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Whose Algorithm Says So: The Relationships Between Type of Firm, Perceptions of Trust and Expertise, and the Acceptance of Financial Robo-Advice☆

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Abstract

Financial advisors seek to accurately measure individuals' risk preferences and provide sound personalized investment advice. Both advice tasks are increasingly offered through automated online technologies. Little is known, however, about what drives individuals' acceptance of such automated financial advice and, from a consumer point of view, which firms may be best positioned to provide such advice.

We generate novel insights on these questions by conducting a real-world empirical study using an interactive automated online tool that employs an innovative computer algorithm to build pension investment profiles, the "Pension Builder," and a large, representative sample.

We focus on the role that two key firm characteristics have on consumer acceptance of pension investment advice generated by computer algorithms running on automated interactive online tools: profit orientation and role in the sales channel.

We find that consumers' perceptions of trust and expertise of the firm providing the automated advice are important drivers of advice acceptance (besides a strong impact of the satisfaction with the consumer–online tool interaction), and that these constructs themselves are clearly influenced by the for-profit vs. not-for-profit orientation and the product provider vs. advisor only role in the sales channel of the firm providing the advice.

We discuss the implications of our findings for marketers and policy makers and provide suggestions for future research.

Keywords: Advice acceptance; Financial advice; Robo-Advice; Algorithm advice; Firm type; Trust and expertise; Interactive decision aid; Pension Builder

"Planning for retirement? Look no further than your tablet or smartphone." "The rise of the robo advisors," "computer algorithms that invest your money for you" "better than you could by yourself" "to help steer [you] to financial products tailored to [your] particular savings goals and risk preferences," "will provide 'fully regulated' retirement advice and will mimic what a human adviser would do, including conducting a risk profile, suitability check, and personal recommendation."

(Wall Street Journal (WSJ) 2015; Financial Times (FT) 2015; Time 2017).

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Twenty-first century online marketing tools—from private insurer apps to government-sponsored websites—offer automated interactive financial advice on investments, insurance, or retirement, and pension planning.[1] Like many other industries, the financial advice industry has welcomed the arrival of low-cost digital marketing (Varadarajan and Yadav 2002; Wind and Mahajan 2001). This is expected to empower consumers (Barrutia and Echebarria 2005) and expand the tools available online—on websites and on mobile and social media—to interact with financial advisors, who can then use them to better, and automatically, customize advice and financial products to consumers (Arora et al. 2008). Consumers themselves are also interested in using such tools, even for complex decisions like retirement planning and investing. According to industry reports, in Great-Britain alone, 30% of pension savers already prefer to use online advice tools rather than speaking to a human financial advisor, more than half (53%) would use a free online retirement planning tool to become informed about "what to do" with their savings (B&CE 2016), and a third would pay for it (Deloitte 2017).

Online computer algorithms in the financial advice industry now flourish in developed economies. Take the *Investment Balance* pension advisor launched by the financial services provider Centraal Beheer-Achmea in the Netherlands; the *Cora*, a "robo-advisor" "much faster than a human advisor," run by private insurer and pension provider Liverpool Victoria in the UK (FT 2015); the *Retirement Manager* of Morningstar Inc.; the *Blue Zone* healthy-life expectancy algorithm developed with the University of Minnesota School of Public Health; or the *ESPlanner* of Boston University economist Laurence Kotlikoff in the US (WSJ 2015). The many examples of automated interactive online tools (often appearing in the press as "robo-advisors"; see the epigraph) that do risk profiling and generate automated personalized financial advice reveal that not only private but also state-sponsored organizations, both profit and non-profit oriented, build and run such marketing tools.

In theory, upon receiving the same input information from consumers, personalized recommendations generated by automated online tools of different organizations can be the same and thus should be *equally accepted by consumers* (Jung et al. 2018).[2] However, the financial advice industry is a context where assessing the quality of advice is challenging, even for professionals (Merton 2006). Therefore, the extent to which consumers accept *what* is said is likely to depend not only on *how* it is said but also on *who says so*. In other words, a financial advice (e.g., a conservative risk profile) automatically generated by the same app(lication) or algorithm, and communicated in the same way and using the same communication channel (e.g., an online website), may lead to different acceptance–rejection rates simply because it comes from a different type of advisor firm.

In this paper, we test this conjecture and investigate (a) which advisor firms are best suited to provide automated pension advice, i.e., whose advice is most accepted, and (b) what are the underlying drivers of the different acceptance rates between these firms. Answers to these questions will provide theoretical insights into how consumers evaluate the automated interactive online advice of advisor firms and how these evaluations affect their advice acceptance, which is crucial for marketers in general and public policy makers in particular who wish to nudge individuals into making choices closer to what is normatively better for them. In addition, they are relevant for providers of investment plans who are increasingly under pressure to move beyond uniform portfolios and allow personalization of investment advice that more accurately matches individuals' preferences for risk–return trade-offs (e.g., Alserda et al. 2019; Bodie and Treussard 2007; Sundaresan and Zapatero 1997). From an academic point of view, answering these questions will enhance our understanding of acceptance of automated digital advice and its link with the type of advisor firm.

Because differences in acceptance rates across types of digital advisors—who generate the same advice—are hard to account for within a classical economics framework, we take a behavioral economics approach informed by insights from psychology research on irrational discounting of unbiased advice—in particular, "egocentric advice discounting." This is an individual's tendency to overweight one's own opinion relative to that of an advisor when deciding whether to accept an advice (Harvey and Fischer 1997; Yaniv and Kleinberger 2000; for a review see Bonaccio and Dalal 2006). In addition, even though individuals seek automated advice to aid important high-stakes decisions in several contexts, including medical ones (e.g., Esmaeilzadeh et al. 2015; Inthorn, Tabacchi, and Seising 2015;), they suffer from "algorithm aversion." This is a tendency to irrationally, and systematically, discount advice that is generated automatically and communicated by computer algorithms (e.g., Dietvorst, Simmons, and Massey 2015; Goodwin, Gönül, and Önkal 2013).

This general tendency to discount advice might be strengthened (or weakened) by the perceptions consumers form about the advisor, which color their overall assessment of advice quality and fit. Crucially, (i) how trustworthy (e.g., Sniezek and Van Swol 2001; cf. Prahl and Van Swol 2017) and (ii) how much of an expert an advisor firm is perceived to be (e.g., Sniezek, Schrah, and Dalal 2004; cf. Prahl and Van Swol 2017), are two of the most important characteristics that consumers assess when having to accept or reject an advice. Accordingly, we predict that perceptions of trust and expertise are part of the underlying mechanisms, i.e., the mediators, by which advisor types affect the likelihood of consumers

[1] The mix of quotes in epigraph appeared in recent articles in the popular and financial press praising such tools.

[2] Ideally, regardless of who the advisor is, consumers should recognize the superior value of *unbiased* personalized (pension) investment advice matching their preferences, and accept it. Notice that advice discounting is rational if (consumers believe) the advice is biased towards the interest of the advisor, even if there is no principal-agent problem. The focus of our study is not on advice discounting per se, but instead on differences in advice acceptance *across* types of advisors. We also address the case where advisors facilitate decisions, but consumers are the ones who generate their own advice (this is further explained below).

accepting the financial advice generated by using automated online interactive tools.

Given the pivotal role of how satisfied consumers feel interacting with the interface of the online tool (which includes the way in which risk preferences of consumers are elicited online in the advice giving process and how the advice is presented online to consumers), we expect that the indirect mediating effect of perceptions of trust and expertise on advice acceptance may partially be a sequential one—through satisfaction. A sequential or serial mediation is important from a conceptual point of view—satisfaction with interactive decision aids is a byproduct of perceptions—and it is necessary empirically to ensure our study has discriminant validity.

Finally, in our more general conceptualization of acceptance of online automated financial advice we consider not only *firm characteristics*, i.e., the type of organization providing the online advice, and, as already mentioned, how the consumer perceives this organization, but also *consumer heterogeneity* (e.g., demographics) that may further determine acceptance of online advice.

In the next section, we set the conceptual background by summarizing the main findings on (online) advice acceptance research in each of these domains. We then focus specifically on the roles that firm type and firm characteristics play. Next, we describe the setup and results from our large-scale empirical study in the context of online financial pension advice that uses a representative sample of the Dutch population and is designed to address the role of firm type and firm characteristics on advice acceptance. Our experimental design also allows us to study the differences in acceptance of a firm's explicit vs. implicit advice. A firm's implicit advice, in which the consumer learns what her best-fitting investment profile is, without being mentioned that that is a recommendation of the firm, can be seen as similar to a "no advice" control group. Thus, in an implicitly provided advice, the firm, without ever explicitly saying how the consumer should invest, is essentially facilitating the use of the computer algorithm running on the automated online interactive tool on which the consumer herself generates the advice. This is a condition of our study design that enables us to identify the baseline effect of automated advice—held constant across the four firm types.[3] Interestingly, implicit advice (versus explicit advice) significantly moderates the effect of the perceptions consumers hold about a financial firm's expertise and trust on the acceptance of that advice. Extending the main scope of our study, we offer an interpretation of this effect based on the competence-warmth dimensions of social cognition (Aaker, Vohs, and Mogilner 2010; Fiske, Cuddy, and Glick 2007) that fits well with our proposed expertise-trust conceptualization. We conclude the paper with a discussion of all our findings, namely the implications for the financial advice industry in general and pension advisors in particular, and suggestions for future research.

