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Persuasion at First Sight? Testing the Reciprocal Relationship of Repeated Interactions With Virtual Assistants, Trust, and Persuasion

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Virtual assistants (VAs) as a new communication source enable businesses to repeatedly interact with consumers, increasing the opportunities for persuasive attempts in the form of (personalized) product- or service-related recommendations. However, knowledge on whether consumers build trusting relationships with VAs through repeated interactions and whether this subsequently influences an assistant's persuasiveness is lacking. This study tests the reciprocal relationship of repeated interactions, trust, and brand-related outcomes in a preregistered 15-day longitudinal within-subjects experiment including 3 measurement points. In daily interactions, participants received recipe suggestions including branded product recommendations from a VA (n = 242). Findings show a positive relationship between VA trust and persuasion and longitudinal effects of increased trust in a VA, resulting in a subsequent increase in positive attitudes toward the recommended brand. We show that persuasion does not happen at first sight, as some interaction is needed for persuasiveness to unfold.

Keywords: virtual assistant, repeated interactions, trust, persuasion

Conversational technology—technology that communicates via human language—changes the way we engage in everyday activities related to news, entertainment, and commercial contexts (e.g., customer

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service or advertising; Moriuchi, 2019). Businesses invest largely into conversational technology, and the market is expected to grow even further (Gartner, 2022). Positioned as virtual assistants (VAs) that fulfill the function of assisting a user, especially in a commercial context, conversational technology has become part of consumer-brand interactions. In the prepurchase phase, they are predominantly employed to predict user preferences and provide recommendations (Liu-Thompkins, Okazaki, & Tse, 2022).

As VAs are becoming increasingly important for brands to communicate with consumers, it is imperative to study the persuasive potential of VAs. VAs can register complex user input, assemble user information, and—in real time—provide personalized output, for example in the form of recommendations (Lou, Kang, & Tse, 2022). For example, a VA that gives advice on (mostly simple) decisions in our daily lives (e.g., what to cook for dinner) based on our preferences can also be used to provide advertising-related messages (e.g., giving branded product recommendations) that can persuade users in their attitudes (e.g., toward a brand) and behaviors (e.g., wanting to buy the recommended product).

Important from a human-machine communication perspective, VAs can function as a new communication partner, taking over the role of a daily virtual companion and implementing social or relational cues (Zierau, Engel, Söllner, & Leimeister, 2020). VAs create the potential for repeated one-on-one interactions and for becoming more than a one-shot marketing *tool*. Instead of mediating the communication between brand and consumer, they appear as a distinct communication *source* with its own characteristics, which implies that users can develop trust toward this source over time (Guzman, 2019; Hoff & Bashir, 2015; van der Goot, 2022).

Although the literature has pointed toward the importance of interpersonal- and brand-trust for persuasiveness (e.g., Hayes, King, & Ramirez, 2016; Huh, Kim, Rath, Lu, & Srivastava, 2020; Kim & Kim, 2021; Schouten, Janssen, & Verspaget, 2020), this relationship may unfold uniquely for the emerging case of VAs as a distinct communication source. Furthermore, although some initial evidence has been provided that social or conversational cues of VA can influence persuasion (Ischen, Araujo, Voorveld, van Noort, & Smit, 2022; Ischen, Araujo, van Noort, Voorveld, & Smit, 2020; Lee, Pan, & Hsieh, 2022; Rhee & Choi, 2020; Yen & Chiang, 2020), the unique role of VA trust for persuasiveness is underexplored.

Moreover, up to this point, VA trust has mostly been examined cross-sectionally (Chattaraman, Kwon, Gilbert, & Ross, 2019; Chen, Lu, Gong, & Xiong, 2023; Youn & Jin, 2021). Few studies have suggested that trust (Ng, 2024; Skjuve, Følstad, Fostervold, & Brandtzaeg, 2022) as well as persuasion (Albers, Neerincx, & Brinkman, 2023) can unfold over time. Prior research has also shown that trust is an essential element of relationship formation, which does not exist in isolation but develops over a series of repeated interactions (e.g., Hayes et al., 2016). Although recent theoretical work (Dehnert & Mongeau, 2022) has proposed that especially the formation of a trusting relationship with a VA (over time) can enhance persuasion, the interplay of repeated interactions with, trust in, and persuasiveness of VAs is still to be empirically tested. To address these shortcomings, this research asks the following question:

RQ1: To what extent does trust built in repeated interactions with a VA influence its persuasiveness in terms of brand attitudes and purchase intentions?

This research question will be answered in the context of consumer-brand interactions, specifically in a recommendation setting in which a VA advertises (branded) products as part of recipe recommendation. This context is appropriate for studying persuasion, as it specifically includes a commercial persuasive attempt. Persuasiveness includes brand-related outcomes (i.e., attitudes toward the brand), as well as purchase intentions. Overall, this study makes a theoretical contribution to the advertising literature as well as to literature on trust and persuasion in human-machine communication and responds to recent calls for testing VA interactions over time (Følstad et al., 2021; Glikson & Woolley, 2020; Guzman, 2019). Methodologically, it contributes by testing a cross-lagged model including repeated interactions, trust, and brand-related outcomes measured at different time points.

Theoretical Background

The Concept of Trust

Trust is a multifaceted concept found in different research domains from interpersonal trust (Coleman, 1990; Rempel, Holmes, & Zanna, 1985), organizational trust (Mayer, Davis, & Schoorman, 1995), to trust in automation (Hoff & Bashir, 2015; Lee & See, 2004), and trust in brands (Hayes et al., 2016). A multitude of definitions of the concepts are used in the literature (Benbasat & Wang, 2005; Hoff & Bashir, 2015; Lee & See, 2004; Mayer et al., 1995), but trust commonly involves a situation of uncertainty and is grounded on the characteristics of the trustee.

First, trust involves a situation of risk or uncertainty (Coleman, 1990; Gefen, 1999; Mayer et al., 1995; Rousseau, Sitkin, Burt, & Camerer, 1998). Trust can mitigate the level of uncertainty that is associated with a situation (Milliman & Fugate, 1988). Based on this assumption, Lee and See (2004) define trust (in automation) as "the attitude that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability" (p. 51). In many cases, VAs guide users in choice situations, for example, selecting the best seats in the cinema, giving information about discounts, or providing recommendations for products or services (Rendell, 2019). This involves uncertainty because the users do not evaluate all options themselves but give the responsibility for giving a recommendation to the VA (Benbasat & Wang, 2005).

