypotheses testing. Similar to Study 3, we conducted OLS regressions and included algorithmic advice (without human fallback option = −1, with human fallback option = 1), the mean-centered relationship index, and the interaction between these variables in our model (see Table 2). There was a significant effect of the interaction between advice and relationship ($b = .40$, $t(114) = 2.73$, $p < .01$). Floodlight analyses revealed a significant positive effect for participants whose mean-centered relationship score was greater than .67 ($b_{JN} = .26$, SE = .13, $p = .05$). An opposite pattern was found for subjects whose relationship score was lower than −.55 ($b_{JN} = −.24$, SE = .12, $p = .05$). That is, participants who had a more communal relationship with the university responded more positively to the human fallback option, while participants who had a more exchange-oriented relationship responded more negatively to this intervention. In sum, these findings provide further support for H4 and H5.

Discussion

Study 5 replicated the findings of Study 4 in a setting where participants received algorithmic advice for a real and complex decision they were facing (i.e., writing a thesis). In line with the results of Study 4, signaling that additional human guidance was potentially available enhanced relationship quality for communal participants, but decreased it for exchange participants. Importantly, all participants considered the advice generated by the algorithm as very helpful and this judgment did not differ across the experimental conditions. Hence, the finding that participants with different relationships responded differently to the advice tool cannot be attributed to the advice as such but to the specific operational setting through which this advice was delivered.

However, there may also be another, competing explanation for our findings. That is, including a human fallback option may also have signaled that more information is potentially available.[4] Put differently, customers may feel that a human advisor may provide information that algorithmic advice cannot provide. From this perspective, communal customers may welcome an advice tool combined with a fallback option as they may not only welcome the human layer but also the additional information potentially provided by the human advisor. On the other hand, exchange customers may react negatively to an algorithmic advice tool paired with a human layer as they may feel that the tool is not adequate in itself and that they will still have to contend with a human advisor if they do not want to forego potentially relevant information. Thus, communal and exchange customers may react differently to advice tools that feature a fallback option because this configuration potentially provides access to more information and not because it provides social support. In Study 6, we wanted to rule out this alternative explanation.

Study 6

Design, procedure, and participants

One hundred ninety-one business students (56.0% male, average age: 23.9 years) from the subject pool of the same university as in Study 5 participated in the study. All students had not yet started their thesis at the time of the study. The procedure of Study 6 was identical to Study 5, with participants receiving a personalized thesis recommendation based on their self-assessed strengths and interests. Unlike Study 5, however, Study 6 featured three different advice conditions. In the first condition, participants only received their recommendation. This condition was identical to the "algorithmic advice only" condition of Study 5. In the second condition, participants received their recommendation and were offered a human fallback option that provided *no* additional information (i.e., the advice tool emphasized that students could reach out to a thesis advisor if they had questions but that the advisor could not provide more information than that contained in the automated feedback). In the third condition, participants received their recommendation and were offered a human fallback option that provided potentially new information (i.e., the advice tool emphasized that the thesis advisor may help students interpret the recommendation provided by the algorithm more thoroughly).

[4] We thank the associate editor and an anonymous reviewer for this suggestion.

We reasoned that the latter conditions would allow us to tease apart the two competing explanations. If communal (exchange) customers embrace (reject) an algorithmic advice tool with a human fallback option because this configuration provides (unsolicited) social support, then we would not expect to observe significant differences across the two fallback conditions. That is, because both the "no new information" and the "new information" condition provide the same level of social support, they should be evaluated more (less) favorably than the "algorithmic advice only" condition by communal (exchange) customers. If, however, communal and exchange customers respond differently to advice tools featuring a human fallback option because this kind of setting potentially provides access to more information, then we would expect the two fallback conditions to perform differently. As the "new information" condition may be considered superior in terms of informational value, it should be evaluated more (less) positively by communal (exchange) customers compared to the "algorithmic advice only" condition. On the other hand, the "no new information" condition does not provide any additional informational value. Hence, there should not be any significant differences compared to the "algorithmic advice only" condition for both communal and exchange customers. In sum, specific patterns of effects related to the two fallback conditions will render either of the two accounts (social support vs. informational value) more or less likely.

