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# Exploring the influence of submission devices on customer referral creation and receiver reactions in customer referral programs

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## Abstract

Customer referral programs (CRPs) are considered an effective means of customer acquisition through which firms stimulate existing customers to refer services and products to potential new customers. Digitalization and technological developments have led to the common practice of using digital devices like smartphones or laptops to create and submit customer referrals. This is the first study to investigate the influence of submission devices in CRPs from both the sender's and receiver's perspective. Based on four experiments, we demonstrate that smartphone-generated referrals are shorter and less positive than those composed on laptops/PCs. These differences in text length and valence negatively influence receiver responses, leading to lower purchase intentions due to the perceived usefulness of the referral mediating this relationship. Our findings underscore the important role of submission devices for online referral behavior and contribute to the growing body of research on device-mediated consumer behavior, offering crucial insights to optimize the promotion and design of CRPs.

## 1 | INTRODUCTION

Customer referral programs (CRPs) have established themselves as an effective and efficient means of customer acquisition. Within these programs, also known as “Refer-a-friend” campaigns, firms stimulate existing customers to refer services and products to their social contacts (Garnefeld et al., 2013; Schmitt et al., 2011). For instance, the refer-a-friend program of the telecommunications company T-Mobile encourages customers to share a referral with social contacts through SMS or social networks. Similarly, the streaming television service YouTubeTV asks its subscribers to send referrals to friends and acquaintances via E-Mail or other online channels. As CRPs have shifted to the online world (Wirtz et al., 2013), digital devices like smartphones or laptops are frequently used to create and submit customer referrals. While all devices offer similar content creation and

submission capabilities, their characteristics, such as screen size, interface or context of use, differ significantly (Wolf, 2023). Thus, the submission device potentially acts as an influential factor for the creation of customer referrals (sender perspective) and induce downstream consequences in terms of receiver responses such as purchase intention (receiver perspective).

An understanding of how submission devices influence the creation of customer referrals and receiver responses could help firms to exploit the full potential of CRPs, for instance by adapting the design and promotion of the programs to the submission device used. However, despite the established research on the effectiveness and design of CRPs particular regarding reward structures (e.g., Garnefeld et al., 2013; Schmitt et al., 2011) and the growing interest in the influence of digital submission devices on electronic word-of-mouth (eWOM) in general (e.g., Melumad et al., 2019; Zhu et al., 2020),

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current research lacks an understanding of the influence of the submission device on customer referrals as a specific type of eWOM. Thus, in this study we aim to explore (1) how customer referrals are influenced by the submission device (i.e., smartphone vs. laptop/PC) and (2) how differences in customer referrals caused by the submission device influence receiver perceptions and response within CRPs.

To address these questions and investigate the influence of submission devices in CRPs from both senders' and receivers' viewpoints, we conducted four behavioral experiments. In line with the social exchange theory (Homans, 1958), our findings reveal significant differences in the text length and valence of customer referrals based on whether they were created using smartphones or laptops/PCs. Moreover, these variations in customer referrals affect how receivers perceive their usefulness, and ultimately how likely they are to purchase a recommended service or product after receiving the referrals. Thus, this is the first study that emphasizes the important and previously overlooked role of submission devices as influential factor in CRPs, offering valuable insights for the design and promotion of such programs. We highlight how managers can tailor CRP strategies to address the fact that today's consumers use different devices to write and submit customer referrals online, while considering the unique characteristics of each device. In summary, our research extends the fast-growing research stream on device-mediated consumer behavior to the context of customer referrals. This provides important implications for CRPs from both the sender's and receiver's perspective.

The remainder of the paper is organized as follows. In the next section, we outline the theoretical background and our hypotheses, including a comparison of recent research investigating the influence of submission devices on eWOM with the present study, as well as the exposure of our theoretical framework. In Sections 3 and 4, we present the research design and results of the first two studies, focusing on the sender's perspective (i.e., the influence of submission devices on customer referrals). Subsequently, in Sections 5 and 6, we discuss our last two studies, concentrating on the receiver's perspective (i.e., the influence of device-mediated customer referrals on the receiver's perception and responses in CRPs). Finally, in Section 7, we conclude the findings and draw theoretical and managerial implications.

## 2 | THEORETICAL BACKGROUND AND HYPOTHESES

### 2.1 | Submission devices and customer referrals

The online environment offers a convenient and low-effort way for consumers to refer products or services to their social contacts (Wirtz et al., 2019). Today's consumers frequently use a multitude of digital devices such as smartphones, tablets, laptops or PCs to access the Internet (Wagner et al., 2020). While all these devices can be used to create and submit customer referrals and other types of eWOM, they differ significantly in their characteristics. The most obvious

differences among device types are their physical properties, including such features as screen size and mode of operation; these further entail divergent contexts (i.e., mobile or stationary) and perceptions (i.e., "work" or "fun" device) of their use (Wolf, 2023). Smartphones are typically characterized by high accessibility due to their portability and ubiquitous nature and limited usability due to smaller screens, inconvenient touchscreen keyboards, and potential impairments from the usage situation. Conversely, stationary devices like PCs exhibit the opposite characteristics (Kim et al., 2021; Yang & Han, 2022). Both differences in accessibility and usability between devices influence the creation of eWOM. According to Kim et al. (2021), this concept is referred to as the "accessibility and usability argument."

Based on the accessibility argument, several studies highlight that the temporal distance between an event (e.g., restaurant visit) and the submission of eWOM (e.g., writing an online review) is lower on mobile devices compared to non-mobile devices (Ransbotham et al., 2019; Yang & Han, 2022). These real-time evaluations lead to more affective and extreme eWOM from mobile devices as highly satisfied and dissatisfied consumers are more likely to reach for their smartphones (Kim et al., 2020; Lurie et al., 2014). Moreover, Melumad and Meyer (2020) find that both online reviews and social media posts show an enhanced depth of self-disclosure if written on smartphones compared to laptops/PCs due to the greater associated psychological comfort and personal nature of mobile devices. Meanwhile, in line with the usability argument, several studies argue that using mobile devices to create and submit eWOM leads to higher cognitive costs (e.g., Lurie et al., 2014). To reduce these cognitive costs, texts written on smartphones are often found to be shorter in length and mention fewer topics than texts created on laptops/PCs (e.g., Han, 2022; Lurie et al., 2014; Zhu et al., 2020). Additionally, it has been suggested that composing negative content requires even more cognitive effort (Schwarz, 1990), leading to eWOM submitted via smartphones being more positive overall (Kim et al., 2020; Mariani et al., 2019; Zhu et al., 2020). However, recent studies indicate that the introduction of mobile channels does not significantly affect the valence of eWOM in the long run (Kim et al., 2021), and some research even suggests that eWOM generated via mobile devices tend to have a more negative tone (Lurie et al., 2014; Yang & Han, 2022). Thus, the research on eWOM suggests that the choice of submission devices has an influence on valence, but the findings are contradictory.

Due to the mentioned differences between mobile and non-mobile eWOM, receivers react differently to such content. Ransbotham et al. (2019) found that smartphone-generated restaurant reviews receive 40% fewer likes than reviews from non-mobile devices. Similarly, several authors observed that mobile reviews on various online platforms are rated as less helpful than non-mobile reviews (Lurie et al., 2014; Mariani et al., 2019; März et al., 2017). However, Melumad and Meyer (2020) demonstrated that reviews on online travel agencies websites written on smartphones are perceived as more interesting and persuasive. Additionally, Grewal and Stephen (2019) highlighted that labeling content as "written via mobile" increases its credibility and subsequently raises readers' purchase

**TABLE 1** Summary of key differences between different types of electronic Word-of-Mouth (eWOM).

	Online reviews	Social media posts	Customer referrals
Type of communication	One-to-many	One-to-many	One-to-one
Audience	Unknown	Unknown and personal network	Personal network
Tie strength between sender and receiver	No ties	No ties, existing weak or strong social ties	Existing weak or strong social ties
Valence of content	Negative, neutral or positive	Negative, neutral or positive	Neutral or positive
Visibility and accessibility	Publicly accessible	Publicly accessible	Private in nature with limited visibility
Established company program	Mostly none (but review reminders and review platform)	Mostly none (but specific marketing campaigns)	Customer referral programs (CRP)
Exemplary studies on the influence of the submission device on content creation (sender perspective)	Han (2022), Kim et al. (2020, 2021), Lurie et al. (2014), Mariani et al. (2019), März et al. (2017), Melumad et al. (2019), Melumad and Meyer (2020), Ransbotham et al. (2019), Yang and Han (2022), Zhu et al. (2020)	Melumad et al. (2019), Melumad and Meyer (2020)	This paper
Exemplary studies on responses to content created on different submission devices (receiver perspective)	Grewal and Stephen (2019), Han (2022), Lurie et al. (2014), Mariani et al. (2019), März et al. (2017), Ransbotham et al. (2019)	-	This paper