Based on Lee and See (2004), who see trust as "an affective evaluation of beliefs that guides people to adopt a particular intention" (Lee & See, 2004, p. 53), we define trust as a mental state (Hoff & Bashir, 2015). Mayer et al. (1995) note that the distinction between trust and its consequences or outcomes has often not been clear. By adopting the definition of trust as a mental state, we can examine its relationship with other attitudinal and behavioral variables (such as attitudes and behavioral intentions in the form of purchase intention).

Second, and importantly for VAs, a trusting relationship involves a trustor and a trustee (Driscoll, 1978; Mayer et al., 1995; Scott, 1980). Research has shown that not only humans but also technological artifacts (Benbasat & Wang, 2005; Chopra & Wallace, 2003) and automated systems (Araujo, Helberger, Kruikemeier, & De Vreese, 2020; Hoff & Bashir, 2015; Söllner, Hoffmann, & Leimeister, 2016) can be the recipients of trust. Trust is grounded on characteristics of the trustee, meaning that the trustor has certain beliefs about the trustee and its performance (Mayer et al., 1995). In line with the definition proposed by Benbasat and Wang (2005), trust is "an individual's belief in an agent's competence, benevolence, and integrity" (p. 76). The beliefs are directed toward different characteristics of the trustee (Hoff & Bashir, 2015; Mayer et al., 1995), in this case the VA. Benevolence beliefs refer to the user believing that the assistant acts or performs in the users' best interest, and integrity beliefs refer to a set of principles or values, such as honesty, that an agent adheres to. Competence beliefs are related to the abilities, skills, and expertise of the assistant to perform effectively given a specific task at hand. This implies that competence beliefs are based on the evaluation of an assistant's performance, while benevolence and integrity beliefs are based on whether the assistant matches the users' values and motivations (Hoff & Bashir, 2015).

Repeated Interactions and Trust

Even though people have initial trust levels toward a trustee, trust develops over time (Gefen, 1999; Hoff & Bashir, 2015). VAs create a potential for repeated interactions in which they can take the role of a (daily) companion (Zierau et al., 2020). This notion is based on the computers as social actors paradigm (CASA), which states that people treat computers as social beings (Reeves & Nass, 1996). As Dehnert and Mongeau (2022) argue, it is likely that VAs can engage with their users in "repeated, supportive, and mutually involving interactions" (p. 396), which can, in turn, facilitate relationship development, including trust.

Furthermore, the more often users interact with an assistant over time, the more likely they might be to strengthen their beliefs about the assistant's performance. Research in the domain of automated systems and robotics, for example, shows that robot performance (e.g., reliability) is the most important factor for trust development (Hancock et al., 2011). Even though this has not been established for VAs yet, we argue that by engaging in repeated interactions with VAs, the advantages of the assistant being always available, learning about user preferences, and providing personalized information are being exploited. The more often users are interacting with a VA that takes users' wishes and preferences into account, the more likely they are to trust in its competence.

Moreover, social exchange theory can provide a useful anchor point to explain trust formation toward VAs. The theory posits that trust develops through repeated reciprocal interactions (Homans, 1961; Thibaut & Kelley, 1959). Although initially sought to explain the development of interpersonal relationships based on a cost-benefit analysis, the theory has found empirical support for interpersonal trust as well as brand trust and the interaction of the two in the context of ad referrals and electronic word-of-mouth (Hayes et al., 2016) and in the context of influencer marketing (Kim & Kim, 2021). Based on the theory, it can be argued that the interaction of the user and VA is reciprocal. The user investment in the interaction (i.e., providing information about preferences) might be perceived as comparatively small in relation to the benefit of receiving a (personalized) recommendation from the assistant. Furthermore, the more often a user then interacts with the VA, the more accurate the recommendation becomes, hence increasing the benefit over time. Through the constitution of a reciprocal successful relationship, trust increases, leading to our first hypothesis:

H1a: *An increase in the number of interactions with a VA results in a subsequent increase in trust in the VA over time.*

Reciprocal Relationship of Repeated Interactions and Trust

We argue for a reciprocal cross-lagged relationship of repeated interactions and trust over time, meaning that repeated interactions influence trust but also, in turn, the increase in trust leads people to return to the VA at a subsequent time point. Based on social exchange theory, the more valuable the resources (i.e., the recommendation) offered, the more reliant the relationship partner becomes on the interaction (Kim & Kim, 2021). Hence, a user who built trust in the VA is inclined to repeatedly interact with the assistant. Furthermore, based on the Technology Acceptance Model (Davis, 1989), previous research by Benbasat and Wang (2005) showed that trust in an online recommendation agent positively influenced usage intention. Zierau et al. (2020) found that trust is one of the main factors driving technological adoption. Therefore, we propose the following:

H1b: *An increase in trust in a VA results in a subsequent increase in the number of interactions with the VA over time.*

Trust and Persuasiveness

Ample research in the persuasion domain has demonstrated that source trust determines persuasive outcomes of a communicated message, such as manufacturer-retailer relationships (Kumar, 1996), brand attitudes (Garretson & Niedrich, 2004), or purchase intention (Gefen, 1999; Koh & Sundar, 2010; Tan & Sutherland, 2011). Trust furthermore plays an important role in consumer behaviours, such as ad referral (Hayes et al., 2016) and electronic word of mouth (Huh et al., 2020). Guenzi, Johnson, and Castaldo (2009) specifically investigate the interplay of different trustees, showing the interrelatedness of interpersonal trust (in a salesperson) and trust in retail stores and products, subsequently influencing loyalty intentions. Kim and Kim (2021) and Schouten, Janssen, and Verspaget (2020) find that trust in social media influencers positively influences brand attitudes and purchase intention. Moreover, research on AI-driven technologies and automated recommendations has shown that trust can reduce reactance (Aljukhadar, Trifts, & Senecal, 2017) and is positively related to user satisfaction (Lee & Choi, 2017), purchase intention (Kim, Giroux, & Lee, 2021), and customer loyalty (Chen et al., 2023).

