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Effects Of Media Exposure On Descriptive Social Norm Perception Formation: Experimental And Observational Studies Of Why And How Repeated Exposure Matters

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Abstract

Although the study of social influence has been a fruitful topic of inquiry in the field of communication, past research has focused almost exclusively on its consequences, and rarely asks how people construct their perceptions of social reality in the first place. This dissertation contributes to our knowledge by thoroughly examining how people form descriptive social norm perceptions in their everyday communication environment through repeated media exposure. We investigated this question with different forms of media exposure, engaged in different lines of theoretical inquiry and utilized observational and experimental methods.

The first study relied on self-report measures and examined how the effects of repeated incidental media exposure to e-cigarette use information across multiple sources may travel through interpersonal conversations and descriptive norm perceptions, and finally reach behavior decisions. We presented evidence of direct and indirect pathways with cross-sectional and longitudinal data among a nationally representative sample of youth and young adults. The second set of studies conducted online experiments to manipulate people's exposure to repeated individual behavior cues embedded in online comments. We confirmed that people were equipped with a "quasi-statistical" sense that allowed them to automatically collect and identify the behavior choice distribution within the online comment boards, based on which they formed the behavior prevalence perceptions in the real world. The results were replicated with both e-cigarette use and Genetically Modified Food label checking behaviors. Applying similar experimental procedures, the third study comprehensively examined the exposure-norm relation with much more elaborated treatment conditions. We observed that descriptive norm perceptions responded to repeated exposure in a dose-response fashion, contingent on the size of the overall information pool.

This work addresses the underlying mechanisms of descriptive social norm perception formation and how they could be better harnessed in promoting behavior changes moving forward. Our examination of user-generated contents on news websites adds to the sparse literature on the intersection between mass and interpersonal communication processes in the context of the unique dynamics and characteristics of social perception formation in our current media landscape.

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EFFECTS OF MEDIA EXPOSURE ON DESCRIPTIVE SOCIAL NORM PERCEPTION FORMATION: EXPERIMENTAL AND OBSERVATIONAL STUDIES OF WHY AND HOW REPEATED EXPOSURE MATTERS

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EFFECTS OF MEDIA EXPOSURE ON DESCRIPTIVE SOCIAL NORM PERCEPTION FORMATION: EXPERIMENTAL AND OBSERVATIONAL STUDIES OF WHY AND HOW REPEATED EXPOSURE MATTERS

Dedication

This dissertation is dedicated to my parents Min Liu and Xinquan Yang, and my husband Wenjian Du, for their unfailing love and support.

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ABSTRACT

EFFECTS OF MEDIA EXPOSURE ON DESCRIPTIVE SOCIAL NORM PERCEPTION FORMATION: EXPERIMENTAL AND OBSERVATIONAL STUDIES OF WHY AND HOW REPEATED EXPOSURE MATTERS

Jiaying Liu

Robert C. Hornik

Although the study of social influence has been a fruitful topic of inquiry in the field of communication, past research has focused almost exclusively on its consequences, and rarely asks how people construct their perceptions of social reality in the first place. This dissertation contributes to our knowledge by thoroughly examining how people form descriptive social norm perceptions in their everyday communication environment through repeated media exposure. We investigated this question with different forms of media exposure, engaged in different lines of theoretical inquiry and utilized observational and experimental methods.

The first study relied on self-report measures and examined how the effects of repeated incidental media exposure to e-cigarette use information across multiple sources may travel through interpersonal conversations and descriptive norm perceptions, and finally reach behavior decisions. We presented evidence of direct and indirect pathways with cross-sectional and longitudinal data among a nationally representative sample of youth and young adults. The second set of studies conducted online experiments to manipulate people's exposure to repeated individual behavior cues embedded in online comments. We confirmed that people were equipped with a "quasi-statistical" sense that

allowed them to automatically collect and identify the behavior choice distribution within the online comment boards, based on which they formed the behavior prevalence perceptions in the real world. The results were replicated with both e-cigarette use and Genetically Modified Food label checking behaviors. Applying similar experimental procedures, the third study comprehensively examined the exposure-norm relation with much more elaborated treatment conditions. We observed that descriptive norm perceptions responded to repeated exposure in a dose-response fashion, contingent on the size of the overall information pool.