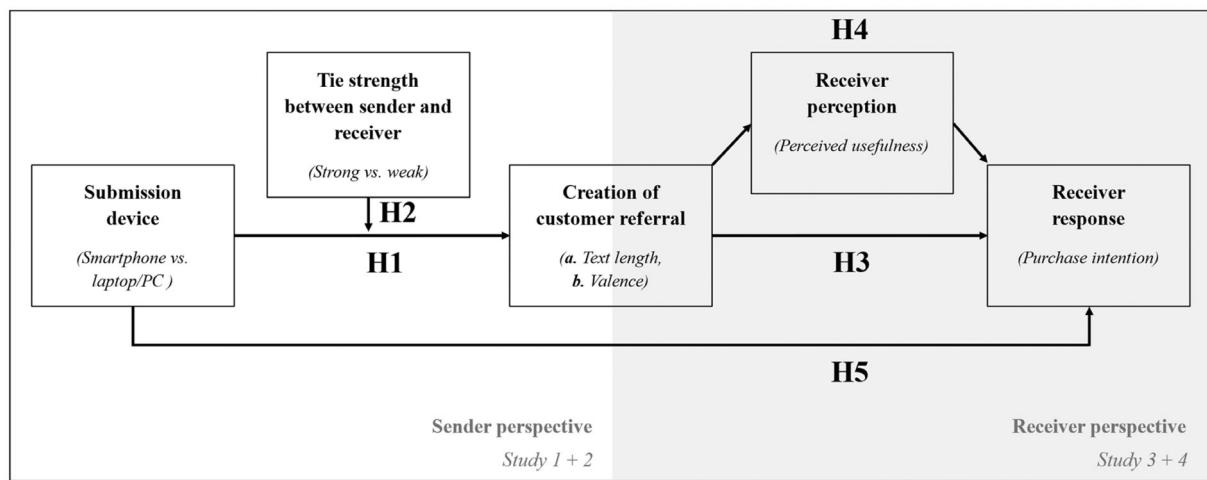
intentions. This effect is particularly pronounced when receivers also use a mobile device, as the alignment between the submission and reading devices reinforces its perceived usefulness (März et al., 2017).

In summary, several studies have shown that the type of submission device influences both the creation and submission of eWOM, as well as downstream consequences in terms of receiver perceptions and reactions, due to differences in device characteristics (refer to Table A1 in the Web Appendix for a comprehensive overview of recent research on the submission device's influence on eWOM). However, there are contradictory findings. Moreover, extant studies focus on specific types of eWOM like online reviews from online platforms such as TripAdvisor or Booking.com (e.g., Han, 2022; Kim et al., 2020) or social media posts from Twitter (e.g., Melumad et al., 2019; Melumad & Meyer, 2020). A notable gap in the literature exists with respect to alternative types of eWOM, particularly customer referrals occurring within CRPs (see Table 1). Unlike online reviews and social media posts, customer referrals are characterized by one-to-one communication within existing social ties and non-negative valence (Berger, 2014). Moreover, companies often stimulate referrals as part of CRPs to encourage existing customers to acquire new customers within their social contacts (Schmitt et al., 2011). The unique characteristics of customer referrals, particularly the significance of tie strength due to their one-to-one nature, necessitate a distinct investigation into how submission devices shape customer referrals and the subsequent responses from receivers (Wolf, 2023). A comprehensive understanding of this offers valuable insights to managers regarding device-related design and promotion strategies for CRPs.

## 2.2 | Hypotheses and conceptual framework

Drawing from the literature on other types of eWOM, and in line with the accessibility and usability argument (Kim et al., 2021), we posit that the type of submission device used significantly influences customer referrals occurring in CRPs. In particular, leveraging the social exchange theory (Homans, 1958), we argue that the different characteristics of digital devices directly influence the creation of customer referrals with regard to text length and valence. The social exchange theory posits that consumers' information-sharing behaviors are driven by a cost-benefit analysis. Given that content creation on mobile devices entails higher cognitive costs due to the limited screen size and less user-friendly touchscreen keyboards (Lurie et al., 2014; Zhu et al., 2020), we anticipate that referrals composed on smartphones are shorter and less positive than those created on laptops/PCs. Consumers react to the higher cognitive costs in referral creation on mobile versus non-mobile devices by writing shorter referrals. As customer referrals are inherently non-negative (see Table 1), we expect that greater brevity of content leads to fewer positive words and, thus, lower valence for referrals written on smartphones. This line of reasoning is supported by recent research that underscores the notion that the low usability of smartphones negatively impacts consumer evaluations (Yang & Han, 2022). Accordingly, we expect the following:

**H1.** Customer referrals written on smartphones are (a) shorter, and (b) less positive than on laptops/PCs.



**FIGURE 1** Theoretical framework.

As already mentioned, unlike online reviews, referrals are one-to-one communication. Thus, besides the submission device, we expect tie strength between sender and receiver to play an influential role in customer referrals (Berger, 2014). Dyadic communication arises from and is constrained by consumers' social relations (Brown & Reingen, 1987). If we also consider the personal nature of smartphones and their special role for consumers (Melumad & Meyer, 2020; Melumad & Pham, 2020), we assume that tie strength serves as a moderator and reinforces the influence of the submission device on customer referrals.

**H2.** The influence of the submission device on customer referrals is enhanced by a strong tie strength between sender and receiver.

Message characteristics such as length and valence directly influence receivers' perception of and reaction to it (Cheung & Thadani, 2012; Verma et al., 2023). Several studies indicate an inverse U-shaped relationship between text length and purchase intention. For instance, Furner and Zinko (2017) demonstrated that eWOM with short or excessive text lengths lead to lower purchase intentions compared to moderate text lengths. Additionally, positive messages have been found to improve the purchase intentions of receivers (Baker et al., 2016). Based on these findings, we assume that differences in customer referrals influence receiver responses in CRPs, and, more specifically:

**H3.** Customer referrals that are (a) shorter, and (b) less positive lead to lower purchase intentions of receivers compared to referrals that are (a) moderate in length, and (b) more positive.

In line with studies from eWOM research, we further argue that text length and valence affect the perceived usefulness of the referral, which in turn influences the purchase intention of receivers (Baek et al., 2012; Kuan et al., 2015).

**H4.** The influence of customer referral characteristics on receivers' purchase intention is mediated by the perceived usefulness of the referral.

In **H1**, we hypothesize that smartphone-generated referrals are shorter and less positive than those created using laptops/PCs. Moreover, we posit that shorter, less positive customer referrals will lead to lower perceived usefulness and eventually lower purchase intentions among receivers (see **H3** and **H4**). Therefore, we expect that customer referrals written via smartphones will ultimately lead to less favorable responses from receivers.

**H5.** Customer referrals written on smartphones lead to lower purchase intentions than those written on laptops/PCs.

The theoretical framework of our study is depicted in Figure 1, which outlines our five hypotheses. To empirically test this framework, we conducted four experiments. In the first two experiments (*Study 1* and *Study 2*), we adopted a sender perspective and explored how the submission device (Smartphone vs. laptop/PC) influences the creation of customer referrals in CRPs online. Additionally, we examined how this relationship is moderated by the strength of the social tie between the sender and the receiver. Subsequently, we shifted our focus to the receiver's perspective. In the following two experiments (*Study 3* and *Study 4*), we investigated the influence of device-mediated customer referrals on the receiver's perception (i.e., perceived usefulness) and on the receiver's responses, particularly regarding their purchase intention.