These effects can be theoretically explained with the Elaboration Likelihood Model (Petty & Cacioppo, 1986). According to the theory, likeability and trustworthiness of a source can function as a peripheral cue that has a significant influence on attitudes in situations of low personal importance. When users are interacting with a VA, they are most certainly following the peripheral route when casually or hedonically looking for a recipe recommendation (Zarouali, Poels, Walrave, & Ponnet, 2018). In case people follow the peripheral route of information processing, they make use of the source of a persuasive message—in this case the VA—to evaluate the message (Petty & Cacioppo, 1986). Based on this argumentation, a body of research suggests that trusting a VA can lead to higher persuasion (Schulman & Bickmore, 2009), similarly to salespeople in a store (Bickmore & Picard, 2005).

A second theoretical explanation stems from the Persuasion Knowledge Model (Friestad & Wright, 1994) and research on source credibility (Pornpitakpan, 2004). If users trust an assistant and perceive it as credible, they are assumed to be less critical in their assessment of a persuasive intent and more likely to form positive attitudes toward the message and the included brand (Pornpitakpan, 2004). The credibility of a source may spill over to the credibility of the message, leading to more persuasion (van Noort, Antheunis, & van Reijmersdal, 2012). We therefore propose trust in the assistant to lead to more favorable affective brand outcomes (i.e., attitudes toward the brand) and behavioral intentions (i.e., purchase intention). This leads to the following hypotheses:

H2: An increase in trust in a VA results in a subsequent increase in positive attitudes toward the recommended brand over time.

H3: An increase in trust in a VA results in a subsequent increase in purchase intention of the recommended brand over time.

The full research model is presented in Figure 1.

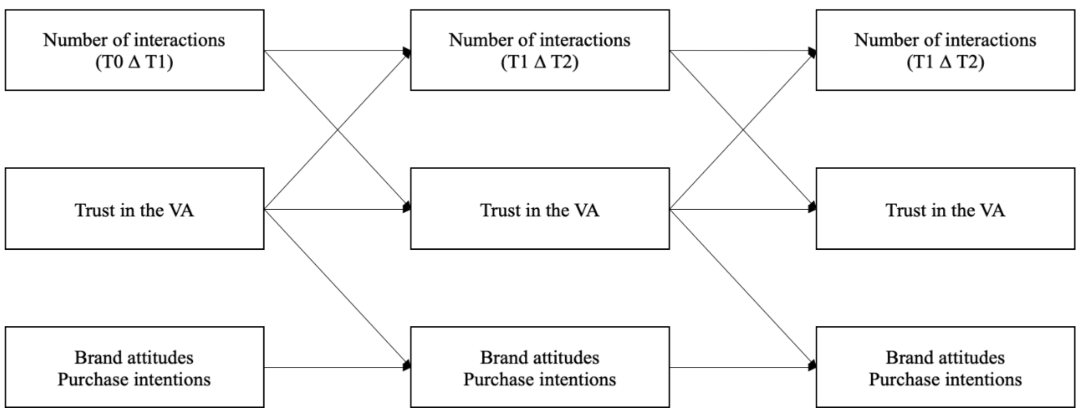

Figure 1. Cross-lagged research model.

Method

Design and Procedure

This study implements a longitudinal within-subjects design with three measurement points, preregistered with OSF before data collection.[2] The study timeline is depicted in Figure 2. In the recruitment phase of (T0), participants gave informed consent, interacted with the VA for the first time, and filled in a recruitment questionnaire assessing demographics and familiarity with VAs (measured with two items adapted from Zhou, Yang, & Hui, 2010). In the interaction with the VA, participants were asked to provide information about themselves (age, gender), their diets (omnivore, vegetarian, vegan), and whether they want to exclude certain products from their meals, which were set as preferences for all subsequent interactions. The interaction with the VA was embedded in an online survey tool accessible via desktop computer, phone, or tablet.

[2] https://osf.io/vau34

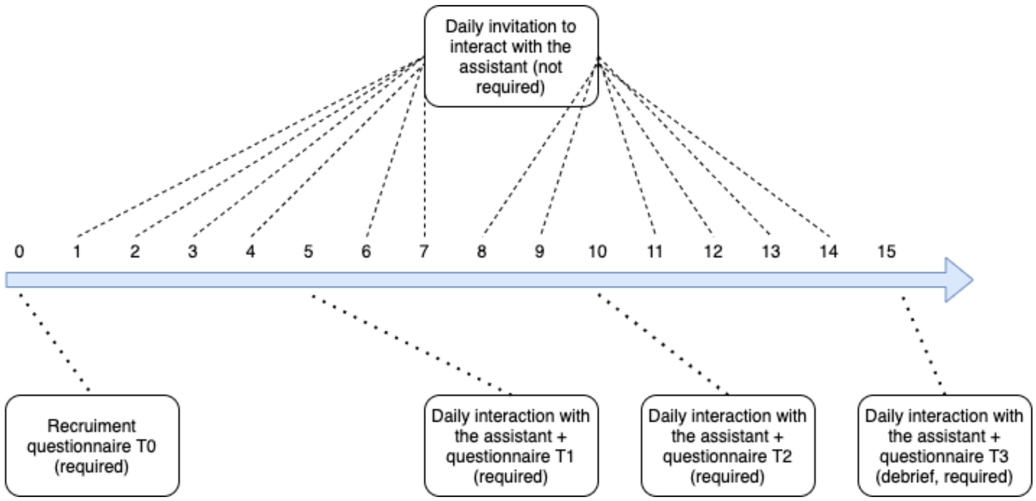

Figure 2. Study procedure timeline.

After the recruitment, participants were invited once a day via e-mail to interact with a VA for receiving a recipe recommendation over the course of 15 weekdays. We based the time frame on a chatbot study by Croes and Antheunis (2021) and only included weekdays to ensure comparability across time intervals, as cooking patterns for most participants differ on weekends.

The interactions with the VA followed a predefined structure. The daily interaction always started with a short greeting by the assistant (e.g., "Great to talk to you again. How are you?"). Subsequently, participants could set certain preferences for the respective interaction, including a specific cuisine (Italian, Japanese, Mexican, Indian, European, Middle Eastern, Thai) or including a specific vegetable or side dish they wanted to use for their meal on that day (e.g., "Can I interest you in an Italian dish today?"). Based on the preference, the VA provided a recommendation for a dish, including name, image, ingredients, and instructions to cook the dish. The VA presented the information in a friendly manner (e.g., concluding with "Goodbye and have a delicious day!"). As a filler item, participants evaluated the relevance of the recommendation after each interaction (with 10 items adapted from Kim & Huh, 2017).