Measurement

Independent variable. We used the same items as in Study 5 to measure type of relationship and formed a relationship index (communal items: $\alpha = .73$, exchange items: $\alpha = .65$).

Dependent measures. Relationship quality was assessed with the same items as in the previous studies ($\alpha = .93$). In addition, we also focused on another behavioral variable, namely, intentions to use the tool in the future. Usage intentions were measured with three items adapted from Venkatesh et al. 2012 ($\alpha = .95$, see Appendix).

Control variables. We used the same control variables as in Study 5.

Analyses and results

Control variables. Performance expectancy and satisfaction with the lectures and support of faculty members emerged as significant covariates for at least one of the dependent variables ($p < .05$). For reasons of consistency, both variables were included in all the analyses. Moreover, the recommendations were generally considered very positively ($M = 5.25$ on a 7-point scale) and these evaluations did not differ across the conditions ($M_{\text{algorithmic\_advice\_only}} = 5.19$, $M_{\text{no\_new\_info}} = 5.31$, $M_{\text{new\_info}} = 5.24$, $F(2, 188) < 1$).

Hypotheses testing. As Study 6 features three different advice conditions, we first specified two dummy variables (i.e., one dummy [D1] comparing "algorithmic advice only" to "no new information", and one dummy [D2] comparing "algorithmic advice only" to "new information"). Next, we conducted OLS regressions where we included the control variables, the two dummy variables, the mean-centered relationship index, and the interactions between the dummy variables and the relationship index (see Table 3). The analysis showed a significant interaction effect between dummy D1 and relationship for both dependent variables (relationship quality: $b = .51$, $t(183) = 4.47$, $p < .001$; usage intentions: $b = .55$, $t(183) = 3.26$, $p < .001$). Floodlight analyses revealed a significant positive effect for participants that scored higher on the relationship index (relationship quality: $b_{JN} = .49$, SE = .10, $p = .05$; usage intentions: $b_{JN} = .86$, SE = .18, $p = .05$), whereas there was a negative effect for participants that scored lower on the relationship index (relationship quality: $b_{JN} = -.23$, SE = .08, $p = .05$; usage intentions: $b_{JN} = .21$, SE = .12, $p = .05$). Hence, participants that were more communally oriented responded positively to the human fallback option (even if this option was not associated with any informational gain), whereas the opposite was true for exchange-oriented customers.

The analysis also revealed a significant interaction between D2 and relationship for both dependent variables (relationship quality: $b = .48$, $t(183) = 3.85$, $p < .001$; usage intentions: $b = .56$, $t(183) = 3.03$, $p < .003$). Floodlight analyses showed a positive effect for participants that scored higher on the relationship index (relationship quality: $b_{JN} = .28$, SE = .08, $p = .05$; usage intentions: $b_{JN} = .94$, SE = .21, $p = .05$) and a negative effect for participants that scored lower on the relationship index (relationship quality: $b_{JN} = -.45$, SE = .09, $p = .05$; usage intentions: $b_{JN} = -.17$, SE = .11, $p = .05$). Hence, participants with a communal (exchange) relationship responded positively (negatively) to a human fallback option and this effect emerged irrespective of whether this option was associated with a higher informational value or not. These results provide renewed support for H4 and H5 and suggest that the effects of a human fallback option are indeed shaped by perceptions of (unsolicited) social support.[5]

Discussion

Study 6 replicates the finding that algorithmic advice with a human fallback option has a positive effect in communal relationships but a negative effect in exchange relationships. More importantly, Study 6 rules out an alternative explanation based on potential differences in informational value across different advice conditions, thereby providing further support for H4 and H5 and our general conceptual model.