### 3 | STUDY 1

#### 3.1 | Method

In our first study, participants of an online experiment were asked to write an online customer referral as part of a CRP from a video streaming provider in an open text box to either a very close friend/

**TABLE 2** Operationalization of the dependent variables in *Study 1* and *Study 2*.

Dependent variables	Operationalization	Description	Exemplary sources
<b>H1a + H2</b>			
Text length	Word count & character count	Number of words and characters contained in the referral.	März et al. (2017)
<b>H1b + H2</b>			
Valence	Valence scores	Valence scores of the referral based on the SentiWS, the GerVADER, and the LIWC dictionary.	Christodoulides et al. (2021), Remus et al. (2010), Tymann et al. (2019)
<i>Further analyses</i>			
Diversity	Topic count	Number of topics mentioned in the referral based on inductive coding (inter-rater reliability in <i>Study 1</i> = 95.19%, in <i>Study 2</i> = 94.71%). Additional details regarding the coding process can be found in Web Appendix C and E.	Zhu et al. (2020)
Emotionality	Emotional words	Proportion of emotional words (general, positive, and negative) in the referral based on the LIWC dictionary.	Melumad et al. (2019)
Self-disclosure	Self-disclosure measures	Measures of the degree of self-disclosure in the referral based on the LIWC dictionary (analytic style, authentic style, the proportion of first person pronouns, mention of family and friends).	Melumad and Meyer (2020)
Content	Further content aspects	Further content aspects including the number of smileys and spelling errors in the referral based on coding.	-

family member (Strong tie) or a distant acquaintance (Weak tie). The initial scenario was designed to resemble a typical invitation to participate in a customer referral or refer-a-friend program (see Web Appendix B1 for more details on the questionnaire). Tie strength was randomly assigned, whereas the participants self-selected the digital device to participate in the experiment. We recruited 204 participants from the German Social Sciences' (SoSci) Panel ( $M_{age} = 49.66$ ,  $SD = 12.43$ , 63.73% female) who took part in our two-condition (Tie strength: strong vs. weak tie) between-subjects experiment. Among these participants, 123 (constituting 60.29%) opted to compose the customer referral using a laptop/PC, while 81 participants (39.71%) chose to utilize their smartphones. The written referrals were then transformed into our dependent variables using text mining and established dictionaries. The text length of the referral was operationalized as the number of words and characters contained in the text (März et al., 2017). Valence was calculated as a score using sentiment analyses based on established German dictionaries (SentiWS, GerVADER, and LIWC).<sup>1</sup> Besides text length and valence, we also tested for other potentially impactful content aspects such as emotionality, degree of self-disclosure, number of smileys, and spelling errors in the customer referral (refer to

Table 2 for insights on the operationalization). Further details on the methodology and questionnaire of *Study 1* are provided in Web Appendix B.

## 3.2 | Results

### 3.2.1 | Manipulation and plausibility check

The experimental manipulation was deemed successful, as indicated by a measure of tie strength according to Wirtz et al. (2019) ( $M_{StrongTie} = 5.27$ ,  $M_{WeakTie} = 2.82$ ,  $p < .001$ , Cohen's  $d = 1.94$ ). Descriptive analysis of the data further shows that the chosen experimental scenario (i.e., writing a customer referral for a video streaming provider via digital devices) seems plausible. Two-thirds of the participants were customers of a streaming provider (67.65%), mostly for more than 2 years (76.81% of all streaming customers). Additionally, 44.93% of the participants reported that, in the past, they had recommended their video streaming provider to individuals in their social environment. The high recommendation rate could be due to respondents being relatively satisfied with their provider (rated at 4.39 out of 7) and having a moderate level of expertise (rated at 3.78 out of 7) and involvement (rated at 3.35 out of 7) with video streaming providers.

The vast majority of participants in *Study 1* owned both a laptop/PC and a smartphone.<sup>2</sup> Notably, smartphones (rated at 4.60 out of 7) were the most likely utilized devices for customer referrals, followed closely by laptops/PCs (rated at 4.40 out of 7). In contrast, tablets

<sup>1</sup>We have used three different dictionaries to operationalize valence in order to provide a more comprehensive, complete and accurate analysis and allow for cross-verification of the results. Valence scores based on SentiWS and GerVADER dictionaries are calculated as the sum of the values (positivity minus negativity score) of detected words in a referral. Detailed explanations of valence score calculations are provided by Remus et al. (2010) for SentiWS and Tymann et al. (2019) for GerVADER. Additionally, we used the emotional tone variable from the German version of the LIWC dictionary (Meier et al., 2018) to operationalize valence. Emotional tone is a summary variable that describes the positivity or negativity of a text within a range from 0 to 100, with higher scores indicating higher levels of positivity. A detailed description of the calculation of LIWC's emotional tone scores is provided by Cohn et al. (2004).

<sup>2</sup>Three participants did not own a smartphone, four participants did not own a laptop/PC.

played a relatively minor role in this context (rated at 2.89 out of 7). These findings emphasize the significance of smartphones and laptops/PCs in referral behavior. Furthermore, the personal nature of devices, in line with Melumad and Pham (2020), was significantly higher for smartphones compared to laptops/PCs ( $M_{\text{Smartphone}} = 5.76$ ,  $M_{\text{PC}} = 4.71$ ,  $p < .001$ , Cohen's  $d = 0.66$ ). This finding again underscores smartphones' special role in consumers' lives.

### 3.2.2 | Hypotheses testing

The results of *t*-tests reveal significant differences between the text length of customer referrals based on the submission device. Specifically, texts composed on smartphones contain significantly fewer words than those composed on laptops/PCs ( $M_{\text{Smartphone}} = 40.01$  words,  $M_{\text{PC}} = 48.99$  words,  $p = .023$ , Cohen's  $d = 0.29$ )—thus providing support for **H1a**. This distribution is further corroborated when examining the number of characters, as texts generated on smartphones contain significantly fewer characters than those generated on laptops/PCs ( $M_{\text{Smartphone}} = 246.94$  characters,  $M_{\text{PC}} = 303.76$  characters,  $p = .023$ , Cohen's  $d = 0.29$ ).

Valence is measured using three distinct dictionaries, SentiWS, GerVADER, and LIWC.<sup>3</sup> Across all three dictionaries, the valence scores obtained for smartphone-generated referrals are consistently lower than those generated on laptops/PCs. The lower valence scores indicate that customer referrals tend to be less positive if composed on smartphones as opposed to laptops/PCs. Notably, for the GerVADER dictionary, these differences reach a significant level at 5% ( $M_{\text{Smartphone}} = 1.13$ ,  $M_{\text{PC}} = 1.49$ ,  $p = .013$ , Cohen's  $d = 0.32$ ). Consequently, **H1b** can be partially confirmed based on these findings. Serial mediation models using PROCESS Model 4 (Hayes, 2017) provide robust support for our line of reasoning. Specifically, the data reveals that the usage of smartphones (vs. PC/laptops) leads to significantly lower word count, which in turn, leads to lower valence scores across all three dictionaries (i.e., device → text length → valence).

Interestingly, and contrary to our assumptions, no significant interaction effects were found between the submission device and the tie strength for text length or valence. The influence of the submission device on the creation of customer referrals is not significantly affected by the tie strength between sender and receiver. **H2** is therefore rejected for *Study 1* (see Table 3).

## 4 | STUDY 2

### 4.1 | Method

*Study 2* employed a randomized assignment of digital devices in a controlled lab experiment to mitigate self-selection effects. The follow-up

study replicated the experimental procedure and the operationalization of dependent variables from *Study 1*. Participants were again requested to write a customer referral in an open text box after receiving a typical invitation to participate in a CRP from a video streaming provider (see Web Appendix D1 for more details on the questionnaire). However, unlike *Study 1*, the manipulation involved the submission device, in addition to the variation in tie strength. In the experimental lab, participants were randomly assigned to utilize either the PC provided or their smartphone. A total of 140 participants, selected as a convenience sample ( $M_{\text{age}} = 23.37$ ,  $SD = 3.98$ , 44.29% female, 90.00% students), took part in the lab experiment, enticed by a 5€ cash incentive. The distribution between scenarios was quite balanced—72 participants (51.43%) used one of the provided PCs, and 68 participants (48.57%) used their smartphones. More details on the methodology and the questionnaire are provided in Web Appendix D.

## 4.2 | Results

### 4.2.1 | Manipulation and plausibility check

In this study, we employed the identical manipulation check for tie strength as in *Study 1*. Once again, the manipulation was successful, as evidenced by the significantly higher mean tie strength ratings observed for the strong tie scenario in comparison to the weak tie scenario ( $M_{\text{StrongTie}} = 6.06$ ,  $M_{\text{WeakTie}} = 3.05$ ,  $p < .001$ , Cohen's  $d = 3.34$ ). Moreover, the descriptive evaluation of *Study 2* confirms the plausibility of the chosen experimental scenario, revealing an even higher affinity of the younger sample in *Study 2* to the topic of video streaming providers compared to *Study 1*. Remarkably, 90.00% of the participants reported being customers of a video streaming provider, with the majority (82.54%) having been subscribers for over 2 years. Similar to *Study 1*, the level of expertise and involvement with video streaming providers is relatively high (rated at 4.78 out of 7 and 4.00 out of 7, respectively). In the second study, we further investigated participants' referral records for various other services, finding that the recommendation rate for video streaming providers is considerably higher than for other services. Specifically, 68.25% of the participants reported that they previously recommended their video streaming provider to people in their social environment. In comparison, the next highest recommendation rates were indicated for telecommunication providers (56.43%), internet service providers (35.71%), and checking account providers (28.57%).