To allow for the VA to give more personalized recommendations over time, all participants are asked on day five (T1) whether they prefer a low-, medium-, or high-calorie diet, and on day 10 (T2) the maximum time they want to spend cooking a dish (less than 30 minutes, less than 60 minutes, no preference). These preferences were then set for all subsequent interactions. This means that the VA got equally more personalized over time for all participants.

We chose the recipe context because VAs are a common-use case for providing recipes and cooking instructions (Rabideau, 2021; Stolwijk & Kunneman, 2022). It furthermore allowed us to include branded product-related recommendations. On days 5, (T1), 10 (T2), and 15 (T3), participants received a branded recommendation for a lemonade (Belvoir elderflower lemonade, ginger beer, and elderflower rose lemonade) to drink with their meal. We chose a lemonade as a product since it goes well with many different recipe recommendations. We decided for an existing but less-well-known brand to avoid familiarity effects. The VA interacted in a friendly but not forcefully persuasive tone (e.g., "I would like to make a special recommendation today that goes perfect with spring and summer dishes: Belvoir elderflower and rose lemonade.") At T1, T2, and T3, participants were also invited to fill in a questionnaire including self-reported measurements of trust, attitudes toward the recommended brand, and purchase intention. After taking part in the study, participants were debriefed that the recommended brands were solely used for experimental purposes.

The VA was specifically designed for this study using a conversational agent research toolkit (Araujo, 2020). Recommendations were made by means of using an API provided by Spoonacular (2021). The materials (including screen videos of the interactions) are available on OSF.[3]

Sample

Participants were recruited through an ISO-certified research company in the Netherlands using quotas for age, gender, and region. Participation during the recruitment was terminated in case participants did not give informed consent (n = 70), did not indicate to feeling (very) comfortable understanding written English text (n = 116), did not pass the attention check (n = 102), or indicated that they did not have an interaction with the VA (n = 48). Of the 402 participants that fully completed the recruitment, a total of 246 participants completed all questionnaires (T1, T2, and T3). We excluded one person based on an invalid score for age and three multivariate outliers (Mahalanobis distance > 18.47[4]), resulting in a final sample of 242.[5] Participants received remuneration for completing the recruitment. They furthermore received a bonus for completing all three measurement points and for completing at least 80% of the daily interactions (10 of 12 interactions).[6]

Within the final sample, participants' ages ranged from 21 to 80 years (M = 45.96, SD = 14.74); 152 were female (62.81%), 89 male (36.78%) and one was non-binary (0.41%). In terms of education, 15 participants can be categorized as having a low level of education (6.20%; no degree, primary education, high school), 84 participants a middle level (34.71%; intermediate vocational education), and 143 participants a high level of education (59.09%; University of Applied Sciences bachelor, University bachelor, master, or doctorate). Initially, participants were rather familiar with VAs (M = 5.18, SD = 1.13).

Measurements

To measure the *number of interactions,* we counted the (fully completed) interactions with the VA participants engaged in between two measurement points. A fully completed interaction was defined as a

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[3] All supplementary materials can be found on OSF, https://osf.io/6v9x2/

[4] Based on a chi-square distribution with df = 4 and p = .001, including number of interactions, trust in the VA, attitudes toward the recommended brands, purchase intention.

[5] According to Kline (2016), a typical sample size for structural equation modeling is about 200 cases.

[6] Following the ethical guidelines of the university, we decided to apply a remuneration strategy incentivizing all parts of the study. Since the reward for the daily interactions is smaller than the other rewards and participants only receive this reward when completing at least 80% of the interactions, we believe that the reward strategy does not impact the validity of the study.

dialogue composed of 10–12 messages, in which the participants received a personalized recipe recommendation after answering questions posed by the VA. Since the time intervals between two measurement points always encompass five weekdays, possible values ranged from 1 (interaction only on the required day) to 5 (interactions on all five days on which participants were invited, $M = 4.74$, SD = 0.38).

The other variables were measured with self-reported items in the questionnaire at T1, T2, and T3. *Trust* was measured with 11 items on a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Items were based on Benbasat and Wang (2005), including beliefs about the three characteristics: Competence-beliefs (e.g., "This virtual assistant is like a real expert in providing recipe-related information"), benevolence-beliefs (e.g., "This virtual assistant puts my interests first"), and integrity-beliefs (e.g., "This virtual assistant provides unbiased recipe-related recommendations"; Cronbach's $\text{alpha}_{T1} = .96$; Cronbach's $\text{alpha}_{T2} = .97$, $M_{T2} = 4.70$, $SD_{T2} = 1.20$; Cronbach's $\text{alpha}_{T3} = .97$).

Brand attitudes were measured with four items on a 7-point semantic-differential scale, including "I think [brand] is negative-positive/uninteresting-interesting/unattractive-attractive/bad-good" (van Reijmersdal et al., 2016). Answer categories included three different brands for all participants ("Belvoir" mentioned in the recommendation, and two other beverage brands, "Fever Tree" and "Whole Earth" that were not mentioned in the recommendation). We used multiple brands to make the brand of interest not too salient for the participants. We use the scores of the recommended brand for the analysis (Cronbach's $\text{alpha}_{T1} = .94$; Cronbach's $\text{alpha}_{T2} = .94$; Cronbach's $\text{alpha}_{T3} = .96$).

Purchase intention of the recommended brand was measured with a consideration set question (Brown & Wildt, 1992; Narayana & Markin, 1975). Participants were asked on a 7-point scale from 1 = very unlikely to 7 = very likely: "If you would want to buy a lemonade brand, how likely is it that you would consider the following brand?" Answer categories again included three different brands. We use the scores of the recommended brand for the analysis. All items are provided in the online supplementary materials available on OSF.