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CHAPTER 1.

INTRODUCTION AND OVERVIEW

Introduction

Imagine that you go to watch an orchestra concert for the first time. As you walk into the elegant modern concert hall, you immediately lower your voice to a whisper as you ask for directions because no one else there seems to be talking aloud. You sit down and silence your phone before the concert starts, as you notice most people around you take out their phones and disable the ringtones. The moment that the musicians finish the last note, everyone else rises in a standing ovation. You most likely will stand up and begin clapping too. By observing and following what others do, the first-time concert-goer will have no problem in acting appropriately in accord with the unwritten social rules in the concert hall. Our daily lives abound with such examples. We often look to others' behaviors, or follow our perceptions of what is commonly done by others, to decide what our next moves are, more frequently than we are aware of. Cialdini and colleagues (1990) dubbed what is typically or normally done among other people as *descriptive norms*, and argue that they can profoundly affect people's cognitions, behaviors and decision making outcomes.

Descriptive norms motivate action by informing people about what is likely to be effective or adaptive in specific situations. They provide information about the correct way to act in a certain situation and thereby serve people's goal of accuracy: If everyone's doing it, then it must be a sensible thing to do (Cialdini et al., 1990). Such a presumption indicates that descriptive norms offer social proof and often function as heuristic cues or mental shortcuts in the decision making process (Cialdini, 1984; Cialdini & Goldstein, 2004; Jacobson, Mortensen, & Cialdini, 2011). The most intriguing aspect about descriptive norms is that people decide to engage in a behavior simply because they perceive enough others follow it as well. That is to say, under the influence of descriptive norms, the reasons that a particular behavior decision is made can be independent of the substance of the behavior itself (Muldoon, Lisciandra, & Hartmann, 2014). Therefore, as long as individuals believe that the majority of people will perform the behavior in similar situations, they most likely will make up their minds following this majority decision too, sometimes even in the absence of convincing arguments or pragmatic concerns – the high prevalence of the behavior conducted by others already serves as justifications.

In the domain of health behavior change, originally, only *subjective norms*, a type of *injunctive norms*, which describes the extent to which individuals believe other people (important others in the case of subjective norms) think they *should* or *should not* engage in a particular behavior (Cialdini et al., 1990), was included as a potential determinant of behavioral intention in influential behavior change theories such as the Theory of Reasoned Action or Theory of Planned Behavior (Ajzen, 1991; Ajzen & Fishbein, 1973; Fishbein, 1967; Fishbein & Ajzen, 1975). While these models have been successfully applied to a variety of health behaviors, it is also clear that there is still a substantial amount of variance left to be explained, and several empirical findings and evidence from meta-analysis pointed out the need to expand the norm component in view of the comparatively weak subjective norms – intention associations (Albarracín, Johnson, Fishbein, & Muellerleile, 2001; Armitage & Conner, 2001; Cooke & French, 2008; Hagger, Chatzisarantis, & Biddle, 2002). The models under the TRA approach were further expanded to include a "perceived norms" component which consisted of both subjective norms and descriptive norms constructs (Fishbein, 2000; Fishbein & Ajzen, 2011; Fishbein & Cappella, 2006). Over the years, abundant evidence has accumulated to suggest the powerful effects of descriptive norms on individuals' cognitions and behaviors across domains (e.g., Burger & Shelton, 2011; Dillard & Shen, 2012; Hong, Rice, & Johnson, 2012; Jacobson et al., 2011; Larimer, Turner, Mallett, & Geisner, 2004; Rivis & Sheeran, 2003; Stok, de Ridder, de Vet, & de Wit, 2014).