All participants in *Study 2* owned a smartphone, and only two participants stated that they did not own a laptop or PC. Again, smartphones (rated at 5.59 out of 7) were rated as most likely to be used for customer referrals, followed by laptops/PCs (rated at 4.42 out of 7) and tablets (rated at 3.47 out of 7). Finally, smartphones received very high ratings for personal nature (rated at 6.00 out of 7). However, in contrast to *Study 1*, we did not inquire about the personal nature of PC usage, as the devices were not self-owned in the lab experiment.

<sup>3</sup>Correlations between the valence scores provided by the dictionaries are as follows: SentiWS × GerVADER  $r = .777^{**}$ , SentiWS × LIWC  $r = .345^{**}$ , GerVADER × LIWC  $r = .364^{**}$  (\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$ ).

**TABLE 3** Mean differences in customer referrals across submission devices and tie strength in *Study 1*.

Study 1/online experiment (n = 204)							
Dependent variables ↓	Independent variables			Tie strength			Dev * TieSt
	Submission device		Sig. (p)	Strong tie	Weak tie	Sig. (p)	Sig (p)
	Smartphone	Laptop/PC					
Text length			H1a ✓				H2 X
Word count	40.01	48.99	.023*	46.43	44.16	.305	.734
Character count	246.94	303.76	.023*	285.84	275.31	.355	.732
Valence			H1b ↗				H2 X
SentiWS Valence Score	0.62	0.76	.097	0.73	0.67	.277	.916
GerVADER Valence Score	1.13	1.49	.013*	1.36	1.33	.440	.660
LIWC Tone	84.57	88.49	.158	85.02	89.37	.123	.057
Further analyses							
Diversity							
Topic count	2.19	2.14	.423	2.05	2.29	.160	.412
Emotionality							
Emotional words	7.78%	7.51%	.343	7.65%	7.58%	.454	.071
Positive emotion	7.18%	7.02%	.402	7.17%	6.97%	.373	.056
Negative emotion	0.37%	0.38%	.456	0.37%	0.39%	.428	.756
Self-disclosure							
Analytic style	25.68	25.43	.478	25.74	25.26	.455	.256
Authentic style	48.39	49.59	.409	45.19	54.08	.041*	.934
First person pronouns	6.88%	7.57%	.148	7.14%	7.48%	.302	.366
Family mentions	0.02%	0.06%	.228	0.08%	0.01%	.097	.185
Friends mentions	0.32%	0.26%	.329	0.30%	0.26%	.358	.463
Content							
Smileys	0.05	0.10	.123	0.08	0.08	.490	.617
Spelling errors	0.37	0.25	.111	0.29	0.30	.430	.707

Note: “✓”—hypothesis was supported; “↗”—hypothesis was partially supported; “X”—hypothesis was not supported.

\*\*\* $p < .001$ ;

\*\* $p < .01$ ;

\* $p \leq .05$ .

#### 4.2.2 | Hypotheses testing

In line with H1a, customer referrals written on smartphones are significantly shorter than referrals written on PCs both regarding word count ( $M_{\text{Smartphone}} = 54.03$  words,  $M_{\text{PC}} = 67.15$  words,  $p = .012$ , Cohen's  $d = 0.39$ ) and character count ( $M_{\text{Smartphone}} = 329.53$  characters,  $M_{\text{PC}} = 412.97$  characters,  $p = .011$ , Cohen's  $d = 0.39$ ). Additionally, consistent with *Study 1*, smartphone-generated referrals are found to be less positive than those generated on the PC across all considered dictionaries (significant at 5% for LIWC tone:  $M_{\text{Smartphone}} = 89.02$ ,  $M_{\text{PC}} = 94.34$ ,  $p = .050$ , Cohen's  $d = 0.28$ ).<sup>4</sup> Thus, we can partially confirm H1b. Once again, serial mediation models underscored the notion that the influence of submission device on valence is mediated by text length (i.e., device → text length → valence).

<sup>4</sup>Correlations between the valence scores provided by the dictionaries are as follows: SentiWS × GerVADER  $r = .633^{***}$ , SentiWS × LIWC  $r = .253^{**}$ , GerVADER × LIWC  $r = .313^{***}$  (\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p < .05$ ).

Similar to *Study 1*, no interaction effects between the submission device and tie strength were found for text length or valence. Therefore, tie strength does not appear to moderate the relationship between submission device and referral creation and H2 is rejected. Furthermore, t-tests showed that customer referrals are significantly more diverse when written on the PC compared to the smartphone ( $M_{\text{Smartphone}} = 2.60$  topics,  $M_{\text{PC}} = 3.22$  topics,  $p = .019$ , Cohen's  $d = 0.36$ ) in line with Zhu et al. (2020) (see Table 4).

## 5 | STUDY 3

### 5.1 | Method

*Studies 1 and 2* demonstrated the influence of the submission device on the creation of customer referrals in CRPs (sender perspective). Next, *Study 3* investigates how variations in text length

**TABLE 4** Mean differences in customer referrals across submission devices and tie strength in *Study 2*.

Study 2/lab experiment (n = 140)							
Dependent variables ↓	Independent variables:			Tie strength			Dev * TieSt
	Submission device			Strong tie	Weak tie	Sig. (p)	Sig (p)
	Smartphone	PC	Sig. (p)				
Text length				H1a ✓			H2 X
Word count	54.03	67.15	.012*	55.76	66.10	.038*	.246
Character count	329.53	412.97	.011*	335.86	411.18	.019*	.220
Valence				H1b ✓			H2 X
SentiWS Valence Score	0.71	0.91	.057	0.72	0.91	.066	.918
GerVADER Valence Score	1.56	1.75	.145	1.59	1.72	.231	.762
LIWC Tone	89.02	94.34	.050*	93.39	90.03	.148	.249
Further analyses							
Diversity							
Topic count	2.60	3.22	.019*	2.51	3.35	.002**	.067
Emotionality							
Emotional words	7.71%	7.18%	.205	8.00%	6.84%	.032*	.999
Positive emotion	6.96%	6.53%	.240	7.37%	6.07%	.016*	.686
Negative emotion	0.41%	0.44%	.438	0.38%	0.47%	.289	.851
Self-disclosure							
Analytic style	22.53	23.65	.399	23.59	22.60	.410	.672
Authentic style	49.29	53.31	.239	44.35	58.77	.005**	.299
First person pronouns	5.73%	6.08%	.266	5.09%	6.78%	.001**	.263
Family mentions	0.12%	0.26%	.075	0.29%	0.09%	.019**	.784
Friends mentions	0.47%	0.38%	.287	0.39%	0.47%	.311	.548
Content							
Smileys	0.19	0.14	.251	0.18	0.15	.334	.757
Spelling errors	0.32	0.46	.183	0.33	0.46	.206	.039*

\*\*\* $p < .001$ ;\*\* $p < .01$ ;\* $p \leq .05$ .

and valence impact the receiver's perception and response to customer referrals (receiver perspective). We thus aim to explore the downstream consequences of the submission device's influence in CRPs from the receiver's perspective and consequently test H3 and H4.

In an online experiment we asked participants to read a fictitious customer referral for a video streaming provider and subsequently rate their perception of the text, encompassing perceived usefulness, perceived effort, and perceived credibility, as well as their response regarding purchase intention for the recommended service. The measurement of all items and constructs utilized 7-point Likert scales and the reliability of the multi-item constructs was confirmed with Cronbach's Alpha values greater than .7. The customer referral presented in the study differed in text length (Short vs. moderate) and valence (Neutral vs. very positive). The texts were randomly assigned to ensure an even distribution of participants between scenarios (see Web Appendix F1 for more details on the questionnaire

and the presented customer referrals). A total of 200 participants, selected as a convenience sample ( $M_{age} = 29.49$ ,  $SD = 11.21$ , 56.00% female) took part in our 2 (Text length: short vs. moderate)  $\times$  2 (Valence: neutral vs. very positive) between-subjects online experiment. Detailed information on the manipulation of referrals and the questionnaire used in *Study 3* can be found in Web Appendix F.