Results

Analytical Strategy

We calculated two random-intercept cross-lagged panel models (RI-CLPM; Hamaker, Kuiper, & Grasman, 2015) with the three variables: (1) number of interactions, (2) trust in the VA, and (3a) attitudes toward the recommended brand, and (3b) purchase intention. We chose the RI-CLPM over the traditional cross-lagged panel model as it controls for time-invariant trait-like individual differences (Hamaker et al., 2015; Mulder & Hamaker, 2020). The model fit was evaluated using the model chi-square—a nonsignificant chi-square indicates a good fit (even though large samples often result in significant chi-squares), the Root Mean Square Error of Approximation (RMSEA—values of 0.06 to 0.08 or lower generally indicate an acceptable level of fit), the Comparative Fit Index (CFI), and the Tucker-Lewis Index (TLI—for both, CFI and TLI values between 0.90 and 0.95 are considered marginally acceptable, whereas values above 0.95 are considered good; Mackinnon, Curtis, & O'Connor, 2022).

Descriptive Statistics and Correlations

Table 1 shows the means and standard deviations for the variables of interest. The number of interactions between the two measurement points slightly increased from 4.69 (SD = 0.58) at T1 to 4.78 (SD = 0.52) at T3 (on a scale from 1 to 5). Since the variable has a very high skewness and kurtosis ($skew_{T1} = -2.21$, $kurtosis_{T1} = 6.79$; $skew_{T2} = -2.68$, $kurtosis_{T2} = 9.35$; $skew_{T3} = -2.67$, $kurtosis_{T3} = 7.86$), we transformed the variable for the RI-CLPM (by exponentiating it; taking 10 to the power of the original variable and dividing by 1,000,000; Kline, 2016).[7]

Table 1. Means (SDs) and Zero-Order Correlations for Number of Interactions, Trust, (a) Brand Attitudes and (b) Purchase Intention.

	T1	T2	T3
Number of interactions	4.69 (0.58)	4.75 (0.56)	4.78 (0.52)
Trust	4.76 (1.23)	4.74 (1.25)	4.81 (1.23)
Brand attitudes	4.55 (1.04)	4.76 (1.10)	4.91 (1.22)
Purchase intention	4.04 (1.50)	4.07 (1.65)	4.30 (1.68)
Cross-sectional correlations[a]			
Number of interactions—Trust	0.01	0.02	0.06
Trust—Brand attitudes	0.37***	0.43***	0.53***
Trust—Purchase intention	0.38***	0.46***	0.55***

****p* < .001.
[a]Pearson's product-moment correlation.

Trust scores remained relatively stable over time, with a mean of 4.76 (*SD* = 1.23) at T1, 4.74 (*SD* = 1.25) at T2, and 4.81 (*SD* = 1.23) at T3. Although brand attitudes slightly and significantly increased from a mean of 4.55 (*SD* = 1.04) at T1 to 4.76 (*SD* = 1.10) at T2 and 4.91 (*SD* = 1.22) at T3 ($F(2, 723) = 6.38$, $p = .002$), purchase intentions were similar at T1 (*M* = 4.04, *SD* = 1.50) and T2 (*M* = 4.07, *SD* = 1.65) and increased at T3 (*M* = 4.30, *SD* = 1.68). A visualization of the variables of interest is provided in Figure 3.

[7] Means for trust, brand attitudes, and purchase intention did not significantly differ for included and excluded participants. We therefore believe that our findings about trust and brand-related outcomes are robust and not only specific for the sample included in the analysis. The robustness check is reported in the online supplementary materials on OSF.

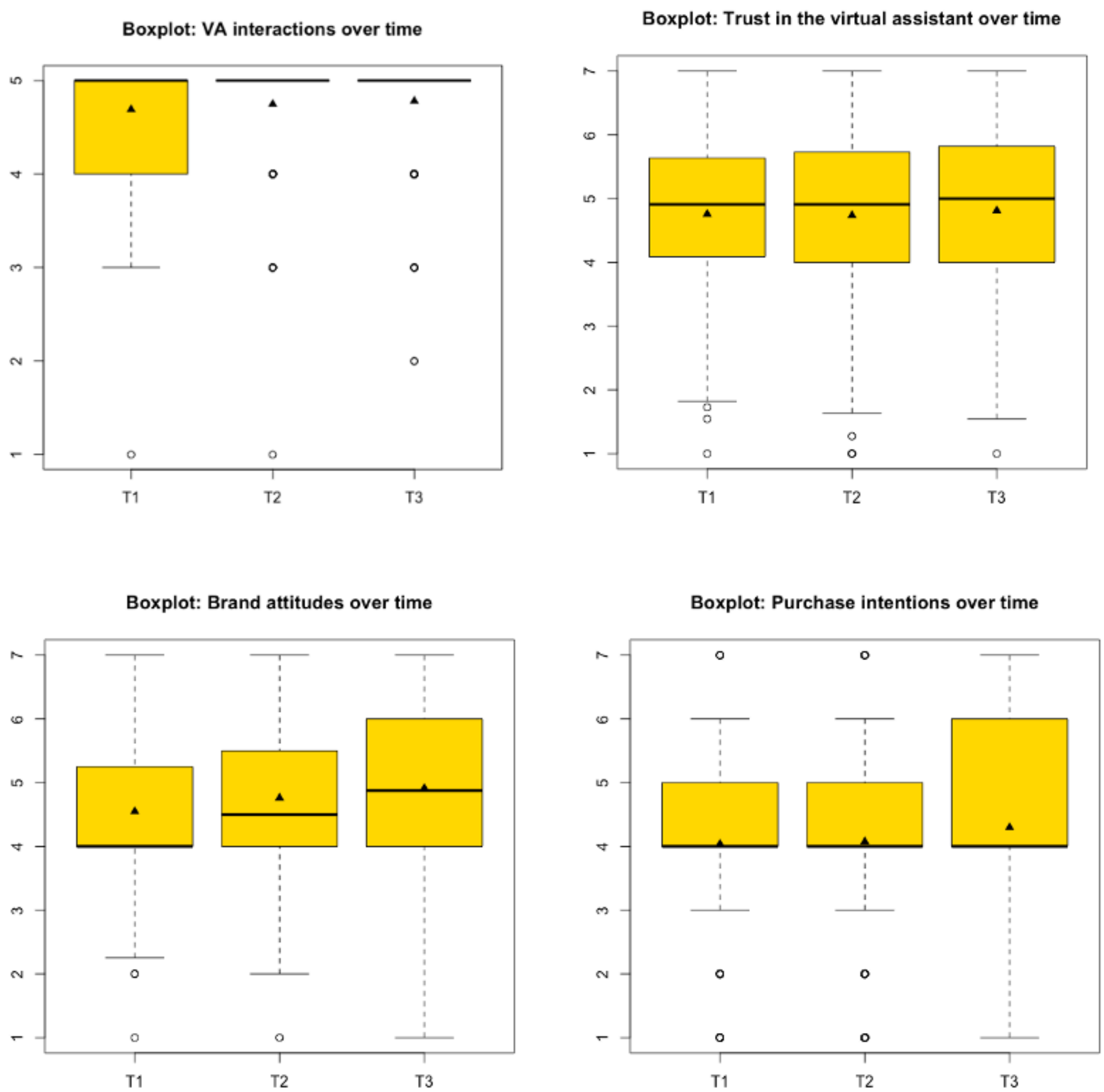

Figure 3. Number of interactions, trust, brand attitudes, and purchase intention over time.
Note. The boxplot shows the minimum score, first (lower) quartile, median, third (upper) quartile, and maximum score. Circles represent outliers. Filled triangles represent mean scores.