Tankard and Paluck (2016) emphasized the distinction between two types of descriptive social norms that have been measured in the literature aiming at predicting intention and behavior change. The first is *actual descriptive norms*, which refers to actual rate or prevalence of a particular behavior in a population that is often reported in comprehensive surveys or consensus (referred to as "collective norms" in Lapinski and Rimal, 2005). The second is *perceived descriptive norms (or descriptive norm perceptions)*, which refers to people's subjective perceptions or estimation of the behavior prevalence (referred to as "perceived norms" in Lapinski and Rimal, 2005). Interestingly, a non-trivial amount of evidence from empirical studies pointed out that individuals' descriptive norm perceptions rarely match actual descriptive norms in their environment (Berkowitz, 2004; Borsari & Carey, 2003; Clapp & McDonnell, 2000; Cruz, Henningsen, & Williams, 2000; Neighbors, Dillard, Lewis, Bergstrom, & Neil, 2006;

Perkins & Wechsler, 1996; Prentice & Miller, 1993; Sandstrom & Bartini, 2010). Despite the fact that individuals often misperceive the prevalence of a behavior in their social midst, their subjectively perceived descriptive norms turned out to be more influential than the actual descriptive norms in guiding their decisions and behaviors (Lapinski & Rimal, 2005; Rimal & Real, 2003; Tankard & Paluck, 2016). Wallen and Romulo (2017) also pointed out that the importance of distinguishing between normative social perceptions or beliefs and actual reality of behaviors that are common within a social group, as they have real-world implications on how to accurately identify changes in behavior (as in "actual reality") and changes in beliefs (as in "normative social beliefs"). From the perspective of promoting behavior change on the societal level as a whole, focusing on changing perceptions could be a fruitful intervention strategy that might ultimately lead to shifts in actual reality of behaviors in a desirable way. Therefore, in this project, we focus on the formation process of descriptive norm perceptions, with the hope that a better understanding of the underlying mechanism could help inform us how to effectively leverage the power of normative perceptions in facilitating and catalyzing cognition and behavior changes. However, literature investigating the influential factors and processes of descriptive norm perception formation still remains remarkably thin.

Considering that information delivered by media plays an important role in shaping people's perceptions about social reality, the field of communication has much to contribute to the effort of understanding the mechanism of descriptive norm perception formation. While face-to-face conversations or direct observations of others' behaviors can greatly influence individuals' descriptive norm perceptions, individuals might have limited attention and access to such information, and it is highly likely that they won't be interacting with everyone in their environment and to the same degree (Tankard & Paluck, 2016). Instead, individuals may formulate their perceptions about prevalence based on the preponderance of a behavior mentioned or depicted in *mass media outlets* such as newspapers, TV shows, websites, blogs etc., or *media-stimulated interpersonal communication channels* such as user-generated comments, discussions, or conversations online (E. L. Cohen, 2013; Lapinski & Rimal, 2005).

Furthermore, considering the nature of descriptive norm perceptions, which are in essence estimations about behavior prevalence, repetition of exposure from media might be especially important in this context. Accumulating theoretical propositions and empirical findings argued for the importance of taking into account the repeated media exposure or exposure dosage in the investigation of mechanisms underlying descriptive norm perception formation. First of all, the most straightforward path for repeated media exposure to affect descriptive norm perceptions is through facilitating acquisition of new summary information about the actual rate or prevalence of a target behavior in a population, and reinforcing the memory encoding in individuals about such summary information (Tankard & Paluck, 2016). Even when the content of exposure is not explicitly about prevalence information, repeatedly seeing mentions of the target behavior in their communication environment might make the behavior especially salient in their mental shortcuts and can be easily called to mind thus increasing the likelihood of availability to the information at the time of judgment about the behavior prevalence

(Bargh, Chen, & Burrows, 1996; Fiske & Taylor, 2013; Higgins, 1996; Hornik et al., 2013; Potter, 1993; Tankard & Paluck, 2016; Tversky & Kahneman, 1982).