[3] We thank the Editor for making this suggestion.

Drivers of Online Financial Advice Acceptance

Most research pertaining to online advice has focused on the development of new methods to improve the quality of the interaction design or has analyzed how consumers make choices contingent on the form of the advice, e.g., online recommendations (Ricci and Werthner 2006; Senecal and Nantel 2004). This literature has mainly investigated online decision aids that support decision makers, namely consumers, who deal with complex decisions (e.g., Benbasat and Wang 2005; Qiu and Benbasat 2009; see Xiao and Benbasat 2007 for a recent review). These software tools or interactive decision aids aim to improve consumer decision quality while simultaneously reducing the effort required to make a decision (Häubl and Trifts 2000). Research has shown that these tools can be very effective when consumers decide to use them and when "the tools can learn" about individual preferences (Diehl, Kornish, and Lynch 2003; Häubl and Trifts 2000; Senecal and Nantel 2004; Urban and Hauser 2004).

In this paper, we focus on a broader, more complete value chain analysis of the online advice process. As mentioned, we do so by looking beyond—and keeping constant the effect of —the interactive decision aid (the finance-based algorithm running on an automated online interface) and by zooming in on the differences in advice acceptance accruing from the different types of firms that typically communicate financial advice ("whose algorithm says so"), and whether those differences change depending on whether the firm explicitly communicates the advice to the consumer or it is the consumer who arrives at, and thus gives herself, the same advice that the firm would have communicated (the firm is in this case "merely" facilitating the generation of automated advice on its website). And in so doing, we consider characteristics of the firm, characteristics of the consumer, and characteristics of the interactions between the consumer and the firm.

Firm Characteristics: The Role of Firm Type

Individuals turn to firms for advice because, in principle, firms have superior knowledge on available products, their characteristics, and their fit to individual preferences. This information asymmetry about product characteristics and consumer needs, however, may hurt the relationship between advisor firms and consumers or advisees (Van Swol 2009). For instance, when an advisor is also the manager of an advisee's product portfolio, such as an investment plan provider advising a consumer investor, there may be a principal–agent problem, i.e., the incentives and preferences of the advisor (the "agent") may not be perfectly aligned with those of the advisee (the "principal"). Hence, to maximize the chances that an individual receives the best product advice, firms need to be willing, and have the ability, to elicit individual risk preferences properly, which is not a trivial exercise (see Donkers, Lourenço, and Dellaert 2012).

Despite these challenges, professional advice differs from promotional or persuasive advertising, in the sense that advice is not necessarily considered manipulative or invasive but rather a means to improve participants' decisions (Yaniv 2004). Moreover, because an advice is prescriptive in nature it is more easily associated with an independent third party (Schrah, Dalal, and Sniezek 2006). In addition, when consumers look after, and then follow, an advice, those decisions inevitably imply a shared responsibility for whatever outcome the advice leads to (Harvey and Fischer 1997).

Jointly, these considerations suggest that consumer perception of the advisor's *expertise*, as well as the extent to which consumers *trust* that the advisor has provided an unbiased advice, are key drivers of the willingness to accept the advice (Shapiro 1987; Singh and Sirdeshmukh 2000; Van Swol and Sniezek 2005; White 2005). We anticipate that a firm's perceived expertise and trust are a function of what type of firm the firm is. In particular, whether the firm is (i-a) for-profit or (i-b) not-for-profit, and whether it is (ii-a) a pension provider or (ii-b) an advisor-only (see Fig. 1). More formally, we expect the perceived expertise and trustworthiness of a firm to be *mediators* of the effects of firm types on acceptance of online advice, as summarized graphically in Fig. 2.

Despite facing common regulations (see Baker and Dellaert 2018) for an extensive discussion about regulation of automated (robo-) advice in the financial services industry), whether an online automated advisor is a for-profit or not-for-profit firm signals consumers different incentives to provide advice, and the extent to which these incentives are aligned (or unaligned) with the incentives of consumers. Recently, it has been shown that consumers stereotypically perceive profit-seeking firms in conflict with social good (Bhattacharjee, Dana, and Baron 2017). Thus, all else being equal, we propose that online automated advisors of not-for-profit firms are likely to enjoy higher levels of trust than those of for-profit firms, especially in light of the poor general perception of the financial industry, which becomes particularly acute in and after financial and economic crises (Mayer 2013).

Likewise, we propose that online automated advisors of firms that do not sell their own investment products are likely to be seen as trustworthier than those of firms selling their own investment products. Especially in the short run, sellers may enjoy high rewards from products with high profit margins, which may create perverse incentives to provide biased advice (e.g., Cadman, Carter, and Hillegeist 2010; Inderst and Ottaviani 2012).

On the other hand, the online automated advisors of both for-profit firms and firms selling their own investment plans are likely to be seen as the result of higher levels of expertise than those of not-for-profit firms and firms selling investment plans of others. Expertise is a competitive weapon that for-profit firms need to survive in highly sophisticated, tightly regulated, competitive markets such as those for investment plans (see e.g., Coates and Glenn Hubbard 2007). Not-for-profit firms simply do not face these challenging market rules and thus expertise is less of an issue. In turn, firms selling their own investment products are almost by definition the ones that know best (and better than anyone else) their own product line.

Consumer Characteristics and the Consumer–Online Tool Interaction Satisfaction

Several individual characteristics may further help explain heterogeneity in automated advice acceptance. In particular, an individual's *gender* and *income* can be expected to affect advice taking, especially in the context of financial decisions (Bhattacharya et al. 2012). Women have been found to be less certain than men about their ability to handle financial matters (cf. Lundeberg, Fox, and Punccohar 1994; Prince 1993), and may therefore be more inclined to accept advice than men. Low-income individuals are also expected to accept advice more readily than wealthier individuals. In a financial decision context, lower income individuals are more vulnerable if they make the "wrong" choice and therefore should discount the advice less (i.e., they should value the advice more) than individuals with higher income.

Age too may affect individuals' interest in financial decisions and hence their willingness to consider and accept financial advice. As people age and face the prospect of reduced ability to remain active in the work force, they are likely to become more interested in financial advice and what future income they can expect in the absence of labor income. Finally, *education* may also influence advice acceptance, but the direction of the effect may be less clear. On the one hand, someone with a higher education may be able to more easily process financial information and advice, i.e., be financially more literate (see e.g., Lusardi and Mitchell, 2011; Lusardi, Mitchell and Curto 2010), which may lead to higher advice transparency and thus acceptance. On the other hand, someone with a lower education level may more easily recognize the need for advice and thus accept it (Lee and Moray 1992).

The acceptance of online financial advice may also depend on aspects of the interaction with the automated algorithm on which the advice is based (Briggs, De Angeli, and Lynch 2002; Dabholkar and Bagozzi 2002; Dellaert and Dabholkar

Whose automated financial advice: For- vs. not-for-profit orientation and product provider vs. advisor-only role in the sales channel and the four types of advisor firms

		For- vs. Not-For-Profit Orientation	
		*For-*Profit	*Not-For-*Profit
***Product Provider vs. Advisor-Only* Role in Sales Channel**	Product Provider	INSURANCE FIRM	PENSION FUND
	Advice-Only	PRIVATELY-OWNED COMPARISON WEBSITE	GOVERNMENT-SPONSORED COMPARISON WEBSITE

Fig. 1. Whose automated financial advice: For- vs. not-for-profit orientation and product provider vs. advisor-only role in the sales channel and the four types of advisor firms.

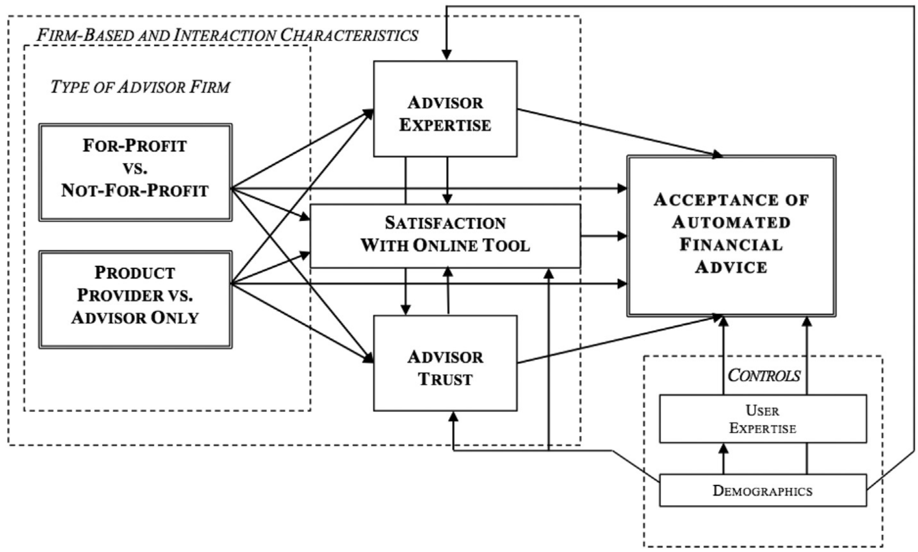

Fig. 2. Conceptual and empirical models of acceptance of automated pension investment advice. The automated financial advice acceptance and other constructs of interest and their relationships according to our conceptualization are presented alongside the control variables in the empirical structural equation model. The four types of advisor firms are hypothesized to have a direct effect on automated financial advice acceptance (the two long arrows in the middle), as well as an indirect one through the mediators, expertise of and trust in the advisor firm, and the consumer–online tool interaction satisfaction (itself affected by perceptions of expertise and trust). Consumer expertise as well as consumer demographics are controlled for in the four outcome variables, as depicted.