General discussion

Algorithms are increasingly able to match and outperform human experts. As an increasing number of professional ser-

[5] In an ancillary analysis, we just focused on the two fallback conditions and ran OLS regressions where we included fallback, relationship, and the interaction in the model. This analysis revealed insignificant effects for fallback, significant effects for relationship, and insignificant interaction effects for both dependent variables. Hence, this analysis suggests that the effects of the two fallback conditions are not significantly different from each other.

Table 3
Study 6: Regression results for relationship quality and usage intentions.

	Relationship quality			Usage intentions		
	b	*t*	*p*	*b*	*t*	*p*
(Constant)	2.20	6.35	.00	3.48	6.80	.00
Service relationship	.61	4.96	.00	.41	2.23	.03
Dummy 1	−.05	−.64	.52	−.11	−.97	.33
Dummy 2	.03	.39	.70	−.13	−1.22	.23
Service relationship × dummy 1	.51	4.47	.00	.55	3.26	.00
Service relationship × dummy 2	.48	3.85	.00	.56	3.03	.00
Satisfaction with lectures and faculty	.33	5.55	.00	.06	.63	.53
Performance expectancy	.23	5.81	.00	.38	6.38	.00
R^2	.39			.24		

vice firms have started introducing algorithmic advice, it is important to understand if and when customers oppose or appreciate algorithmic advice. In this context, a key issue is how existing service relationships shape customers' responses to algorithmic advice and how algorithmic advice affects these relationships. We address this issue in six studies across different advice settings (i.e., investment, insurance, student counseling). Studies 1 and 2 demonstrate that communal customers are more reluctant to choose algorithmic advice over human advice than exchange customers. Study 3 shows that introducing algorithmic advice into existing relationships has an adverse effect on communal customers (but not on exchange customers) and that this effect is determined by the perception that algorithmic advice tools do not effectively deliver the required level of social support. Based on these findings, Studies 4, 5, and 6 test an intervention to overcome resistance to algorithmic advice, namely, giving customers a human fallback option. As expected, this intervention reduces the negative effect of algorithmic advice for communal customers but adversely affects exchange customers. Importantly, Study 6 rules out a competing explanation, showing that the effects of a human fallback option cannot be attributed to a potentially higher informational value.

Theoretical implications

Our findings make several contributions to the literature. First, by investigating the role of service relationships in the context of algorithmic advice, we shed new light on when customers may accept or reject algorithmic advice. Extant studies (e.g., Hildebrand and Bergner 2021; Logg et al. 2019; Longoni et al. 2019) have not considered that algorithmic advice is often targeted at a firm's existing customer base and have not examined how customers' relationships with the firm providing the advice tool may affect their responses. In our research, we explicitly address this question. Our findings show that customers in communal relationships may oppose algorithmic advice more strongly, whereas customers in exchange relationships may accept it more readily. Hence, our studies show that considering service relationships may provide a fuller understanding of customer reactions to algorithmic advice, especially when companies have not used algorithmic advice in the past.

Second, we add to the literature by investigating the relational consequences of algorithmic advice. To date, most studies have focused on the acceptance of algorithmic advice by, for example, examining when people may oppose algorithmic advice (e.g., Longoni et al. 2019) or when they may follow the recommendations generated by algorithmic advice (e.g., Dietvorst, Simmons, and Massey 2015). Our studies extend this research by suggesting that the introduction of algorithmic advice may jeopardize existing service relationships. Importantly, these findings also provide a new perspective on the link between service relationships and new technologies. For instance, Reinders, Dabholkar, and Frambach (2008) argue that new technologies may harm customers' attitudes towards a service provider because people often do not have the freedom to decide whether they want to use a technology or not. Giebelhausen Robinson, Sirianni, and Brady (2014) argue that new technologies (e.g., self-service kiosks) can deteriorate service relationships by physically distracting customers from noticing rapport-building behaviors of employees. Extending these arguments, our studies show that algorithmic advice may be incompatible with communal relationship norms, thereby harming critical relationship outcomes. In doing so, we contribute to earlier research calls from the field (Ostrom et al. 2021; van Doorn et al. 2017).