Secondly, in line with the classic mere-exposure research where researchers found that mere exposure to a stimulus category can affect individuals' attitudinal preferences (Zajonc, 1968), Kwan, Yap, and Chiu (2015) also found similar effects in the domain of descriptive norm perception formation. Using experimental methods, they observed that repeated incidental exposure to novel stimulus objects increased participants' perceptions about how widely these objects are known to other people in the population. This might have important implications on the underlying mechanism of how repeated incidental media exposure might influence descriptive norm perceptions about a target behavior through an increased sense of familiarity; in other words, behaviors that are frequently mentioned or depicted in the media might be assumed to be widely known or performed in the population.

Thirdly, repeated exposure to media content about a target behavior might provoke mediating processes that could in turn lead to shifts in descriptive norm perceptions. There might be two possible mediating processes going on based on previous literature. One is rooted in a well-known model called the Influence of Presumed Media influence (IPI) which proposes that if people are repeatedly exposed to some mass media content, they are most likely to assume that other people are also exposed to the same content too, especially considering the prominence of this particular piece of content mentioned in the media environment. Based on this presumption, they will further assume that such exposure affects other people's cognitions and behaviors;

then they will react and try to adapt to this subjective perceptions by changing their own cognitions and behaviors (Gunther, Bolt, Borzekowski, Liebhart, & Dillard, 2006; Gunther & Storey, 2003; Tal-Or, Cohen, Tsfati, & Gunther, 2010; Tsfati & Cohen, 2005). Following this line of argument, it is possible that repeated exposure to media content about a target behavior will lead to presumed exposure and influence on other people's decisions of whether engage in the behavior or not, which will then affect individuals' perceptions about the behavior prevalence in the population. In addition to this potential mediating process, repeated media exposure might also be able to trigger interpersonal communication process, such that the more frequently the behavior is mentioned or depicted in the media, individuals are more like to bring it as a conversation topic into their social context. The conversations or discussions about the target behavior with other people might help individuals learn descriptive norms about the behavior in the group or for a larger population (Hornik, 2006; Hornik et al., 2013; Hornik & Yanovitzky, 2003; Jeong, Tan, Brennan, Gibson, & Hornik, 2015).

Last but not least, repeated exposure to media content, especially user-generated media content, that contains individual behavior cues, i.e., indications about whether other people engage in a target behavior or not, might deliver the descriptive norm information in a relatively implicit way, based on which individuals might be able to gauge the distribution of behavior preferences (Tankard & Paluck, 2016). To be specific, for example, if individuals read through a set of online comments left by previous viewers, and they repeatedly (say, 80% of the time) see commenters indicate that they engage in the behavior, individuals are very likely to form a raw impression that the dominant behavior choice is to engage in the behavior (versus not). Some scholars argued that out of fear of isolation, human beings have developed an almost instinctual *quasi-statistical sense* that automatically collects and infers distribution information about opinions and behaviors in their surrounding environment through observational learning and inferential processing (Deutsch & Gerard, 1955; Noelle-Neumann, 1993; Scheufele & Moy, 2000). In other words, behaviors practiced by others as mentioned in the media content can serve as cues and evidence for individuals to form the quasi-statistical picture about the reality. The dosage of exposure is crucial in terms of determining the perceived distribution and dominance of the behavior choices. The subjective perceptions of behavior distribution formed in this way might be quite powerful in affecting people's cognitions and behaviors, and the levels of exposure repetition needed to be able to generate the perception formation also warrant further investigation.

In view of the above considerations, this dissertation is dedicated to exploring and understanding the role of repeated media exposure, including both mass-media and user-generated media content, in influencing descriptive norm perception formation. Specifically, we investigated the questions with three major studies, each tapping into different conceptualization of repeated media exposure and exploring different aspects of the underlying mechanism of descriptive norm perception formation.