2009).[4] When assessing the impact of firm characteristics in our empirical study, we use a single-item measure, that of "overall satisfaction with the online tool." Not surprisingly, the literature on interaction satisfaction is vast (see e.g., Davis 1989; Davis, Bagozzi, and Warshaw 1989; Rogers 2003; Van der Heijden 2003) and suggests there are numerous factors at play when it comes to consumer interactions with online automated marketing tools.

Subjective appreciations about different types of firms and what they do—including their use of online automated interactive systems—may color how users perceive the interactions with automated tools. Trust and expertise, in particular, are likely to influence users' perceptions and subsequent acceptance of such tools (Tseng and Fogg 1999; Waern and Ramberg 1996). Also, marketing studies show that trust is correlated with future interaction intentions (Doney and Cannon 1997; Ramsey and Sohi 1997). And research in human–computer interaction suggests that technology acceptance is influenced by the ability of that technology to deliver correct advice (Tseng and Fogg 1999). Moreover, consumers' interaction satisfaction is positively associated with perceived effort of automated online decision aids (Bechwati and Xia 2003). How much users see themselves as experts also affects the satisfaction with interactive recommendation agents (Su, Comer, and Lee 2008).

[4] In a nutshell, consumers evaluate how much they need to contribute for the advice to be generated and how valuable the advice is that they receive in return. This includes (a) the actions that consumers need to take independently, such as collecting information on financial products, as well as (b) the joint steps that they need to take in interaction with the firm and the firm's computerized tools, such as making risky choices and revealing their risk preferences online, and (c) assessing the quality of the advice provided by the firm.

In sum, in our framework satisfaction with the online tool is impacted by perceptions of expertise and trust, which are themselves influenced by firm type (for-profit vs. not-for-profit and product provider vs. advisor only). In other words, we propose there is a sequential or serial mediation effect of firm type on advice acceptance: (i) from firm type to satisfaction through perceptions of expertise and trust, and (ii) from perceptions of expertise and trust to advice acceptance through satisfaction. This comprehensive conceptualization, that gives consumer–online tool interaction satisfaction a pivotal role in the acceptance of online automated advice, allows us to also assess the discriminant validity of satisfaction vis-á-vis advice acceptance.

Empirical Study with an Automated Advisor for Retirement Investment

To investigate the mediating role of consumer perceptions of firm expertise and trust (and the one through satisfaction with the consumer–online tool interaction) and how these perceptions depend on the type of firm providing online automated financial advice, we collect data from a large representative sample of the population in the Netherlands. We use our own automated algorithm "brought to life" as an online, highly interactive tool that helps users build their own risk preferences on a simple drag-and-drop and point-and-click interface, and employ it in a pension and retirement context.

Pensions involve high-stakes decisions and are largely the result of, among other factors, personal savings or home ownership, life expectancy, and health (Fornero, Rossi, and Brancati 2014; Nyce et al. 2013), and advice is crucial to guide individuals into their preferred retirement trajectories (see e.g., Van Schie, Dellaert, and Donkers 2015). Moreover, financial pension advice for retirement is under the spotlight again in face of recent socioeconomic changes such as increasing retirement age (Vogel, Ludwig, and Börsch-Supan 2015; Vuuren 2014).

The data were collected online with *The Pension Builder*, an automated pension tool we developed in collaboration with two large Dutch pension providers (through the research center Netspar—Network for Studies on Pensions, Aging and Retirement). Its main interactive, automated features are explained next.

"The Pension Builder" Online Automated Tool for Retirement Advice

The Pension Builder automated tool is built on recent advances in interactive online pension risk preference elicitation and advice. In particular, the Pension Builder builds on the Distribution Builder introduced by Goldstein, Johnson, and Sharpe (2008) that can be used to elicit risk preferences. We implemented a prototype of the Pension Builder as recently proposed by Dellaert et al. (2016), which is adapted to the Dutch consumer pension decision-making context (see also Donkers et al. 2013). Fig. 3 shows the Pension Builder interface respondents used in the study.

The Pension Builder provides consumers with an intuitive device to express their preferences over risky investment outcomes and to make joint decisions on the risks and returns of financial outcomes. Importantly, the automated online tool draws on previous research on risk representations, demonstrating that individuals are best capable of understanding probabilities when these are presented graphically as frequencies of occurrence of a risky event (Fagerlin, Zikmund-Fisher, and Ubel 2011). Using the interactive automated interface, users can learn how decisions on investment risk and retirement age affect the distribution of their monthly net retirement income. Shifting towards higher retirement ages or more risky investment profiles will result in higher expected retirement income, visualized by the distribution of markers moving to the right, i.e., to higher income levels. At the same time, more risk will also result in a more dispersed (i.e., risky) distribution. One specific benefit of this type of automated interface is the embedded interactivity that aids consumers, and the firms they deal with, discovering their preferences.

To capture important aspects of the retirement savings and retirement timing decisions of consumers, the new interactive graphical Pension Builder that we built expands previous, more generic algorithms, in a number of ways. Two important innovations in particular are worth mentioning: (1) respondents are presented with a projected monthly retirement income including their base state-pension, which is the basis they should use when thinking of risk–return trade-offs; and (2) respondents are allowed to shift their desired retirement date. The desired retirement date is a fundamental driver of pension wealth and pension wealth needs. For example, retirement one year later calls for higher contributions to pension wealth while withdrawals from pension wealth are postponed. The new automated online tool was pretested and

The *Pension Builder* interactive decision tool*

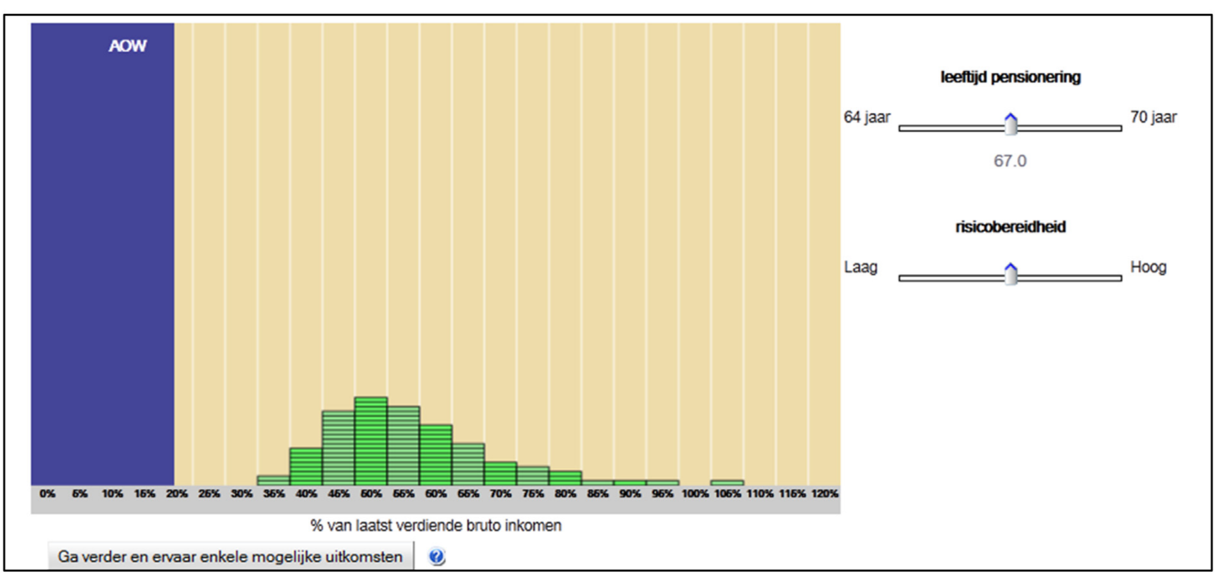

Fig. 3. The *Pension Builder* interactive decision tool. Users of the Pension Builder have two sliders at their disposal to reveal their preferences for retirement: an Age at Retirement slider (from 64 to 70 years old in steps of 1 month; "leeftijd pensionering" in Dutch) and a Risk slider (from "Low" to "High"; "risicobereiheid" in Dutch). The horizontal "x-axis" of the graphical interface expresses income at retirement as the percentage of the last earned gross income (from 0% to 125% in steps of 5 percentage points (p.p.)). Users of the interactive decision tool can move the sliders to learn about the consequences of various choices, as these sliders move the 100 green markers that represent the distribution of their income at retirement. In the process, users also experience a number of draws from the distribution. The violet background color, in this case spanning from 0% to 20% of (gross) income at retirement, indicates the part of retirement income provided by the state pension. Note that the shape and location of the distribution are aligned with the user-situation, based on their age and income.

improved in several rounds with employees at Netspar partner organizations as well as novice users. This resulted in further refinements of the wording and the graphical interface of the automated tool and the underlying computer algorithms.