Within-wave cross-sectional correlations showed that trust was positively related to brand attitudes, ranging from 0.37 to 0.53 (*p's* < .001); and positively related to purchase intention, ranging from 0.38 to 0.55 (*p's* < .001). Cross-sectional correlations of the number of interactions and trust were nonsignificant. This means that *within one time point*, higher levels of trust in the VA are positively related to higher levels of brand attitudes and purchase intention.

Stability correlations *across time points* are shown in Table 2. Stability correlations were nonsignificant for a number of interactions at T1 and T2 and significant for T2 and T3 with a value of 0.32. Stability correlations for trust ranged from 0.76 to 0.87 (*p's* < .001), for brand attitudes from 0.50 to 0.70 (*p's* < .001), and for purchase intention from 0.63 to 0.74 (*p's* < .001). This means that levels of trust at one timepoint are positively related to levels of trust at the subsequent timepoint. The same applies to brand attitudes and purchase intentions, but not the number of interactions.

Table 2. Stability Correlations for Number of Interactions, Trust, (a) Brand Attitudes and (b) Purchase Intention.

	T1–T2	T2–T3
Number interactions[a]	0.10	0.32***
Trust[a]	0.76***	0.87***
Brand attitudes[a]	0.50***	0.70***
Purchase intention[a]	0.63***	0.74***

****p* < .001.
[a]Pearson's product-moment correlation.

Testing for Measurement Invariance

Before running the RI-CLPM, we tested for measurement invariance to see whether our items were reflective of the latent constructs. Following Mackinnon, Curtis, and O'Connor (2022), we ran a series of CFA models with increasingly strict equality constraints. We first calculated a configural model as the baseline and compared it with increasingly parsimonious models, including constrained factor loadings across waves (metric model), additional constrained item intercepts across waves (scalar model), and additional constrained residual variances across waves (residual model). Fit statistics are shown in Table 3 and corresponding factor loadings are presented in online supplementary materials.[8] Both the model including the number of interactions, trust, and brand attitudes and the model including the number of interactions, trust, and purchase intention show sufficient model fit. The configural model performs slightly better than the more restrictive models. However, following Cheung and Rensvold (2002), a ΔCFI of less than −0.01 suggests that the more parsimonious model should be chosen. Therefore, we have chosen the residual model.

[8] https://osf.io/6v9x2/

Table 3. Nested Model Fit Indices.

	Model			
	Configural	Metric	Scalar	Residual
Model including attitudes				
npar	192	160	128	99
df	1032	1064	1096	1125
χ2	**2187.223**	**2232.701**	**2312.967**	**2395.424**
Robust RMSEA	0.064	0.063	0.064	0.064
Robust CFI	0.926	0.925	0.921	0.919
Robust TLI	0.919	0.920	0.919	0.919
Model including purchase intention				
npar	158	132	106	86
df	661	687	713	733
χ2	**1602.488**	**1637.619**	**1697.609**	**1747.560**
Robust RMSEA	0.072	0.071	0.071	0.071
Robust CFI	0.921	0.920	0.917	0.915
Robust TLI	0.912	0.914	0.914	0.914

Note. χ2 in bold font indicates significant values.

Relationship Between Number of Interactions, Trust, and Brand Attitudes

To test the relation among the number of interactions, trust, and brand attitudes, we calculated a RI-CLPM testing the relationship among the number of interactions, trust in the VA, and brand attitudes. Since we experience convergence issues when adding the structural part to the residual model identified in the first step, we instead used the mean scores for all latent constructs to calculate the RI-CLPM (Hamaker et al., 2015; Mulder & Hamaker, 2020).[9] Evaluating the model fit, CFI is sufficient, whereas the other indices show a less-sufficient model fit (χ2[3] = 11.34; *p* = .010; RMSEA = 0.107; CFI = 0.991; TLI = 0.890). The results are presented in Figure 4. Since prior familiarity with VAs was positively related to trust and brand attitudes, a robustness check was conducted. We ran another model with prior familiarity with VAs as a time-invariant predictor of the observed variables (Mulder & Hamaker, 2020; see online supplementary materials), leading to similar results and demonstrating the robustness of the findings.

Across waves, within-participant deviations in trust at T1 predicted subsequent within-participant deviations in trust in T2 (*beta* = 0.45; *SE* = 0.18; *p* =.012) and within-participant deviations in trust at T2 predicted subsequent within-participant deviations in trust in T3 (*beta* = 0.57; *SE* = 0.10; *p* < .001; see the middle row of within-participant deviations in Figure 4). Within-participant deviations in brand attitudes in T1 predicted within-participant deviations in brand attitudes in T2 (*beta* = 0.48; *SE* = 0.10; *p* < .001; see the bottom row of within-participant deviations in Figure 4).

[9] As a robustness check, we also ran traditional cross-lagged panel models with the metric and residual measurement models, leading to similar results for both brand attitudes and purchase intention.

To answer our hypotheses, we are interested in the cross-lagged effects between the within-person centered variables. We find that participants who had more trust in VAs relative to their own average at T2 had higher than their own average scores on brand attitudes at T3 (*beta* = 0.34, *SE* = 0.11, *p* = .002, see the cross-lagged effect from middle to bottom row of within-participant deviations in Figure 4). All other cross-lagged effects were nonsignificant. Our results cannot confirm H1a and H1b; we do not find a longitudinal effect of the number of interactions on trust and the VA or vice versa. We find partial support for H2—an increase in trust in a VA results in a subsequent increase in positive attitudes toward the recommended brand over time, but only between the last two time points.