## 5.2 | Results

### 5.2.1 | Manipulation check

Text length of customer referrals was manipulated using word count. The short referrals contained 36 words, while the moderately long texts contained 187 words. These results are consistent with the definition of short and moderate texts by Furner and Zinko (2017), who

**TABLE 5** Mean differences in receiver perceptions and responses across customer referrals in *Study 3*.

Study 3/online experiment (n = 200)								
Dependent variables ↓	Independent variables:			Text length			TextL * Val Sig. (p)	
	Text length			Valence				
	Short	Moderate	Sig. (p)	Neutral	Very positive	Sig. (p)		
Purchase intention (PI)			H3a ✓			H3b ✓		
3-item construct ( $\alpha = .88$ )	3.79	4.32	.006**	3.59	4.46	.000***	.380	
Perceived usefulness (PU)								
4-item construct ( $\alpha = .93$ )	4.43	4.91	.013*	4.26	5.04	.000***	.115	
Further analyses								
Perceived effort (PEff)								
6-item construct ( $\alpha = .93$ )	3.36	4.92	.000***	3.83	4.42	.003**	.929	
Perceived credibility (PCred)								
3-item construct ( $\alpha = .88$ )	4.64	5.03	.021*	4.80	4.87	.364	.352	

\*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p \leq .05$ .

**TABLE 6** Results of the mediation analyses in *Study 3*.

Study 3/online experiment (n = 200)						
	Indirect effect	95% CI	Total effect	Sig. (p)	Direct effect	Sig. (p)
Text length → PU → PI	0.27	0.03; 0.53	0.53	.012*	0.26	.133
Valence → PU → PI	0.42	0.20; 0.67	0.87	.000***	0.44	.013*
Further analyses						
Text length → PEff → PI	0.64	0.37; 0.97	0.53	.012*	-0.11	.613
Valence → PEff → PI	0.21	0.05; 0.40	0.87	.000***	0.66	.001**
Text length → PCred → PI	0.15	0.00; 0.33	0.53	.012*	0.38	.051
Valence → PCred → PI	0.03	-0.12; 0.18	0.87	.000***	0.84	.000***

\*\*\* $p < .001$ ; \*\* $p < .01$ ; \* $p \leq .05$ .

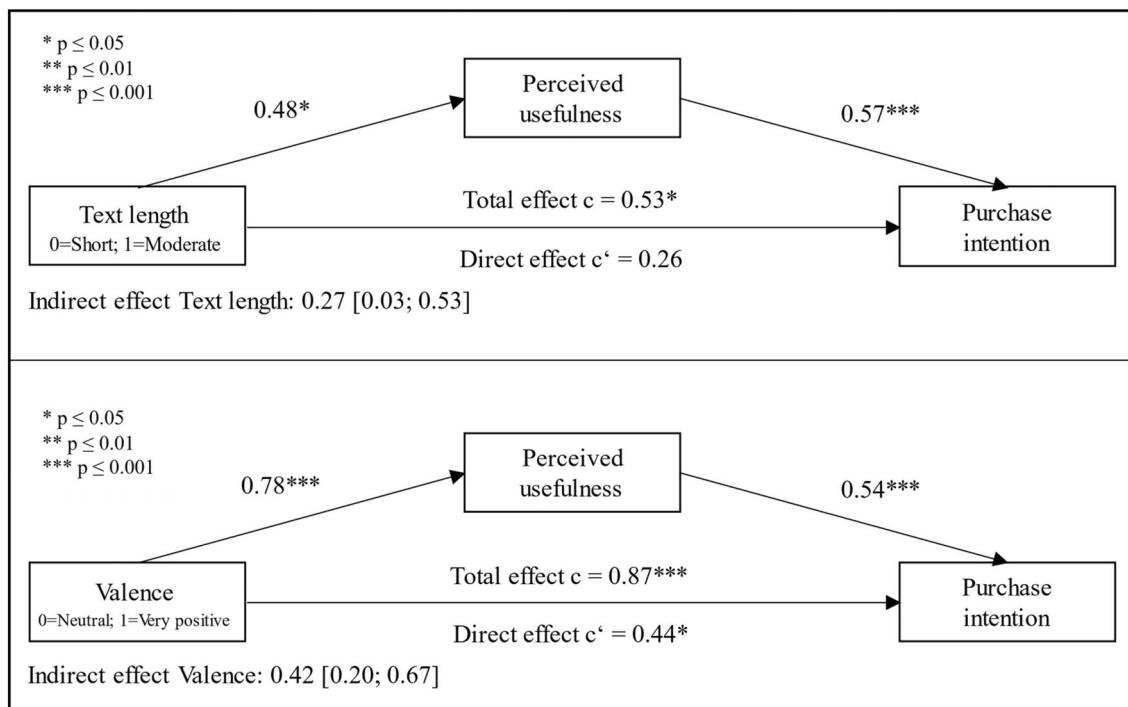
classified texts with less than 39 words as short and texts with 40–311 words as moderate. Additionally, distinct wording was employed and verified with SentiWS Valence Scores to manipulate the valence of customer referrals. The valence manipulation was considered successful as neutral referrals were perceived as significantly less positive than very positive referrals ( $M_{\text{Neutral}} = 4.60$ ,  $M_{\text{VeryPositive}} = 5.96$ ,  $p < .001$ , Cohen's  $d = 1.12$ ).

## 5.2.2 | Hypotheses testing

*Study 3* sheds light on the significant influence of variations in customer referrals on receiver responses (see Table 5). Shorter referrals elicit significantly lower purchase intentions among receivers compared to referrals of moderate text length ( $M_{\text{Short}} = 3.79$ ,  $M_{\text{Moderate}} = 4.32$ ,  $p = .006$ , Cohen's  $d = 0.36$ ). The influence of different valence scores on purchase intention seems even more pronounced, as neutral referrals lead to lower purchase intentions

than very positive ones ( $M_{\text{Neutral}} = 3.59$ ,  $M_{\text{VeryPositive}} = 4.46$ ,  $p < .001$ , Cohen's  $d = 0.61$ ). Thus, we can support both H3a and H3b. Notably, there is no interaction effect between text length and valence on purchase intention, underscoring both text characteristics' distinct and independent influences on purchase intention in CRPs.

The results further show that the customer referrals are perceived as significantly less useful if they are shorter in length ( $M_{\text{Short}} = 4.43$ ,  $M_{\text{Moderate}} = 4.91$ ,  $p = .013$ , Cohen's  $d = 0.32$ ) or less positive in terms of valence ( $M_{\text{Neutral}} = 4.26$ ,  $M_{\text{VeryPositive}} = 5.04$ ,  $p < .001$ , Cohen's  $d = 0.53$ ). In line with H4, mediation analyses using PROCESS Model 4 (Hayes, 2017) provide evidence that perceived usefulness acts as a significant mediator in the relationship between text length and purchase intention (indirect effect = 0.27, 95% CI [0.03; 0.53], total effect = 0.53,  $p = .012$ , direct effect = 0.26,  $p = .133$ ), as well as between valence and purchase intention (indirect effect = 0.42, 95% CI [0.20; 0.67], total effect = 0.87,  $p < .001$ , direct effect = 0.44,  $p = .013$ ) (see Table 6 and Figure 2).



**FIGURE 2** Mediation effects of perceived usefulness on the influence of text length and valence on purchase intention.

### 5.2.3 | Further analyses

In addition to perceived usefulness, we also asked respondents to rate the sender's perceived effort to write the referral (Grewal & Stephen, 2019) and the perceived credibility of the referral (Williams & Drolet, 2005). Both of these factors have been shown to influence receiver responses in prior eWOM research (e.g., Grewal & Stephen, 2019; Verma et al., 2023). Our findings highlight that customer referrals with shorter text length are considered less effortful ( $M_{\text{Short}} = 3.36$ ,  $M_{\text{Moderate}} = 4.92$ ,  $p < .001$ , Cohen's  $d = 1.20$ ) and less credible ( $M_{\text{Short}} = 4.64$ ,  $M_{\text{Moderate}} = 5.03$ ,  $p = .021$ , Cohen's  $d = 0.29$ ). Similar to perceived usefulness, both perceived effort and credibility mediate the influence of text length on purchase intention, contributing to the overall explanation of the observed effects. Regarding valence, only perceived effort demonstrates significant differences, with higher ratings observed for very positive customer referrals ( $M_{\text{Neutral}} = 3.83$ ,  $M_{\text{VeryPositive}} = 4.42$ ,  $p = .003$ , Cohen's  $d = 0.40$ ), whereas perceived credibility does not show such distinctions. Accordingly, only the mediation model for perceived effort achieves significance (refer to Table 6). The mediation models for the influence of text length and valence on purchase intention through perceived effort and perceived credibility are displayed in Web Appendix G.

## 6 | STUDY 4

### 6.1 | Method

In Study 4, conducted as a lab experiment, we once again adopted the receiver perspective and examined how their reactions and

perceptions in CRPs (purchase intention, perceived usefulness, perceived effort) vary depending on different content aspects of customer referrals. Our objectives were threefold: (1) to verify the findings of Study 3, (2) to enhance validity by investigating the influence of real customer referrals within CRPs composed on different digital devices (Smartphone vs. PC), and (3) to test H5, that is, the direct influence of the submission device on receiver responses.