Experimental Design

Structure of the Survey Task

The structure of the study was explained to respondents after they agreed to participate. They were first shown a short video explaining the basic features and workings of the Pension Builder automated tool. They then answered several short questions to make sure that they understood how it worked and were requested to watch the video again if the questions were answered incorrectly. We note that once these questions are answered correctly, it is unlikely that participants form different perceptions regarding the different firms' ability to actually implement such artificial intelligence tool, which is what the online automated tool is in the end, and the reputation for it. Next, respondents were asked their age and income level, which that were used to generate the distribution of their net retirement income; hence, the automated algorithm showed a unique income distribution for that respondent's situation. Finally, respondents were asked to use the sliders for retirement age and risk–return trade-off to “build” their preferences in the Pension Builder.

Participants were randomly assigned to either a firm's explicit advice condition (ExpAdvice) or a firm's implicit advice condition (ImpAdvice). The participants' investment preferences elicited through the Pension Builder online interface on a firm's website were used in *both* conditions to generate a personalized best-fitting investment profile (“defensive,” “neutral,” or “offensive”). In the explicit advice condition, participants were told that the firm, based on their choices, recommends that they invest according to their best-fitting investment profile. In the implicit advice condition, participants were told, based on their choices, what their best-fitting investment profile was, without mentioning explicitly that that is a recommendation of the firm. The implicit advice condition can be seen as a control condition, in the sense that there is no explicit firm-provided financial advice, thus allowing us to test the baseline effect of the automated firm-advice—held constant across the four firm types. Moreover, we can determine the effect of potential interactions between explicit versus implicit advice and the perceptions of expertise and perceptions of trust on advice acceptance.

In the Appendix, we present the survey instructions used to frame the explicit vs. implicit advice before the investment profile was generated online. For instance, while the explicit advice condition instructions mention, at some point, that the firm “*has created a new retirement simulator and you will have to indicate when you want to retire and how much risk you want to take with your pension investments*” and that the firm “*will give you appropriate advice about your pension investments based on your preferences*,” the implicit advice condition instructions mention that the firm “*has created a new retirement simulator that you can use to help yourself make your choice*” [and] “*choose when you want to retire and how much risk you want to take with your pension investments*,” and then “*try out various options and decide for yourself which one suits you best*.”

In all conditions, participants were asked to indicate the likelihood that they would accept the advised best-fitting investment profile provided to them. At the end of the study, participants also answered several questions regarding their personal characteristics and their evaluation of the firm (one of the four possible ones) responsible for the automated advisor algorithm and interface providing the advice.

Experimental Manipulation of Firm Characteristics

To test the impact of firm characteristics on consumer advice acceptance and the mediating role of perceived firm expertise and level of trust in the firm, we randomly assigned respondents to one of the four different types of firms (crossed with the explicit and implicit advice conditions explained above (eight conditions in total)). These firm types were selected on the basis of a review of different types of organizations that currently provide online pension advice in the Dutch pension market, which lends external validity to our study. Moreover, the types of firms selected ensure variation in participants' perceived level of firm expertise and trustworthiness. Specifically, we classified pension advisors based on the following: their profit orientation as either “for profit” or “not-for-profit” organizations and their role in the sales channel as either a “product provider” selling its own pension products or an “advisor-only.”

We selected a representative firm type for each of the four combinations, resulting in the following four types of firms (see Fig. 1): (1) For profit & product provider: *Insurance firm*, (2) For profit & advisor-only: *Privately-owned comparison website*, (3) Not-for-profit & product provider: *Pension fund*, and (4) Not-for-profit & advisor-only: *Government-sponsored comparison website*. When introducing the Pension Builder task to respondents, we framed the Pension Builder service as if it were provided by one of these four firms. Importantly, the for-profit vs. not-for-profit and product provider vs. advisor only distinctions were not made explicit, only the four firm types were. Yet, to make sure these distinctions are something ordinary consumers are attuned to, not our own attributions, we conducted a separate online study among a representative sample of 201 Dutch participants.

The results confirmed that, as expected, the for-profit firms (insurers and commercial comparison websites) jointly are perceived higher in profit orientation than the not-for-profits (pension funds and information websites of the government)

($t = 10.74$, $p < .001$). Also, the product providers (insurers and pension funds) are perceived to provide more of their own products than advisors only (commercial comparison websites and information websites of the government) ($t = -4.51$, $p < .001$).[5]

Measurement of Perceptions, Dependent Variable, and Respondent Characteristics

To measure consumer perceptions of firm expertise and level of trust in the firm, we adapted items from existing validated scales to our context. More specifically, we measured expertise using six items for which respondents indicated their agreement on a 7-point scale (1 = totally disagree to 7 = totally agree) with regard to a *firm of type X* (i.e., one of the four firm types as shown to the respondent). The items were defined as follows (translated from Dutch): (a) "A *firm of type X* has much experience in the pension domain," (b) "A *firm of type X* is skilled in the pension domain," (c) "A *firm of type X* has a lot of expertise in the pension domain," (d) "A *firm of type X* has a good understanding of the pension product market," (e) "A *firm of type X* has a lot of knowledge about many different products in the pension market," and (f) "A *firm of type X* is capable of finding the best product for me." For trust, we employed a 3-item measurement scale. Respondents were again asked to answer on the same 7-point scale (1 = totally disagree to 7 = totally agree). The items were: (a) "When it comes to providing information about pensions and pension products, I trust a *firm of type X*," (b) "When it comes to providing information about pensions and pension products, a *firm of type X* is honest," (c) "When it comes to providing information about pensions and pension products, I believe what a *firm of type X* tells me."

As a measure of consumer acceptance of online advice, we asked respondents to indicate how likely it was that they would follow the online advice provided to them on a 0%–100% probability scale (Elrod, Louviere, and Davey 1992). This is our main dependent variable. We also asked respondents to evaluate the online interaction. In this study we use their overall satisfaction with the Pension Builder interface as a summary measure of their interaction evaluation (see our theoretical background and conceptualization above). This was measured on a 7-point scale (1 = very dissatisfied to 7 = very satisfied).[6] Finally, we asked respondents to report several personal characteristics, including age, gender, income, education, and user expertise (using the same 7-point scale (1 = totally disagree to 7 = totally agree) and the following items: "I have a lot of experience in the field of pensions," "I am proficient at pensions," "I have a lot of expertise in the field of pensions," "I have a good overview of the market for pension products," "I have knowledge about many different products in the market," "I am able to find the best product for me").

Data and Analysis

SSI, a professional panel data firm using large consumer panels in the Netherlands that ensure a representative sample of the Dutch population, collected the data for our study. Respondents were invited to participate in the survey if they belonged to the working population and worked at least 12 hours per week. Out of 6,473 respondents who started the study, we only analyze responses of 1,649 respondents who watched the explanatory video and for whom we obtained valid data.[7] In our sample, 38.1% are women, the average age was 45.2 years old (with a range from 21 to 65 and a standard deviation of 11.3 years old), and 17.5% had a bachelor degree or higher. The average gross yearly income is 41,947 euros per year (with a range from 15,500 to 280,000 euros and a standard deviation of 24,991 euros).

To check for scale validity, we conducted a confirmatory factor analysis on the firm expertise and trust scales. The results reflect two different factors for the firms' perceived level of expertise and trust (since one item of the expertise scale also partially loaded on the trust scale, this item was eliminated from further analysis). The resulting Cronbach's alphas were 0.97 for both scales. Jointly, these results support the validity of the scale measures. The main descriptive statistics of all variables and their correlations are presented in Table 1. The average acceptance rate is 58.5% with a standard deviation of 23.5%.

[5] On average, participants were 44.1 years old (SD = 12.5 years old), 51.7% were females, 32.4% had a tertiary education degree (i.e., a bachelor degree or higher), 66.6% had a secondary education degree, and 1% had primary education. Participants were asked to consider websites that provide advice about financial products, in particular about possible investments for their pension. They were presented with four different organizations that could offer such an advice website: their insurer, their pension fund, a commercial comparison website, and an information website of the government. Afterwards, participants were asked the following two questions: "please indicate where you think each organization stands with regard to [being focused on making a profit / how many financial products of their own they offer]." Both perceptions were measured on a Likert scale from 1 (= 'not at all focused on making a profit'/ 'offers many of their own products') to 7 (= 'fully focused on making a profit'/ 'offers no products of their own at all').