Third, there has been little research on the practical interventions that firms can use to increase the acceptance of algorithmic advice. In this respect, previous research has suggested that companies should provide examples of algorithms performing human tasks (Castelo et al. 2019), use a human-like conversational style (Hildebrand and Bergner 2021), or frame the results of advice as personalized to a person's unique characteristics (Longoni et al. 2019). We add to this literature by examining another intervention, namely, signaling to customers that human advice is still there if needed by providing a fallback option.

To the best of our knowledge, this is the first empirical test of this intervention in the context of algorithmic advice. Interestingly, this intervention may be a double-edged sword. Whereas it may have a positive effect for communal customers (compared to providing algorithmic advice only), it may deteriorate relationship quality for exchange customers. These findings are important as they indicate that interventions designed to overcome resistance to algorithmic advice may need to take the specific relational context into account. Relatedly, we contribute to the discussion about hybrid conceptualizations of algorithmic and human tasks (e.g., Huang and Rust 2022; Sampson 2021) by suggesting that giving customers the option to request additional human advice is sufficient to overcome resistance to algorithmic advice in communal relationships. Hence, one may argue that combining algorithmic and human advice on a regular basis is not necessary to maintain a good relationship.

Managerial implications

The issues addressed in this research also have managerial implications. First, firms that have not used algorithmic advice in the past need to consider the relationships they maintain with their customers before introducing algorithmic advice. For example, 59.1% of the customers participating in Study 3 had a communal relationship with their bank (i.e., a score on the relationship scale above the mean), while 40.9% had an exchange relationship (i.e., a score below the mean). If a majority of customers have a communal relationship, algorithmic advice may not be very successful, especially when it is offered at the same price as human advice. Hence, managers may refrain from offering algorithmic advice to such customers or should introduce algorithmic advice primarily as a service for new customers. In contrast, if a majority of customers have an exchange relationship, algorithmic advice may be more favorably received. Hence, managers may be well-advised to offer algorithmic advice to such customers.

However, many professional service providers have to overcome cost challenges (e.g., KPMG 2022). Hence, they may want all their customers to use digital tools such as algorithmic advice and may therefore limit customers' access to human advice options. In this case, allowing communal customers to request additional human guidance when using algorithmic advice may be an effective intervention to avoid relationship damages. In addition to maintaining a good relationship, another advantage of this strategy is that it is less costly than strategies that combine algorithmic and human advice regularly (e.g., human advisors supported by algorithmic advice). Interestingly, exchange customers may consider such fallback options less positively, suggesting that the introduction of such offers requires a precise understanding of the relational orientations of a firm's customer base. That is, managers may have to decide which segment they want to attract most and design their advice processes accordingly.

Finally, on a more general level, our findings suggest that managers can use different contact options to attract and serve different customer segments. Contact options that include human elements are most likely to appeal to communal customers. For instance, firms targeting communal customers may complement their automated phone systems with the possibility to talk to a real service employee. Similarly, an automatically generated email could integrate contact details or a picture of an employee that may be contacted for additional help. In contrast, pure technology-based contact options are more likely to appeal to exchange customers. To increase the usefulness of such options, firms should refrain from providing any form of unsolicited human support. For example, a chatbot may refer to online resources such as explainer videos or Q&As rather than to additional human help. Summarizing, it seems important that managers closely evaluate the ramifications of offering different contact options.

Limitations and future research

Our studies also have limitations that call for future research. First, we focused on professional service domains only (i.e., investment advice, insurance advice, student counseling). Although professional service providers deal with emotions, their services tend to be utilitarian in nature, that is, driven by functional goals rather than hedonic, sensory experiences. As customers may respond differently to advice in utilitarian and hedonic domains (Longoni and Cian 2022), future research may want to examine if service relationships exert a similar influence when algorithmic advice concerns a decision related to sensory experiences. For example, it may be interesting to investigate the impact of service relationships when customers receive algorithmic advice on finding the right clothes, makeup, or hairstyle.