To achieve this, we randomly selected 10 customer referrals for video streaming providers written by participants of our lab experiment in Study 2. Half of the selected referrals were composed on smartphones, and the other half on PCs (five each), derived from the strong tie scenario. Moreover, the customer referrals underwent a pre-test to ensure general intelligibility. To maintain anonymity, we edited the texts to remove the sender and recipient names and we replaced named streaming providers with one fictitious streaming provider (for more details on the selection and post-editing process of the customer referrals, refer to Web Appendix H). In a within-subjects design, participants of Study 4 were exposed to all 10 referrals and asked to indicate their perceptions and purchase intention for each (see Web Appendix I1 for more details on the questionnaire).<sup>5</sup>

In sum, a convenience sample of 184 participants ( $M_{\text{age}} = 22.06$ ,  $SD = 3.33$ , 53.80% female, 94.6% students) participated in our within-subjects lab experiment. All participants used the PC provided in the experimental lab and were given a 5€ cash incentive for their participation. To mitigate potential fatigue effects resulting from our within-subjects design and in line with a similar research approach

<sup>5</sup>To eliminate potential order effects caused by the within-subjects design (Charness et al., 2012), we rotated the sequence of the referrals using a Latin square.

employed by Furner and Zinko (2017), we measured purchase intention using a single item [“Based on this referral only (please ignore any previous referral about this streaming provider that you have read): How likely is it that you would subscribe to this streaming provider?”; 1 = very unlikely to 7 = very likely]. Consistent with *Study 3*, perceived usefulness was measured using a 4-item scale (Soh et al., 2009). Besides perceived usefulness and purchase intention, we also measured perceived effort and perceived valence for each referral in the study (refer to Web Appendix I for detailed information on our methodology and questionnaire). All variables were measured on 7-point Likert scales and exceeded a Cronbach's Alpha of .7 for the scenarios, indicating good internal consistency.

## 6.2 | Results

### 6.2.1 | Manipulation and plausibility check

The 10 selected customer referrals (five composed via smartphone and five via PC) were, on average, shorter and less positive when written on a smartphone ( $M_{\text{Smartphone}} = 31.20$  words,  $M_{\text{Smartphone}} = 0.25$  SentiWS Valence Score) compared to those written on a PC ( $M_{\text{PC}} = 45.50$  words,  $M_{\text{PC}} = 0.58$  SentiWS Valence Score). Thus, the chosen referrals align with the findings of *Study 1* and *2*. This is also in line with the perceived valence by the participants in *Study 4* as shown by the results of a repeated-measures *t*-test comparing the aggregated mean values of perceived valence for all texts per device.<sup>6</sup> Specifically, customer referrals composed on smartphones were perceived as significantly less positive than those composed on the PC ( $M_{\text{Smartphone}} = 4.57$ ,  $M_{\text{PC}} = 4.78$ ,  $p < .001$ , Cohen's  $d = 0.28$ ). Thus, the referrals displayed in *Study 4* show typical text length and valence variations depending on the submission device.

In addition to measuring receivers' perceptions and reactions to different customer referrals in CRPs in *Study 4*, we also sought to validate the scenario's plausibility, thus complementing the results from the initial two studies with the perspective of receivers. Once again, the chosen experimental scenario seems very plausible, as indicated by the following findings: 90.22% of the participants reported using a video streaming provider, and 81.52% of these participants acknowledged having received customer referrals for such services from individuals in their personal environment. Notably, 63.86% of these streaming users became aware of their provider through referrals from friends/family members (56.63%, i.e., strong ties) or acquaintances (7.23%, i.e., weak ties), surpassing other means such as

<sup>6</sup>To assess the disparity in perceived valence among customer referrals from different devices, the perceived valence (PV) values for texts 1–5, which were written on a PC in *Study 2*, were first aggregated into a single variable ( $PV_{\text{PC}}$ ). In the same way, texts 6–10, composed on a smartphone during *Study 2*, were merged into  $PV_{\text{Smartphone}}$ . Subsequently, we performed repeated measures *t*-tests to examine the variations in perceived valence. The same procedure was adopted for the analysis of the influence of the submission device on the purchase intention, perceived usefulness (calculated as a multi-item construct), and perceived effort (calculated as a multi-item construct).

advertising (18.67%) or social media (7.23%). Furthermore, consistent with *Studies 1* and *2*, a substantial proportion of the streaming users (63.86%) reported having previously recommended their video streaming provider to individuals in their social environment. These results once again highlight the significant role of CRPs within the chosen service sector.

### 6.2.2 | Hypotheses testing

The first objective of *Study 4* was to verify the findings of *Study 3*. Utilizing multi-level regression models to analyze the results from the within-subject experiment, we observed a significant positive association between the perceived valence of the customer referrals and purchase intention ( $\beta = .42$ ,  $p < .001$ ; see Model 4 in Table 7). We also found a slightly, yet non-significant positive relationship between text length and purchase intention ( $\beta = .003$ ,  $p = .135$ ). These findings lend additional support to hypotheses H3a and H3b. Furthermore, our investigation revealed that perceived usefulness significantly influences purchase intention ( $\beta = .43$ ,  $p < .001$ ) and that both text length and valence positively influence perceived usefulness. Specifically, longer texts were associated with significantly higher levels of perceived usefulness ( $\beta = .01$ ,  $p < .001$ ; see Model 3 in Table 8), and valence had an even more pronounced positive influence on perceived usefulness ( $\beta = .71$ ,  $p < .001$ ). As shown in Tables 7 and 8, these outcomes provide additional evidence for the mediating role of perceived usefulness in the relationship between text length and valence on purchase intention, reinforcing the support for H4.

To test hypothesis H5, which proposes a direct influence of the submission device on purchase intention, we conducted a repeated measures *t*-test to assess potential differences in purchase intention based on the submission device used to write the customer referral in *Study 2* (see Table 9). The results revealed a marginal, though non-significant, decrease in purchase intention in CRPs for referrals composed on smartphones compared to PCs ( $M_{\text{Smartphone}} = 4.47$ ,  $M_{\text{PC}} = 4.48$ ,  $p = .383$ ). As a result, we did not find a significant direct effect of the submission device on the receivers' response and, therefore, could not confirm H5.

### 6.2.3 | Further analyses

We observed a substantial difference in perceived effort, with smartphone-generated referrals being perceived as significantly less effortful than PC-generated ones ( $M_{\text{Smartphone}} = 3.49$ ,  $M_{\text{PC}} = 4.18$ ,  $p < .001$ , Cohen's  $d = 0.92$ ). Given that perceived effort has been shown to influence purchase intention (as observed in *Study 3*), this notable difference could be of significant interest to managers.

In order to gain further insights into the receiver's perception of customer referrals in CRPs, we included an open text box at the end of our survey. Participants were asked to write down important aspects that influenced their evaluation of the referral (“What did you

**TABLE 7** Results of multi-level regression analyses for purchase intention in *Study 4*.

Dependent variable: purchase intention	Study 4/lab experiment (n = 184)														
	Model			M1: Null model			M2: + scenario			M3: + text length, valence			M4: + perceived usefulness		
	Estimate	SE	Sig. (p)	Estimate	SE	Sig. (p)	Estimate	SE	Sig. (p)	Estimate	SE	Sig. (p)			
Intercept	4.52	0.05	.000***	4.67	0.10	.000***	0.77	0.13	.000***	0.68	0.12	.000***			
Scenario				−0.03	0.02	.066	0.01	0.01	.272	0.02	0.01	.082			
Text length							0.01	0.00	.003**	0.00	0.00	.135			
Valence							0.73	0.02	.000***	0.42	0.02	.000***			
Perceived usefulness										0.43	0.02	.000***			
Deviance	6859.93			6856.54			5536.06			5115.56					
AIC	6865.93			6864.54			5548.06			5129.56					
BIC	6882.48			6886.61			5581.17			5168.19					

\*\*\*p &lt; .001;

\*\*p &lt; .01;

\*p ≤ .05.