[6] The interaction satisfaction average scores of not-for-profit advisors are larger than those of for-profit advisors, but the difference is only marginally significant ($M_{not\text{-}for\text{-}profit} = 4.734$, $SD = 1.557$; $M_{for\text{-}profit} = 4.604$, $SD = 1.542$; $t(1{,}649{,}2) = 1.705$, $p = .10$). There is no statistically significant difference between pension product providers vs. advisors-only ($p > .10$). The interaction satisfaction average scores across the four advisor types are the following (in decreasing order): Pension fund = 4.78, Government-based sponsored comparison website = 4.67, Privately-owned comparison website = 4.61, and Insurance firm = 4.60.

[7] This low continuation rate may be due to several factors, such as internet connection difficulties, lack of time to watch the full video and participate, and lack of fit with the respondent's interests, although we have no data to support any of these possibilities. We note that in our study lack of fit cannot be attributed to self-selection—if, to start with, some consumers were more inclined to seek online pension advice than others—because who gives the advice is exogenously determined in the experimental design. Quantifying the impact of self-selection on advice acceptance in 'the real' is an important research question, however, and one we see worth pursuing in the future.

Table 1
Main descriptive statistics (top panel) and correlation matrix (bottom panel).

	Advice Acceptance	Expertise	Trust	Satisfaction	Age	Income	User expertise
Mean	58.51	4.64	4.24	4.67	45.21	41,947.21	3.42
S.D.	23.48	1.32	1.49	1.55	11.35	24,991.32	1.51
Max.	100	7	7	7	65	280,000	7
Min.	0	1	1	1	21	15,500	1
N	1,522	1,649	1,649	1,649	1,649	1,633	1,649

	Advice Acceptance	Expertise	Trust	For profit	Product provider	Satisfaction	Age	High education	Gender	Income
Expertise	0.577									
Trust	0.600	0.764								
For profit	−0.072	−0.100	−0.252							
Product provider	0.046	0.211	0.031	−0.005						
Satisfaction	0.757	0.588	0.633	−0.051	0.016					
Age	−0.057	0.027	−0.080	−0.024	0.015	−0.074				
High education	0.018	−0.014	−0.044	−0.005	0.026	−0.034	−0.091			
Gender	−0.088	−0.075	−0.064	0.019	−0.029	−0.088	−0.114	0.018		
Income	0.026	0.043	0.011	0.001	−0.027	0.036	0.094	0.230	−0.222	
User expertise	0.236	0.258	0.337	−0.055	0.009	0.292	−0.098	0.043	−0.190	0.150

Whereas approaches to mediation such as Baron and Kenny's (1986) assume independent causal steps to investigate the conceptualized relationships, we used an econometric structural equation model (SEM) that estimates these effects simultaneously (Iacobucci 2008; Zhao, Lynch Jr, and Chen 2010). Instead of separately estimating (i) the effect of firm type on expertise and trust, (ii) the effect of firm type on advice acceptance and satisfaction, and the combined effects of (iii-a) firm type and expertise and trust on satisfaction and of (iii-b) firm type, expertise and trust, and satisfaction on advice acceptance, a SEM model estimates the various relationships while handling estimation uncertainty jointly and efficiently. Fig. 2 provides a schematic representation of the empirical model. The presence of mediation effects can be assessed by evaluating the significance of the estimates of the direct effects on the different paths (all estimated at once, as just mentioned): if (a) firm type has (does not have) a significant direct effect on advice acceptance and (b) firm type has a significant effect on say perceptions of expertise, and perceptions of expertise have a significant effect on advice acceptance, then firm type has a partially (fully) mediated effect on advice acceptance. We estimated our model in Stata. The results, much in line with what we anticipated in our conceptualization, are reported in Table 2.[8]

[8] We estimated the model using the `gsem` [Generalized Structural Equation Model] command, which makes use of more observations whenever possible, as is the case in the *Expertise*, *Trust*, *User expertise*, and *Satisfaction with the online interaction* equations. The model's Log likelihood is −16,448.7. Model fit comparisons of models estimated with the `gsem` command, however, are not straightforward due to the use of a different and typically larger number of observations. Estimating the model with Stata's `sem` command instead, leads to a standardized root mean squared residual (SRMR) equal to 0.058 and below 0.08, an indication the model fits the data well (see Kline 2011). The coefficient of determination (CD), an R^2 equivalent measure, is 0.269.

Results

The Impact of Firm Type on Perceived Expertise and Trust, and on Satisfaction

First, we determine whether the two criteria (for profit vs. not-for-profit and product provider vs. advisor-only) we use to classify the types of firms, affect respondents' perceptions of expertise and trust. In respect to perceptions of trust, as expected, our results show that for-profit firms are trusted significantly less than, respectively, not-for-profit ones ($\beta = -0.491$; $p < .001$). Firms that provide their own products are also trusted less than advisor-only firms ($\beta = -0.378$; $p < .001$). As predicted, we find that consumers perceive firms that provide their own pension products as having significantly higher expertise than advisor-only firms ($\beta = 0.566$; $p < .001$). We also find that for-profit firms are perceived to have significantly lower expertise than not-for-profit firms ($\beta = -0.224$; $p < .001$).

In turn, we find that perceptions of expertise and perceptions of trust both have a significant positive effect on interaction satisfaction ($\beta = 0.296$; $p < .001$ and $\beta = 0.449$; $p < .001$ for expertise and trust, respectively), as expected. We also find that consumers are significantly less satisfied interacting with the automated decision tool of firms that provide their own pension products than of advisor-only firms ($\beta = -0.183$; $p < .01$). Consumers are significantly more satisfied interacting with the automated decision tool of for-profit firms than that of not-for-profits ($\beta = 0.270$; $p < .001$).

Clearly, then, a for-profit orientation can be seen as a double "perceptual" jeopardy for online automated advisors because it negatively impacts consumer perceptions of both expertise and trustworthiness, which then carry over to interaction satisfaction. To make things worse for for-profits, which receive poorer perceptions of expertise than not-for-

Table 2
Structural effects of type of advisor firm, expertise and trust on likelihood of acceptance of automated pension investment advice[§].

		Acceptance of automated online pension advice			Perceived expertise of online advisor firm			Perceived trust of online advisor firm			Satisfaction with interactive decision aid			Perceived user expertise		
			95% L	95%U		95% L	95% U		95% L	95% U		95% L	95% U		95% L	95% U
For profit advisor	b	0.112	−1.457	1.681	−0.224	−0.344	−0.104	−0.491	−0.576	−0.406	0.270	0.152	0.387			
	se	0.800			0.061			0.043			0.060					
	z	0.140			−3.660			−11.310			4.500					
	p	0.889			0.000			0.000			0.000					
Product provider advisor	b	0.148	−1.416	1.713	0.566	0.446	0.686	−0.378	−0.465	−0.291	−0.183	−0.301	−0.065			
	se	0.798			0.061			0.044			0.060					
	z	0.190			9.240			−8.510			−3.040					
	p	0.853			0.000			0.000			0.002					
Perceived expertise of advisor firm	b	3.272	1.963	4.582				0.843	0.809	0.877	0.296	0.225	0.367			
	se	0.668						0.017			0.036					
	z	4.900						48.190			8.200					
	p	0.000						0.000			0.000					
Perceived trust of advisor firm	b	1.185	−0.041	2.412							0.449	0.385	0.513			
	se	0.626									0.033					
	z	1.890									13.670					
	p	0.058									0.000					
Satisfaction with online tool	b	9.151	8.514	9.789												
	se	0.325														
	z	28.140														
	p	0.000														
User expertise	b	−0.364	−0.901	0.172	0.222	0.181	0.263	0.135	0.105	0.165	0.072	0.031	0.113			
	se	0.274			0.021			0.015			0.021					
	z	−1.330			10.600			8.840			3.470					
	p	0.183			0.000			0.000			0.001					
Age	b	−0.009	−0.077	0.058	0.004	−0.001	0.009	−0.011	−0.015	−0.007	−0.005	−0.011	0.000	−0.017	−0.023	−0.010
	se	0.035			0.003			0.002			0.003			0.003		
	z	−0.270			1.430			−5.780			−2.080			−5.100		
	p	0.789			0.153			0.000			0.037			0.000		
High education	b	3.008	0.985	5.031	−0.094	−0.258	0.069	−0.170	−0.285	−0.054	−0.071	−0.225	0.083	0.026	−0.168	0.220
	se	1.032			0.083			0.059			0.078			0.099		
	z	2.910			−1.130			−2.880			−0.900			0.260		
	p	0.004			0.260			0.004			0.367			0.793		
Gender (Females = 1)	b	−1.290	−2.905	0.325	−0.002	−0.132	0.127	0.029	−0.062	0.120	−0.093	−0.214	0.028	−0.546	−0.697	−0.395
	se	0.824			0.066			0.047			0.062			0.077		
	z	−1.570			−0.040			0.620			−1.500			−7.090		
	p	0.118			0.971			0.536			0.134			0.000		
Income (in thousands of euros)	b	−0.016	−0.048	0.016	0.001	−0.002	0.003	−0.001	−0.003	0.000	0.001	−0.002	0.003	0.007	0.004	0.010
	se	0.016			0.001			0.001			0.001			0.002		
	z	−0.970			0.700			−1.430			0.600			4.480		
	p	0.334			0.481			0.153			0.551			0.000		
Implicit Advice (ImpAdvice)	b	2.932	−2.563	8.428										−0.019	−0.161	0.123
	se	2.804												0.073		
	z	1.050												−0.260		
	p	0.296												0.794		
ImpAdvice x Perceived expertise of advisor	b	−1.977	−3.726	−0.228												
	se	0.892														
	z	−2.220														
	p	0.027														
ImpAdvice x Perceived trust of advisor	b	1.459	−0.076	2.995												
	se	0.783														
	z	1.860														
	p	0.062														