Second, in the first four studies, we used descriptions and website mock-ups to manipulate different advice conditions. It is possible that the quality of these materials may have impaired the effectiveness of our manipulations. That is, participants may have considered the design artificial compared to real websites. In a similar vein, companies may inform their customers about the launch of algorithmic advice in advance. In this case, customers may feel more familiar with algorithmic advice than the customers in our studies.

Third, our results are limited to the current timeframe when algorithmic advice is just beginning. Future research needs to reconsider the effects when algorithmic advice is more widely used and becomes commonplace. Specifically, it would be interesting to investigate how service relationships develop when algorithmic advice is the standard type of advice. Based on our findings, one may speculate that algorithmic advice will make it more difficult for firms to build communal relationships with their customers.

Finally, future studies may investigate if algorithmic advice systems can provide social support. In this research, we have argued that customers using algorithmic advice may feel that they do not receive sufficient social support. This argument is in line with studies showing that people do not ascribe emotion-related abilities to machines (e.g., Castelo et al. 2019; Haslam et al. 2008). However, a recent paper by Gelbrich, Hagel, and Orsingher (2021) has argued that digital assistants such as fitness apps can trigger perceptions of social support in similar ways as humans do. Future research may therefore investigate differences in perception of human social support and machine imitations of such social support more closely.

While a number of issues remain to be explored, this research extends the literature in two important ways. First, it shows that service firms that offer algorithmic advice need to consider the nature of existing service relationships. Second, it also shows what service firms can do to avoid relationship damages when introducing such systems, especially when their customers share a communal relationship with them.

Appendix Constructs and measurement items by study

Construct	Wording of Measurement Items	S1	S2	S3	S4	S5	S6
Type of relationship (adapted from Clark and Aragón 2013)	Communal relationship • [Service provider] and its employees treat me in a selfless manner and care about my needs. • When making a decision, I take the needs and feelings of [service provider] and its employees into account. • [Service provider] and its employees are especially sensitive to my feelings. • [Service provider] and its employees are responsive to my needs and feelings. • If [service provider] and its employees need my support, I would help them. • When I have a need that [service provider] and its employees ignore, I'm hurt. Exchange relationship • When I select the services of [service provider], I generally expect something in return. • [Service provider] and its employees should feel obligated to repay favors I have done to them. • I would feel exploited if [service provider] and its employees failed to repay me for a favor. • I keep track of benefits I have given to [service provider] and its employees. • When I select the services of [service provider], [service provider] and its employees ought to return the favor right away. • When I [do business with/invest time using the services of] [service provider] and its employees, they pay me back adequately.	X	X	X	X	X	X
Customer loyalty (adapted from Homburg et al. 2011)	• I consider [service provider] as my first choice for [type of service]. • I intend to stay loyal to [service provider]. • I intend to do more business with [service provider] in the future. • I intend to additionally purchase other products and services of [service provider]. • I recommend [service provider] to other people. • I say positive things about [service provider] to other people.			X			
Switching intentions (adapted from Bansal and Taylor 1999)	Rate the probability that you would go to another service provider than [service provider] if you are interested in [type of service]. • Unlikely…Likely • Improbable…Probable • No chance…Certain			X			
Relationship quality (adapted from Mende et al. 2013)	• I am satisfied with [service provider]. • I am content with [service provider]. • I am happy with [service provider]. • [Service provider] is trustworthy. • [Service provider] keeps its promises. • [Service provider] is truly concerned about my welfare. • I enjoy being a [patient/customer/student] of [service provider]. • I have positive feelings about [service provider]. • I feel attached to [service provider].				X	X	X
Satisfaction with social support (adapted from Doeglas et al. 1996)	Do you expect [service provider] to demonstrate as much of the following behaviors as you like when using this type of advice? • Being warm and affectionate to me. • Being friendly to me. • Sympathizing with me. • Showing understanding to me. • Lending me a friendly ear.			X	X		
Usage intentions (adapted from Venkatesh et al. 2012)	• I intend to use the thesis advice tool when I write my thesis. • I will try to use the thesis advice tool as soon as it is available. • I plan to use the thesis advice tool when it is available.						X

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