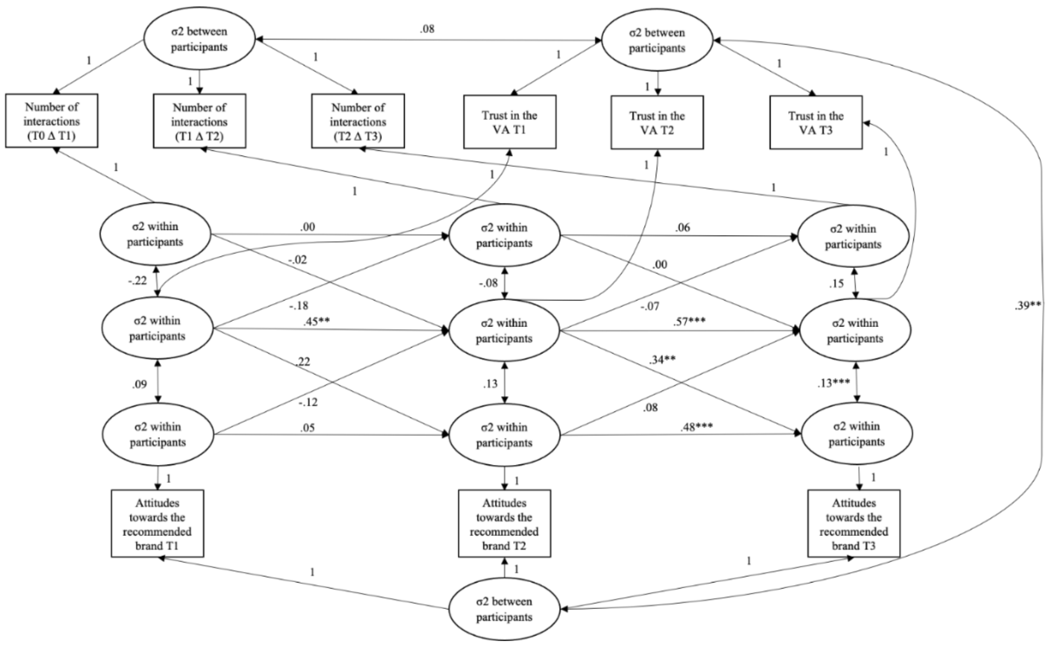

Figure 4. RI-CLPM for the relationship between number of interactions, trust, and brand attitudes.

Note. Rectangles indicate observed variables; circles indicate latent variables (within and between components).

Relationship Between Number of Interactions, Trust, and Purchase Intentions

About purchase intention, we calculated a RI-CLPM testing the relationship among the number of interactions, trust in the VA, and purchase intention using mean scores for all latent constructs. Evaluating the model fit, CFI is sufficient, whereas the other indices show a less-sufficient model fit ($\chi2[3] = 20.859$; $p < .000$; RMSEA = 0.157; CFI = 0.982; TLI = 0.786). The results are presented in Figure 5. Since prior familiarity with VAs was positively related to trust and purchase intention, a robustness check was conducted. We ran another model with prior familiarity with VAs as a time-invariant predictor of the observed variables (Mulder & Hamaker, 2020; see online supplementary materials), leading to similar results and demonstrating the robustness of the findings.

Similar to the previous model, we see that within-participant deviations in trust at T2 predicted subsequent within-participant deviations in trust in T3 (*beta* = 0.54; *SE* = 0.13; *p* < .001, see the middle row of within-participant deviations in Figure 5). Furthermore, within-participant deviations in purchase intention in T1 predicted within-participant deviations in purchase intention in T2 (*beta* = 0.47; *SE* = 0.18; *p* = .011), and within-participant deviations in purchase intention in T2 predicted within-participant deviations in purchase intention in T3 (*beta* = 0.54; *SE* = 0.18; *p* =.007; see bottom row of within-participant deviations in Figure 5). We do not see any significant cross-lagged effects between the within-person centered variables. Thus, in combination with the results of the first model, we reject H1a and H1b because there is no longitudinal effect of the number of interactions on trust and the VA or vice versa. In the current model, we also do not find any support for H3; an increase in trust in a VA does not show any subsequent increase in the intention to purchase the recommended brand over time.

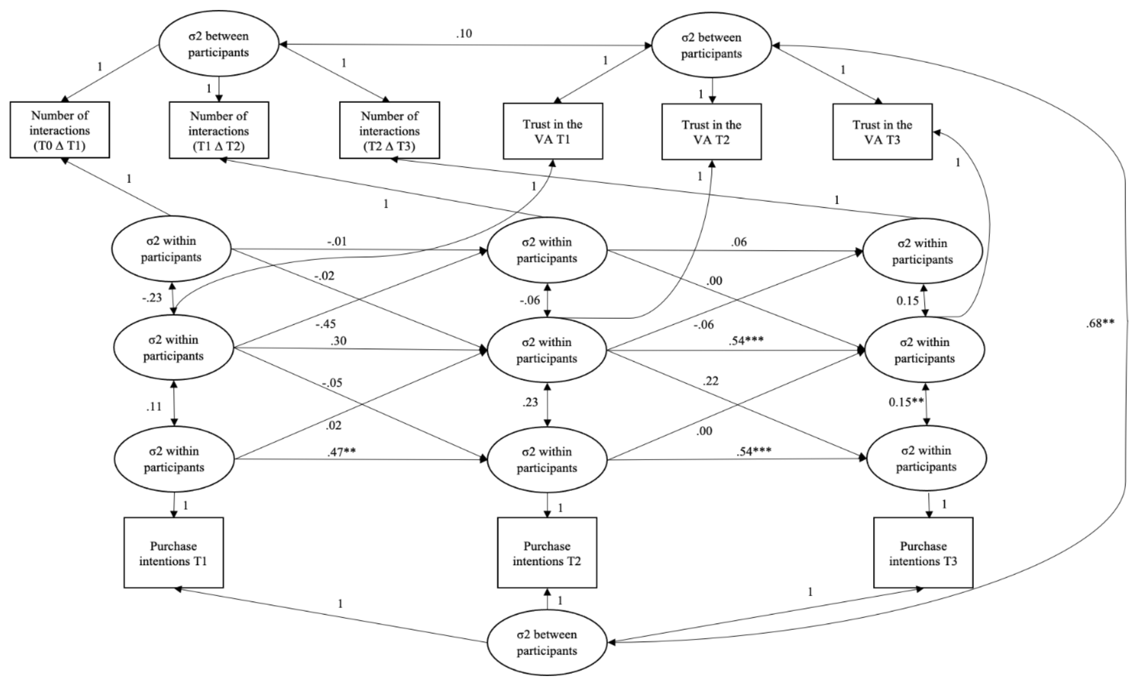

Figure 5. RI-CLPM for the relationship between number of interactions, trust, and purchase intention.