[§] *Error terms assumed to follow a normal distribution. Number of observations in advice acceptance equation (in remaining equations) is 1,508 (1,633). Estimates for intercepts and error variances omitted for the sake of space (available upon request). "b" stands for point estimate, "se" for standard error, "z" for standardized effect, and "p" for p-value.*

profits, perceived expertise has a positive significant impact on perceived trust ($\beta = 0.843$; $p < .001$). Since our scenario estimates are average effects in respect to a common baseline (a not-for-profit advice-only firm, i.e., a government-sponsored comparison website) and the measurement scales are the same for trust and expertise (from 1 to 7), we can have a sense of the relative impact of firm type on trust and expertise. Our results show that being a for-profit advisor firm

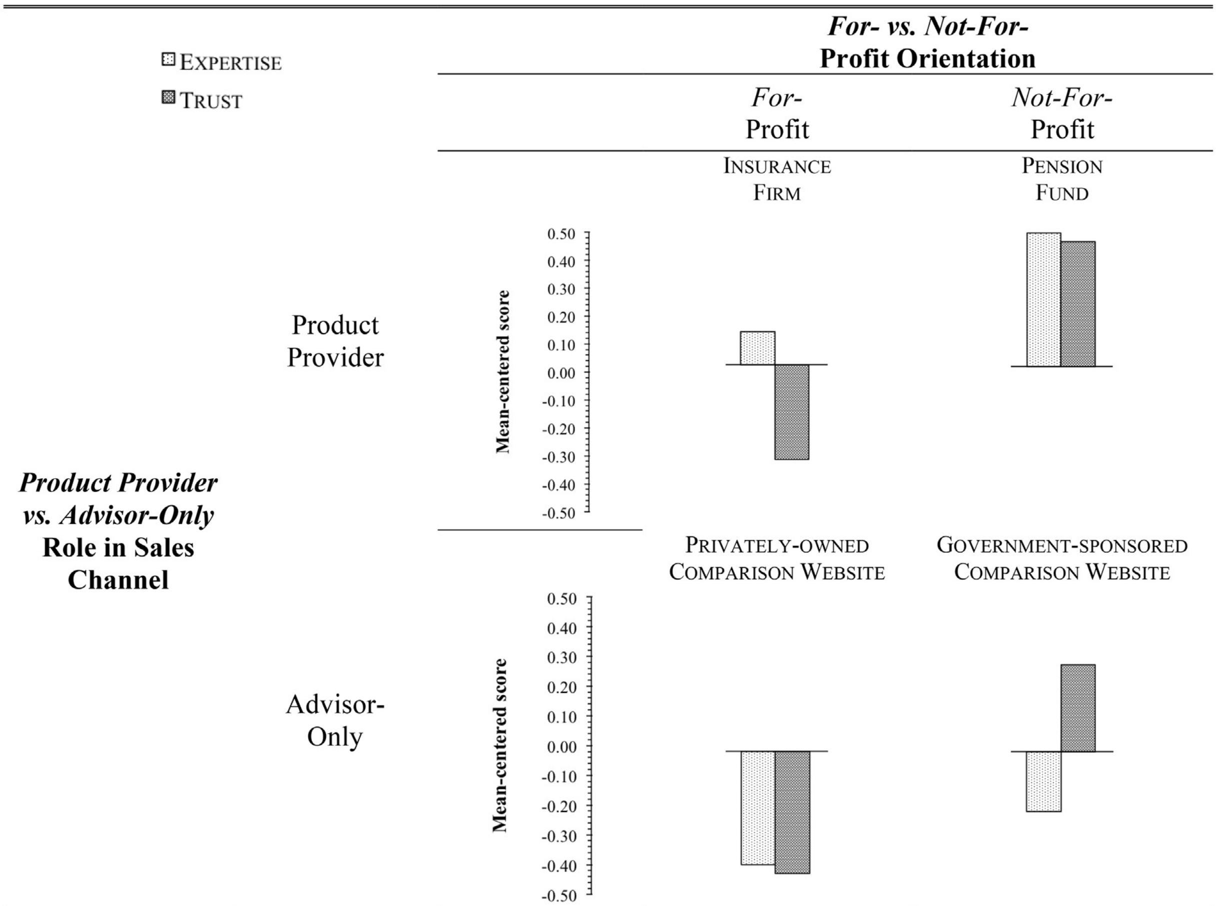

Fig. 4. Evaluation scores for perceived expertise and trust by type of advisor firm.

(vs. a not-for-profit one) is more important than being a pension product provider (vs. an advice-only firm) in the formation of trust ($|-0.491| > |-0.378|$), but not in the formation of perceptions of expertise ($|-0.224| < 0.566$).

In other words, firms that have a for-profit structure clearly face a much greater challenge in convincing consumers to trust them than not-for-profit firms do, so they will need to find other aspects in their strategy to compensate for this disadvantage. Fig. 4 graphically illustrates the differences in perceived levels of expertise and trust between the four separate firms representing the four different firm types (note that the graph is based directly on evaluation scores observed in our survey, not on estimates of the model parameters).

Mediators of the Effect of Firm Type on Advice Acceptance

Turning to our focal dependent variable, our results clearly indicate that consumer perceptions of both expertise and trust are significant and positive predictors of acceptance of online pension advice, with higher levels of both perceptions being associated with a higher likelihood of acceptance of a firm's (explicit or implicit) recommendation ($\beta = 3.272$; $p < .001$ and $\beta = 1.185$; $p < .10$ for expertise and trust, respectively).[9] Judging by their standardized coefficients, the importance of expertise in driving the acceptance of online pension advice is higher than that of trust (4.900 and 1.890 for expertise and trust, respectively).[10] The likelihood of acceptance of online pension advice is not affected directly by the type of firm ($\beta = 0.112$; $p > .10$ and $\beta = 0.148$; $p > .10$, for profit orientation and role in the sales channel, respectively), but it is indirectly through the full mediating effect of both perceived expertise and trust, as a firm's profit orientation and role in the sales channel do affect both perceptions (as discussed previously).

For the same reason, satisfaction with the online tool, which, in line with the literature on decision support systems (e.g., Li and Gregor 2011; Liang, Lai, and Ku 2006), is a strong and significant positive predictor of advice acceptance ($\beta = 9.151$; $p < .001$), also mediates the effect of firm type on advice acceptance, as a firm's profit orientation and role in the sales

[9] Dropping the “implicit advice” interactions from the model leads to the same results, but the effect of perception of trust becomes more pronounced ($\beta = 1.987$; $p < .001$).

[10] Standardized coefficients indicate relative predictive strength insofar as the independent variables have similar distributions. A McNemar test for paired binomial data did not reject the distributional equality of the two variables ($p > .10$).

channel do not affect advice acceptance directly but do have a significant impact on satisfaction (see the previous discussion of results). Because of that and the significant impact of satisfaction on advice acceptance, our results also indicate that firm type ("who delivers the advice") has an effect on the satisfaction with the online interactive decision tool that is partially mediated by perceptions of expertise and perceptions of trust ("partially" because firm types do have a direct effect on satisfaction; see again the previous discussion of results). The total indirect effect of a for-profit firm type on advice acceptance (through the mediators "expertise" and "trust" and from those through the mediator "satisfaction") is negative and significant ($\beta_{indirect} = -2.472$ se = 1.015, $p < .05$; 95% CI = −4.462 to −0.483), while the total indirect effect of a pension product provider firm type (through the same paths) is positive and significant ($\beta_{indirect} = 2.235$ se = 0.928, $p < .05$; 95% CI = 0.416 to 4.055).[11]

The partial mediation helps explain the strong effect of satisfaction on advice acceptance (note again that our scenario estimates are average effects with respect to a common baseline and, like trust and expertise, satisfaction is measured on a scale from 1 to 7): firm type also directly affects satisfaction with the online tool. Assuming all other drivers to be constant, an increase in satisfaction by one unit (from say the current average, 4.67, to 5.67) increases the likelihood of online pension advice acceptance by roughly 9.2 percentage points (recall that advice acceptance likelihood ranges from 0% to 100%). Not surprisingly then, online pension advisors should ensure that consumers in general (who are increasingly heterogeneous), and senior consumers in particular (who are closer to retirement) are satisfied with their interactions with automated tools available online.[12] However, as our results on the impact of consumer characteristics suggest, this may be easier said than done.