**TABLE 8** Results of multi-level regression analyses for perceived usefulness in *Study 4*.

Dependent variable: perceived usefulness	Study 4/lab experiment (n = 184)											
	Model			M1: Null model			M2: + scenario			M3: + text length, valence		
	Estimate	SE	Sig. (p)	Estimate	SE	Sig. (p)	Estimate	SE	Sig. (p)	Estimate	SE	Sig. (p)
Intercept	3.78	0.05	.000***	4.07	0.10	.000***	0.21	0.14	.120			
Scenario				−0.05	0.02	.000***	−0.01	0.01	.389			
Text length							0.01	0.00	.000***			
Valence							0.71	0.02	.000***			
Deviance	6917.82			6905.27			5717.63					
AIC	6923.82			6913.27			5729.63					
BIC	6940.38			6935.34			5762.74					

\*\*\*p &lt; .001;

\*\*p &lt; .01;

\*p ≤ .05.

look for or what was important to you when evaluating the customer referral?"). Almost all respondents (95.11%) provided written responses, which were subsequently qualitatively analyzed and coded by two researchers (inter-coder reliability = 96.53%; see Web Appendix J for more details).

The qualitative analysis based on the coding procedure revealed several important aspects that were frequently mentioned in connection with the evaluation of customer referrals in CRPs. In particular, respondents emphasized the importance of statements about price or price-performance ratio (in 38.29% of responses), indicating high importance of cost-related considerations. In addition, 37.14% of respondents emphasized the importance of receiving personalized and non-copied text, which

indicates customized content's value. Beyond that, 36.00% of responses focused on details about the provider's series and movie selection, and 29.71% of participants emphasized the value of informative content within referrals in general. These findings underscore the critical role of perceived usefulness in evaluating referrals, with respondents valuing substantive information related to price and selection, as well as informative content. However, other aspects, such as the referral's personal style, might serve as an influencing factor in recipients' reactions in CRPs. Furthermore, in addition to text length and valence, text features such as formulation and the use of smileys (mentioned as important by 21.71% and 3.43% of respondents, respectively) can also influence the evaluation.

**TABLE 9** Mean differences in receiver perceptions and responses across customer referrals in *Study 4*.

Study 4/lab experiment (n = 184)			
Dependent variables ↓	Independent variable:		
	Smartphone	PC	Sig. (p)
Purchase intention			H5 X
Subscription likelihood (1 item)	4.47	4.48	.383
Perceived usefulness			
4-item construct ( $\alpha = .93\text{--}.94$ ) <sup>a</sup>	3.77	3.83	.139
Further analyses			
Perceived effort			
3-item construct ( $\alpha = .91\text{--}.94$ ) <sup>a</sup>	3.49	4.18	.000***

Note: Summary variables of purchase intention, perceived usefulness and perceived effort for each device were calculated by aggregating the respective mean values from the referrals (five referrals per device).

\*\*\* $p < .001$ ;

\*\* $p < .01$ ;

\* $p \leq .05$ .

<sup>a</sup>Cronbach's  $\alpha$  of the multi-item constructs is calculated for each of the 10 referrals. Thus, it is indicated as a span (minimum–maximum). Refer to Web Appendix I3 for details.

## 7 | CONCLUSION

### 7.1 | General discussion and theoretical implications

If managers are to improve their customer referral or refer-a-friend programs, they need to understand influencing factors on the creation of customer referrals as well as receiver responses to different referral characteristics (Schmitt et al., 2011). Against this background, our study aims to advance a theoretical framework for the important and previously overlooked role of submission devices as influential factor in CRPs. Specifically, we examine the influence of the submission device on the creation of customer referrals in terms of text length and valence. Additionally, we investigate whether tie strength between the sender and receiver of those referrals interacts with the submission device and whether differences in referrals that can be ascribed to the submission device affect perceptions and responses of the receiver.

In line with the social exchange theory (Homans, 1958), the results of our paper indicate significant variations in text length and valence of customer referrals based on the submission device used for their creation (*Study 1* and *Study 2*). Limited screen sizes and less user-friendly touchscreen keyboards of mobile devices result in higher cognitive costs for consumers (Lurie et al., 2014; Zhu et al., 2020), leading them to write shorter referrals compared to those using laptops or PCs. Furthermore, as expected, the greater brevity of content results in fewer positive words and, therefore, lower valence for referrals written on smartphones. Thus, our findings support H1, which

posits that customer referrals differ depending on the submission device, with smartphone-generated referrals being shorter and less positive than those composed on laptops/PCs.

In turn, both text length and valence, directly and indirectly affect receivers' purchase intentions (*Study 3* and *Study 4*). Therefore, our findings also support H3, suggesting that differences in customer referrals significantly influence receiver responses. As expected, shorter and less positive referrals lead to lower purchase intentions in CRPs. Finally, H4 receives empirical support, because the perceived usefulness of the referral mediates the influence of text length and valence on receivers' purchase intention. Thus, the results underscore the submission devices' substantial influence on online customer referrals from both a sender's and receiver's perspective.

Nevertheless, the findings do not provide support for H2, proposing that the influence of the submission device is moderated by the tie strength between sender and receiver, nor do they support H5, suggesting that the submission device for customer referrals directly influences purchase intentions (for a comprehensive overview of all studies, refer to Table 10).

Our findings extend the current research investigating the impact of the submission devices on eWOM to customer referrals as part of CRPs. Consistent with several other studies on online reviews and social media posts, we find that texts written on smartphones are shorter than those written on laptops/PCs (e.g., Mariani et al., 2019; Zhu et al., 2020). Additionally, we corroborate research claiming a detrimental effect of mobile devices on valence (Lurie et al., 2014; Yang & Han, 2022). Based on the social exchange theory (Homans, 1958), these findings provide support for the usability argument, emphasizing that the lower usability of mobile devices compared to non-mobile devices negatively affects both text length and valence of customer referral (Kim et al., 2021). In contrast, the accessibility argument (i.e., the influence of submission devices is caused by high portability and ubiquitous nature of mobile devices) seems to play a minor role in explaining the influence of submission devices on customer referrals. This may be because customer referrals are typically firm-initiated and not driven by the intrinsic motivation of consumers, unlike other types of eWOM such as online reviews or social media posts (Schmitt et al., 2011).

Our further analyses found that referrals tend to be more emotional if the smartphone is used, which aligns with Kim et al. (2020) and Melumad et al. (2019). However, the differences between submission devices are non-significant in both *Study 1* and *2*. Moreover, we do not identify any significant disparities between submission devices concerning self-disclosure, which contrasts with the findings of Melumad and Meyer (2020) (see Tables 3 and 4). This observation underscores the distinct nature of customer referrals in CRPs compared to online reviews or social media posts, emphasizing the significance of investigating the influence of the submission devices across various types of eWOM.

In addition to examining the influence of submission device on customer referrals as a specific type of eWOM, this study is, to our knowledge, the first to investigate the interaction effects between the submission device used and the tie strength between sender and

**TABLE 10** Overview of all four studies and summary of findings.

	<i>Study 1</i>	<i>Study 2</i>	<i>Study 3</i>	<i>Study 4</i>
Perspective	Sender	Sender	Receiver	Receiver
Research design	2-condition (Tie strength: strong vs. weak tie) between-subjects experiment	2 (Submission device: own smartphone vs. PC) $\times$ 2 (Tie strength: strong vs. weak tie) between-subjects experiment	2 (Text length: short vs. moderate) $\times$ 2 (Valence: neutral vs. very positive) between-subjects experiment	Within-subjects experiment (10 referrals written in <i>Study 2</i> , five smartphone-generated and five PC-generated)
Dependent variable(s)	Text length and valence of written referrals in CRPs	Text length and valence of written referrals in CRPs	Purchase intention within CRP	Purchase intention within CRP
Sample size (n)	204 participants from online experiment	140 participants from experimental lab	200 participants from online experiment	184 participants from experimental lab
M <sub>Age</sub> (SD)	49.66 (12.43)	23.37 (3.98)	29.49 (11.20)	22.06 (3.33)
Gender	66.73% female	44.29% female	56.00% female	53.80% female
Distribution between scenarios	1. Smartphone, strong tie = 48 2. Smartphone, weak tie = 33 3. Laptop/PC, strong tie = 66 4. Laptop/PC, weak tie = 57	1. Smartphone, strong tie = 36 2. Smartphone, weak tie = 32 3. PC, strong tie = 36 4. PC, weak tie = 36	1. Short, neutral = 46 2. Short, very positive = 54 3. Moderate, neutral = 48 4. Moderate, very positive = 52	-
Main results	<b>H1a</b> ✓ Smartphone-generated referrals are shorter <b>H1b</b> ✓ Smartphone-generated referrals tend to be less positive <b>H2</b> X No interaction between submission device and tie strength	<b>H3a</b> ✓ Shorter referrals elicit lower purchase intentions <b>H3b</b> ✓ Less positive referrals elicit lower purchase intentions <b>H4</b> ✓ Perceived usefulness mediates the relationship between text length and purchase intention as well as between valence and purchase intention		<b>H5</b> X No direct effect of the submission device on purchase intention

receiver. Given the unique characteristics of customer referrals as one-to-one communication and the personal nature as well as the special role of mobile devices in consumers' lives, we hypothesized that the influence of the submission device on customer referrals is enhanced by a strong tie strength between sender and receiver (see **H2**). However, contrary to our initial hypotheses, we did not observe any interaction effect on the investigated characteristics of referrals across both *Study 1* and *2*. This finding underscores the robust influence of submission devices on customer referrals, transcending different tie strengths. One possible explanation for this lack of interaction effects is that even weak tie strength leads to write customer referrals to a certain extent. This in turn results in a negligible difference between weak and strong ties in both *Study 1* and *2*, which may be too small to impact the creation of referrals significantly.