Note. Rectangles indicate observed variables; circles indicate latent variables (within and between components).

Discussion

VAs as a communication source provide a unique possibility for businesses to interact with users, including persuasive attempts. Repeated interactions with a VA create the potential to form trusting relationships with them, which can subsequently influence persuasion. Empirical research on the interplay of trust in these new types of communication sources and persuasiveness is lacking, however, despite the increasing usage of VAs for persuasiveness. Hence, this study examined whether persuasiveness can be the result of a dynamic process developing over time when users repeatedly interact with an assistant and develop trust toward the assistant as the communication source.

First, we show that VA that acts as a trusting source of communication persuades users. We find that VA trust is positively related to persuasive outcomes (i.e., brand attitudes and purchase intention) within one time point and to a certain extent longitudinally for brand attitudes. Second, we find that brand-related attitudes and behavioral intentions slightly increased over the course of three weeks, while VA trust was relatively high and stable over time. This shows that persuasion does not take place at first sight: Some interaction is needed for persuasiveness to unfold.

This study contributes to the recent literature on VAs, with regard to trust (Chattaraman et al., 2019; Youn & Jin, 2021) and persuasion (Ischen et al., 2020; Rhee & Choi, 2020; Yen & Chiang, 2020). By testing the reciprocal interplay of the two concepts, we provide an empirical test of recent theoretical work (Dehnert & Mongeau, 2022), which has proposed that especially the formation of a trusting relationship with a VA (over time) can enhance persuasion. Our findings show that levels of trust toward the VA after two weeks of interactions moderately influenced brand attitudes after three weeks of interactions. This means that trust in the VA can lead to more positive brand-related outcomes after some time. Most other reciprocal effects between trust and brand-related outcomes were absent, showing that although for affective outcomes such as brand attitudes the positive effects of trust might already unfold after a few weeks, for behavioral outcomes such as purchase intentions this is not (yet) the case.

Furthermore, we advance the understanding of VAs and its relationship with brand-related outcomes and persuasion, as we show that there is a positive relationship between trust and brand-related outcomes *within one time point* and that brand-related outcomes (positive attitudes and purchase intentions) slightly increased over time (i.e., *across time points*). In line with previous research (e.g., Rhee & Choi, 2020), our finding supports that trust in a VA as a source can spill over to attitudes toward the message and a brand recommended in this message. This finding extends the work of previous scholars who have studied the relationship between source or brand trust (e.g., Hayes et al., 2016; Huh et al., 2020), interpersonal trust (Guenzi et al., 2009), or trust in automation (e.g., Kim et al., 2021) and persuasion.

We demonstrate that VA trust is relatively stable over time, and we find that trust scores were relatively high over a study period of three weeks. As argued by Hoff and Bashir (2015), trust can be dispositional, situational, and learned over time. The VA used in this study was able to *maintain* high levels of trust, indicating that repeated interactions can be related to trust maintenance. However, participants might have had relatively high levels of dispositional trust in the assistant, possibly because of high familiarity with VAs before starting the daily interactions, which then did not vary much during the 15-day study period. Since trust in the assistant was relatively high from the beginning of the study, this might have led to ceiling effects in the number of interactions. A possible (lack of) variation in how often people interact with an assistant should be considered in future research.

Maintaining high levels of VA trust is particularly interesting considering previous research on (embodied) relational agents specifically "designed to establish and maintain long-term social-emotional relationships" (Bickmore & Picard, 2005, p. 293). These agents include nonverbal behaviors (e.g., displays of hand gestures, walking on and off the screen; Bickmore & Picard, 2005, p. 293; Cassell et al., 1999) and show that these cues can increase trust. Our study corroborates this line of research using a nonembodied, text-only assistant. The VA in our study implemented social cues such as small talk and verbal acknowledgments of previous interactions (i.e., asking for and referring to previously set preferences). Our findings suggest these cues might have been sufficient to create a trusting relationship with the assistant after the first week of interactions, and moreover, that this maintained trust was high throughout the study period. This finding extends earlier research on relational agents by showing that even "simpler" text-based agents with small relational cues can lead to stable, high levels of trust in an assistant.

Limitations and Suggestions for Future Research

Overall, our study provides a strong methodological contribution and extends previous cross-sectional research on trust formation in VAs (Youn & Jin, 2021) by adding a longitudinal dynamic. However, it comes with one major methodological challenge of examining the concept of the number of interactions. Participants in our sample had a very high number of interactions leading to low variance in this concept already at the first measurement point, which might explain some of the nonsignificant cross-lagged results. This might be due to our experimental setup, in which we had to filter out participants not filling in questionnaires at certain time points. Future research should investigate why users (do not) continue to interact with a VA: Studying the role of different types of interactions and varying quality of interactions might be worthwhile. Since this is one of the first longitudinal studies using actual VAs, future research should also think about different ways of recruiting and incentivizing participants for such research.

Furthermore, our study focused on the relationship between the number of interactions, trust, and persuasion in a specific cooking-related context. We believe that this provides a useful starting point to examine how VAs may be implemented with a persuasive intent in practice. However, using this specific context comes with some shortcomings. First, the VA in this study was not affiliated with the brand recommended to avoid specific associations with the assistant from the start of the interaction. In a real-life setting, however, VAs themselves can be branded, which might further influence perceptions and persuasive outcomes. Second, it must be acknowledged that using a specific scenario comes with the difficulty of accounting for possible individual differences (e.g., the general preference for cooking). Providing users with the opportunity to set preferences in the interaction addressed this shortcoming. However, we suggest for future research to examine VA trust in different, as well as more general contexts (e.g., by studying VAs integrated in smart speakers).

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