The Impact of Consumer Characteristics and the Moderating Effect of Implicit Advice

Age is estimated to negatively and significantly affect satisfaction with the consumer–online tool interaction ($\beta = -0.005$; $p < .05$), which means that, on average, and all else equal, older consumers are less satisfied using automated tools to generate pension advice than younger ones. The fact that user expertise is positively and significantly related to interaction satisfaction ($\beta = 0.072$; $p < .001$), as it is to perceptions of firm expertise ($\beta = 0.222$; $p < .001$) and trust ($\beta = 0.135$; $p < .001$), and older consumers have significantly less user expertise than the young on average ($\beta = -0.017$; $p < .001$), makes the segment of senior consumers even more challenging for financial advisors operating online—the kind of challenge they face with female consumers too, who also perceive themselves as having significantly lower user expertise than males ($\beta = -0.546$; $p < .001$). As expected, older consumers also perceive firms as less trustworthy than younger consumers do ($\beta = -0.011$; $p < .001$), which makes them a particularly sensitive group for the "least-trusted" for-profits and product providers (as opposed to the "most-trusted" not-for-profits and advisors-only).

All in all, compared to the effects of perceived firm expertise, trust in the firm, and interaction satisfaction, the impact of consumer demographics is limited, and is essentially linked to self-perceived user expertise. In fact, we only found a significant effect of higher education on online advice acceptance ($\beta = 3.008$; $p < .01$), indicating that those with a bachelor degree or higher are more inclined to accept the online advice than consumers with lower education. At the same time, highly educated consumers trust an online pension advisor significantly less than the less educated ($\beta = -0.170$; $p < .01$). All other effects of consumer demographics are insignificant.

Interestingly, generating a firm's implicit advice significantly weakens the positive effect of perceptions consumers hold about a financial firm's expertise ($\beta = -1.977$; $p < .01$) but strengthens the positive effect of perceptions consumers hold about a financial firm's trust ($\beta = 1.459$; $p < .10$) on the acceptance of pension advice. We interpret these effects on the basis of the universal dimensions of competence and warmth in social cognition (Aaker, Vohs, and Mogilner 2010; Fiske, Cuddy, and Glick 2007) that fit well the expertise-trust characteristics we focus on. Specifically, the competence dimension (i.e., expertise) on which advisors and advice are judged is less important for those who have the impression they have generated the advice themselves. The warmth dimension (i.e., trust) of the advisor, on the other hand, may even become more important, because those who have the impression they have generated the advice themselves are likely to maintain or even emphasize what maximizes their best-interest—and thereby may highlight the potential non-aligned principle-agent incentives and the role trust plays.

[11] Note that both the total indirect effect of for-profit and that of pension product provider on advice acceptance are the sum of seven products of coefficient estimates, corresponding to all the paths in between (see Figure 2): via expertise (−0.224*3.272 = −0.733 se = 0.262 and 0.566*3.272 = 1.853 se = 0.477), via trust (−0.491*1.185 = −0.582 se = 0.410 and −0.378*1.185 = −0.448 se = 0.315), via satisfaction (0.270*9.151 = 2.469 se = 0.580 and −0.183*9.151 = −1.678 se = 0.541), via expertise to trust (−0.224*0.843*1.185 = −0.224 se = 0.171 and 0.566*0.843*1.185 = 0.566 se = 0.400), via expertise to satisfaction (−0.224*0.296*9.151 = −0.607 se = 0.197 and 0.566*0.296*9.151 = 1.534 se = 0.320), via trust to satisfaction (−0.491*0.449*9.151 = −2.019 se = 0.281 and − 0.378*0.449*9.151 = −1.553 se = 0.247), via expertise to trust to satisfaction (−0.224*0.843*0.449*9.151 = −0.776 se = 0.226 and 0.566*0.843*0.449*9.151 = 1.961 se = 0.307). The standard errors used in the statistical tests above are bootstrapped (see Preacher and Hayes 2008; Zhao, Lynch, and Chen 2010).

[12] As we have discussed in our literature review and conceptualization section, the online interaction process is a very elaborate one as it depends on several aspects within three different domains: the consumer, the communication, and the information system. Hence, successful online pension advisors probably need to perform well on all or at least most of these aspects to do well on satisfaction (which we implicitly assumed to be a proper summary measure of all three interaction-domains).

Discussion and Implications

The increasingly difficult challenge firms face today is how to reassure consumers that online algorithms are unbiased—and, in that sense, competent—and trustworthy. These two dimensions are very important in the financial advice industry, in particular when it comes to advising consumers about pensions that involve high-stakes decisions that impact the quality of living after retirement (the Dutch traditional standard age of retirement is 65 while average life expectancy is more than 15 years greater, 81.5). In this paper, we investigate how the type of automated advisor firms—in particular, in terms of profit orientation and role in the sales channel—may affect acceptance of automated financial advice. In our study of pension investments for retirement, we use an innovative online automated tool, the Pension Builder (see Dellaert et al. 2016), to generate the financial advice provided on behalf of an *insurance firm* (a for-profit firm selling its own pension products), a *privately owned comparison website* (a for-profit firm providing only advice), a *pension fund* (a not-for-profit firm selling its own pension products), or a *Government-sponsored comparison website* (a not-for-profit firm providing only advice). In so doing, we keep constant the effect of the finance-based algorithm running on the Pension Builder automated online interface (our interactive decision aid) and look for the differences in advice acceptance accruing from the different firms that typically communicate financial advice, and whether those differences change depending on whether the firm explicitly communicates the advice to the consumer or does it only implicitly, giving the consumer the impression she is his/her own advisor.

While controlling for the expected effect of consumers' interaction satisfaction with an automated tool, we find that the type of advisor firm—i.e., whose advisor consumers interact with and get advice from—influences the acceptance of financial advice. Importantly, we find that this effect is fully mediated by how positively consumers perceive the advisor firm in terms of expertise and trustworthiness.

As we propose, not-for-profit firms are likely to enjoy higher levels of trust, and this is perhaps all the more evident in light of and during financial crises that may hurt the perception of the financial industry in general (Mayer 2013). Also, as we predicted, comparison websites that do not sell their own pension products are perceived to have relatively less expertise—on top of that, and to make things worse, privately owned websites are perceived untrustworthy. It may be that Dutch consumers regard the regulatory requirements in the Netherlands as a strong enough buffer against the biased advice that could result from selling products with high profit margins (e.g., Cadman, Carter, and Hillegeist 2010; Inderst and Ottaviani 2012), which is more likely to be ensured among government-sponsored websites.[13]

Moreover, consumers may trust that a *computer-to-human interaction*, such as the one individuals have with the Pension Builder, makes automated pension advisors use less discretionary criteria than is customary in financial *person-to-person interactions*, even if the advice is generated by for-profit firms (see e.g., Cerqueiro, Degryse, and Ongena 2011 in the context of discretionary rules that even banks follow). Automated advisor algorithms are shown to not only outperform humans in simple tasks (e.g., Dietvorst, Simmons, and Massey 2015; Grove et al. 2000), they are also seen as deserving no more regulations than those upon "imperfect" human advisors (Ji 2017; Philippon 2016).

When it comes to perceptions of expertise, for-profit firms, much like pension plan providers, are seen as having higher levels of expertise than not-for-profit firms and independent intermediaries. This suggests, as we anticipated in our conceptualization, that without a high level of expertise these firms would have a hard time surviving in a highly sophisticated competitive market such as that for pension products (see e.g., Coates and Glenn Hubbard 2007).

Besides the firm that supplies the advice, consumer satisfaction with the online tool on which pension advice is generated also has a strong positive effect on online advice acceptance. This underscores the importance of designing attractive and easy-to-use online interfaces for consumer adoption of online advice. Finally, when we control for the impact of individual characteristics on firm and interaction evaluation, we find that online advice is more likely to be accepted by consumers with a higher education.

Jointly, these findings demonstrate the importance of: (1) building algorithm–human relationships that are based on trust and expertise that are clearly perceived by human consumers; (2) carefully designing online automated advice processes to promote acceptance of automated advice; and (3) targeting channels of online and offline advice to consumers who prefer to receive advice on each type of channel, e.g., making sure that algorithm-averse consumers have the opportunity to seek for and receive offline advice.

As summarized in Fig. 4, automated advisors of pension funds score high on both expertise and trust, while automated advisors of privately owned comparison websites score low on both perceptions. In turn, automated advisors of insurance firms score high on expertise but low on trust, while the opposite happen for automated advisors of government-sponsored comparison websites. The online automated advice of a pension fund (which has high scores on both expertise and trust), is thus the one most likely to be accepted, followed by that of an insurance firm (enjoying high scores on expertise yet low scores on trust) and a government-sponsored comparison website (enjoying high scores on trust yet low scores on expertise). The online automated advice of a privately owned comparison website (which has low scores on both expertise and trust) is the least likely to be accepted.