In *Studies 3* and *4*, our investigation reveals that the identified differences in text length and valence, directly and indirectly, impact receivers' perceptions and responses in CRPs. Specifically, valence demonstrates a stronger positive influence on perceived usefulness and purchase intention than text length, while text length exerts a stronger positive impact on perceived effort and perceived credibility than valence. Moreover, the influence of referral characteristics on purchase intention appears to be mediated by perceived usefulness, perceived effort, and perceived credibility (the latter is only for the influence of text length on purchase intention). The fact that no significant direct impact of submission devices on purchase intentions was

found in *Study 4* suggests that the variations in text length and valence between devices may be too subtle in the selected referrals to have a substantial impact on purchase intention. However, it is worth noting that perceived effort is considerably higher for customer referrals written on laptops/PCs in *Study 4*, and thus, an indirect effect of submission device on receiver responses can be assumed. Additionally, our qualitative analysis of crucial content aspects in customer referrals from *Study 4* underscores that evaluating referrals in CRPs is a multi-faceted process involving several factors. As CRPs play a vital role in acquiring new customers (e.g., in *Study 4*, over 60% of streaming users became aware of their provider through referrals from individuals in their social circles), understanding influential factors in the creation of such referrals, and their effects on receivers' perceptions and reactions are of utmost importance.

## 7.2 | Managerial implications

This research provides valuable insights for managers seeking to optimize CRPs. Our findings indicate that smartphones have a detrimental impact on referral characteristics, making them shorter and less positive. Moreover, they affect receiver perceptions and responses by indirectly lowering perceived usefulness, effort, credibility, and purchase intention. To address these challenges, managers can adopt two strategies:

1. *Encourage customers to use laptops/PCs:* Given the tendency of smartphone-generated referrals to be less effective, managers should encourage customers to use non-mobile devices for creating customer referrals in CRPs. For instance, invitations to CRPs could be sent out on workdays and via email since laptops/PCs are perceived as “work devices” and are commonly used during working times (also for private tasks) and for working tasks (such as checking e-mails) (Canova & Nicolini, 2019; Park & Lee, 2017). Additionally, if laptops/PCs (vs. smartphones) are used to access the website, managers might consider implementing a higher visual hierarchy or a more prominent display of CRPs. Similarly, search engine advertising and optimization could be adapted to highlight CRPs in online searches via non-mobile devices.
2. *Improve the creation and perception of smartphone-generated customer referrals:* Considering the continuous diffusion of smartphones and their growing importance in CRPs,<sup>7</sup> managers should not only focus on influencing device choice but also improve the referral creation process on smartphones. This can be achieved by reducing cognitive costs induced by small screens and the general low usability of these devices through the implementation of easy-to-use systems in online CRPs. For instance, text length could be enhanced using auto-completion of texts, pre-defined text modules or pre-formulated texts (Kim et al., 2020; März et al., 2017). These tools can also be utilized to improve valence and other important aspects for the perception of referrals, such as the general formulation and use of smileys. Additionally, managers should encourage writers of customer referrals, regardless of the submission device, to include substantive information about the recommended services and personalize the referrals, as both aspects have been shown to be crucial to receivers' perception (as indicated in the qualitative coding of crucial factors impacting referral evaluation in Web Appendix J).

In conclusion, this research highlights the need for managers to address the challenges posed by smartphone usage in CRPs and adapt its promotion and design to device-specific characteristics. By implementing the aforementioned strategies, managers can maximize the effectiveness of their CRP and successfully counter the increasing significance of smartphones in this context, ultimately leading to positive outcomes regarding receiver perception and response.

### 7.3 | Limitations and future research directions

Our research is not without limitations, providing multiple avenues for future research. First, we investigate customer referrals in CRPs, which, unlike online reviews or social media posts, typically occur in a

private setting (e.g., via instant messaging). Therefore, to the best of our knowledge, no public field data are available. Consequently, our findings are based on referrals written in online and lab experiments, which may not fully represent real-world referrals. For instance, we observed that referrals in *Study 1* (online experiment) are considerably shorter and less positive compared to *Study 2* (lab experiment), regardless of the submission device. This disparity can likely be attributed to the influence of experimental conditions, where the laboratory setting offers controlled conditions and fewer situational influences and impairments. Nonetheless, we find consistent effects of the submission device on referral characteristics in both the online and lab experiments, reinforcing our findings. Conducting two experiments also allowed us to control for potential self-selection effects and lab-related conditions. Nevertheless, future research is encouraged to gather customer referrals from real-world CRPs to validate our findings. Furthermore, in *Study 3*, we operationalized text length following Furner and Zinko (2017). As we found the written referrals in *Studies 1* and *2* to be generally shorter compared to the online reviews studied by Furner and Zinko (2017), the question arises as to what extent their classification approach is generally valid and can be transferred to customer referrals. Other classification schemes for text length might be conceivable.

Second, in both *Studies 1* and *2*, we operationalized the valence of customer referrals using a text-mining approach and dictionary-based sentiment analyses. An essential underlying assumption for calculating valence is that each word possesses a predetermined polarity, either “positive” or “negative,” independent of its context (Taboada et al., 2011). Consequently, the valence scores are calculated as the sum of the values of detected words in a referral and do not necessarily correspond to the subjective assessment (i.e., perceived valence), which can consider the overall context. This said, in *Study 4* we found that the smartphone-generated referrals were perceived as less positive than the referrals generated using laptops/PCs. This perception aligns well with the valence scores derived from the dictionaries used for calculation, thereby emphasizing the suitability of the selected dictionaries for calculating the valence scores in the first two studies.

Third, we only focused on one product (i.e., a video streaming provider). Future investigations should expand our research to other contexts, such as utilitarian products (Oba & Berger, 2023). Another limitation of this study is that all experiments were conducted in Germany using convenience samples, highlighting the need for future cross-cultural research to generalize our findings globally. Finally, it is worth noting that in the scenarios of our experimental studies, we did not specify any rewards for participants acting as senders or receivers in the CRPs. Given the variations in cognitive effort required to compose customer referrals across different submission devices, an argument could be made that users employing smartphones might perceive a higher demand for rewards. This contention finds support in the notably higher perceived personal nature of smartphones, as observed in *Study 1*, potentially fostering a more self-centered mindset among smartphone users (Melumad & Meyer, 2020). Exploring the acceptance of diverse reward structures in CRPs contingent on the

<sup>7</sup>As an illustration, a clickstream dataset available to the authors reveals that a major German insurance company's online CRP is accessed via smartphones 59.79% of the time, via laptops/PCs 36.57% of the time, and via tablets 3.64% of the time (consisting of 13,425 visits over a one-year period [01.07.2020–31.07.2021]). Similarly, in both *Studies 1* and *2*, respondents rated smartphones as the most likely used device for submitting customer referrals in CRPs (see manipulation and plausibility checks).

submission device used appears to be a promising avenue for further research.

Beyond that, various directions for future research on device-mediated customer referrals remain. For example, future work could investigate the proper timing of calls to action within CRPs both in terms of time factors, acknowledging the differences in device choice depending on the time of day and the day of the week, and in terms of duration between events (e.g., subscription to provider and invitation to recommend a product or service; Jung et al., 2023). Furthermore, we urge future researchers to explore how the device used for receiving customer referrals impacts receivers' perceptions and responses (Babić Rosario et al., 2020). For instance, März et al. (2017) highlighted that alignment between the submission and reading device for eWOM influenced receivers to perceive it as more helpful. A similar effect could be anticipated for customer referrals. Finally, it would be worthwhile to investigate how new technologies (e.g., dictation modes) and devices (e.g., smartwatches) shape customer referrals (Oba & Berger, 2023).

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

## DATA AVAILABILITY STATEMENT

The experimental datasets generated during and/or analyzed during the current study are available from the corresponding author upon request.

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## SUPPORTING INFORMATION

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