We focused our research questions and empirical study on expertise and trust in relation to firm type, and therefore can only conjecture what firms in the financial industry can do to

[13] The use of the terms "consumer" and "firm" may not do full justice to the unique case of a pension fund and its plan members. Specifically, it is worth noting that a fund plays a fiduciary role, i.e. it acts on behalf of its members, and thereby both parties have a common goal.

counter poor perceptions in those two dimensions. For instance, financial firms can incentivize users who trust them and who regard them as experts to place their (positive) reviews online, hoping that that user-generated content not only carries over to other users but also enjoys a higher level of credibility (Nielsen 2015). This is what the Santander bank has done in its “Prosperity” video campaign using “warm, engaging, funny, and real” user-generated video footage to communicate its commercial proposition “in a compelling and honest way,” which is but one of many recent examples in the industry.[14] In line with the CMOs' expectations in the financial world, research in marketing has shown not only that user-generated content has an effect on sales (Dhar and Chang 2009) and stock performance (Tirunillai and Tellis 2012) but also that the effect of consumers' word-of-mouth in an online context is stronger than that of traditional marketing (Trusov, Bucklin, and Pauwels 2009). Betting on user-generated content and marketing activities in general that may boost perceptions of expertise and trust may thus very well payoff, especially in interaction with the types of firms that have an edge delivering automated financial advice (in particular, pension funds).

Although we lack data on the profit margins faced by the different types of firms offering online automated advice, the 5.41 percentage points higher advice acceptance rate that the online automated advice of a pension fund faces compared to the same online automated advice coming from a privately owned comparison website, may represent a commercial value of as much as $38.5 per consumer seeking advice.[15] This is an appealing prospect for financial advisors having to deal with slim profit margins (FT 2017).

Among the different consumer characteristics we control for, higher education is the only one that impacts advice acceptance directly and positively. The positive effect of higher education is in line with the view that those financially literate process financial information more easily (Lusardi and Mitchell 2011; Lusardi, Mitchell and Curto 2010) and are thus more prone to accept an advice, rather than the view that those with a lower education recognize the need for advice (Lee and Moray 1992).

Interestingly, higher education and age negatively impact both trust and (to a lesser extent) the satisfaction with the interaction with the automated tool used to generate the advice to be provided by the firm. Finally, compared to males, females are on average clearly less satisfied with their interaction with the advisor algorithm and interface and they perceive, though less clearly, an online advisor firm as less trustworthy and as less of an expert, on average. This suggests that advisor firms going (or already) online will be particularly interested in targeting young males without higher education.

Limitations and Future Research

The rise of automated advice-generating algorithms announced in the media, industry reports and in research editorials across several disciplines has yet to generate an equally rich stream of research findings, both empirical and theoretical. In that respect, it would be of great value to test which conceptual framework best fits this new phenomenon. One unifying concept that may bind the three components of acceptance of automated pension advice—firm, consumer, and their interactions—is that of an implicit psychological reciprocity contract, in which consumers contribute personal information and effort in exchange for more useful advice by the firm (Rousseau 1989; Zeithaml 1988).

Like never before, increasing opportunities to express preferences to firms and even create one's preferred products help consumers build identities in the marketplace (Firat and Dholakia 1998). At the same time the co-creation process may take consumers closer to a worker mindset (Etgar 2008; Zwick, Bonsu, and Darmody 2008), with the same mutuality and reciprocity found in labor expectations (Dabos and Rousseau 2004). In economics, Akerlof (1982) introduced the term “gift-exchange” to refer to the reciprocal relation between firms and workers, and the “gift-exchange game” has been applied successfully in the lab and in the field, showing, e.g., that higher remunerations lead to increased effort (e.g., Maximiano, Sloof, and Sonnemans 2007). Resting on an unwritten psychological reciprocity contract, consumers working with complex automated algorithms on websites of financial advisors may also very well expect high(er) returns or lower risks (see also footnote 4).

These “effort-accuracy” mechanisms are close to the economics perspective that sees (advice for) consumption as part of a consumer's production process (Becker 1965), where the marginal effects of more input (information and/or effort) depend on the (believed) production function. These conceptualizations would, in turn, easily link to the three stages of Murthi and Sarkar (2003), namely learning and matching (the third one, evaluation of advice, is more of a post-interaction stage). An overarching challenge here, as in other behaviors of consumers seeking financial advice, is the ensuing endogeneity of the advice: it may not take long for automated algorithms to learn consumer preferences based on the input or effort of consumers, which in turn depends on the expected returns from the advice.

Future research could also benefit from testing consumer perceptions and acceptance of online advice in a real world setting—where marketing activities take place on a daily basis and user generated content plays an increasingly important role—with, say, actual pension funds or insurance firms offering pension products. It would be particularly interesting if advice acceptance could be compared across different providers, to investigate if the type of firm does indeed play an important role in consumer online advice acceptance—even when a consumer is already coupled with a certain type of firm. In addition, it would be interesting to see the type of firm consumers choose when they are given the freedom to choose

[14] See https://www.moreaboutadvertising.com/2017/01/santander-tries-a-dose-of-user-generated-prosperity/ and https://www.marketingweek.com/2017/01/25/bank-brands-purposeful-approach/; both accessed 1 July 2019.

[15] According to Deloitte (2017), the cost of a typical financial planning session with an (*human*) advisor is roughly $712 in the UK (at the current exchange rate; see also https://www.unbiased.co.uk/cost-of-financial-advice, cf. Deloitte 2017).

between different robot (i.e., automated, algorithm-based) advisors. Although we designed a controlled setting to ensure that we could draw valid conclusions regarding the impact of the type of firm providing advice on advice acceptance, we only asked respondents to self-report advice acceptance.

This sequential process of advisor selection and advice acceptance would be worthwhile modeling econometrically, to establish the economic value of interaction design and firm type. Similarly, it would be valuable studying the sequential process that goes from the acceptance of online advice to the actual steps consumers take in their pension strategies. For example, will consumers more or instead less easily adopt additional savings or investment strategies when given advice online than when they are advised in person?

Finally, in future applications of online advice, it is important to assess how consumers respond to advice that combines multiple components of their retirement portfolio. For example, depending on whether or not a consumer has private savings or investments, the retirement investment advice may shift. Thus, interactions may need to be more extensive and may need dynamic updating from time to time to capture possible changes in consumer circumstances. This may offer further opportunities for increasing perceived firm expertise and trust, but it may also lower consumer satisfaction with the interaction process, all depending on how “all-in-one” the online interactions are designed.

Appendix A.

*A.1. Explicit [Implicit] Advice Survey Instructions Before Investment Profile Is Generated Online**

1. There are more and more online tools that **[one of the four firm types] can use to advise customers on *[that people can use when making]*** financial decisions. This research focuses on a tool **developed to advise people on the *[to assist you in coming to a]*** trade-off between risk and return when investing their pension assets.

2. To be able to provide you with good advice on the trade-off between risk and return in your pension investments, the owner needs your age and income. ***[Your age and income play a role in making the trade-off between risk and return in your pension investments.]***

3. **To provide advice to people in making choices for their retirement investments, the owner has created a new retirement simulator. You will be asked to indicate *[You can use online tools while making your choice for your pension investments. The owner has created a new retirement simulator that you can use to help yourself make your choice. In this pension simulator you can choose]*** when you want to retire and how much risk you want to take with your pension investments. A short instructional video now follows. You can then use the simulator to experience the various options. **The owner will give you appropriate advice about your pension investments based on your preferences. *[In this way you can try out various options and then decide for yourself which one suits you best.]***

4. Now please click on the instructional video and view the video completely.

5. We summarize the most important things in the owner's pension simulator.

6. The pension simulator determines a hundred possible outcomes based on the owner's calculation model that accurately reflects the uncertainty about the future. What is possible **depends on the chosen *[depends on your choice of your]*** retirement date and the amount of risk that you want to take, but of course also on developments on the stock market and in the economy. Each block represents one of the possible outcomes of the calculation model for these economic developments.

In the simulator you can **play with the age at which *[determine for yourself what age]*** you want to retire and how much risk you want to accept for your pension investment. You can use the sliders to set this. This way you can immediately see the effect of retirement age and the amount of risk on your expected gross pension income. Bear in mind that after your retirement you will have more of your gross income than before your pension. You therefore need less than 100% of your last-earned gross wage as a pension.

7. If everything is clear, you can now start with the simulator, **in which you can indicate your preferences for the *[and use the simulator to determine your desired]*** retirement age and the risk of your own pension investment. Otherwise you can click here to watch the video again.

8. Ultimately, you must choose a specific investment profile for your pension investments. **Based on the institutions you have chosen, the owner advises on *[You have indicated your ideal situation through the pension simulator. The pension simulator also determines]*** which investment profile best matches your preferences.

[at this point the respondent's investment profile is generated online and shown on-screen].

**** Translated from Dutch.***

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None.

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