Dissertation Overview

The first study (Chapter 2) relies on self-report measures and looks at how repeated incidental media exposure may travel through interpersonal conversations and descriptive norm perception changes, and finally reach behavior decisions. Specifically, we first established that repeated routine exposure to media contents mentioning the behavior topic is positively associated with behavior change, and that one significant indirect path was through increased descriptive norm perceptions. To further unpack the underlying chains of influence, we then looked into a mediating mechanism between repeated media exposure and descriptive norm perceptions, and observed that increases in incidental encounters of the behavior topic not only can directly shape perceptions of prevalence estimation, but can also operate through an indirect pathway by triggering interpersonal communication processes that lead to descriptive norm perception changes. We presented evidence with both cross-sectional and longitudinal data among a nationally representative sample of youth and young adults.

The second major study includes a pilot study (Chapter 3), and two ensuing main studies (Chapter 4). The pilot study seeks to understand whether people's descriptive norm perceptions about reality could be impacted by perceptions of behavior prevalence in a more immediate environment formed through their own subjective experiences or observations. To answer this question, within the behavior context of e-cigarette use, we experimentally constructed online comment boards, and manipulated the exposure dosage of normative information contained in online comments with a pre-specified behavior prevalence ratio to examine whether people's "quasi-statistical" sense can correctly detect the behavior choice distribution; and more importantly, whether people would infer behavior prevalence in the real world based on the perceived behavior choice distribution we constructed using the online comment boards. In this way, we hope to simulate the perception formation process that happens automatically in people's normal course of life with online comment boards, the media platform that approximates real-world social group settings where individuals can infer descriptive norm information (i.e., individual behavior cues) through repeated exposure to user-generated media contents. The pilot study also explored two variations in experimental manipulation that might potentially make the normative cues more salient: doubling exposure dosage and adding visual cues. The results revealed that people could correctly identify the numerical majority of the behavior choice based on the comments they read, and such perceived behavior choice distribution affected their descriptive norm perceptions about e-cigarette use in the real world accordingly. In addition, while there was some evidence that the double-dosage condition magnified effects, the addition of visual cues had no effect.

Based on the findings of the pilot study, in Chapter 4, we further conducted two main studies, with a modified experimental design, to examine the robustness of the results we observed from the pilot study. To be specific, we first replicated the pilot study with the same target behavior, e-cigarette use (study 1). We then applied the experimental design to a different behavior, checking for GMO labels on food products (study 2). GMO labels also tap into issues that are fraught with uncertainty and ambiguity and are going through heated debates in the American public, but has a very different nature and characteristics compared to those that are specific to the e-cigarette vaping behavior. The results from the two studies successfully replicated the main conclusions of the pilot study, and together they revealed an “incongruence bias” between news-induced and comments-induced norms. The findings suggested that the constructed behavior choice distribution perceptions resulting from repeated exposure to normative information contained in the online comments may have overridden the anchor norm perceptions set by reading the news article, but only when the directions of news-induced and comments-induced norms were incongruent. This pattern was striking particularly considering the non-representative, atypical nature of the online commenters sample, as well as the non-coercive anonymous online comment boards we created. These results served as strong evidence of internalization or private acceptance of the constructed behavior prevalence perceptions, based on which people make generalized prevalence estimation to populations. We discussed important theoretical implications of the results and the potential in applying constructed social groups to optimize effectiveness of health interventions utilizing normative appeals.

These studies explicated why repeated media exposure, operationalized respectively as numbers of media sources mentioning a behavior topic and numbers of online comments containing individual behavior cues, matters in the formation of descriptive norm perceptions. The third major study (Chapter 5) deals with the questions of how each dose of exposure is associated with normative perception formation, and whether there is any exposure threshold that can instigate the norm formation process. Applying similar experimental procedures from Chapters 3 and 4, we designed much more elaborated treatment conditions (230 conditions), comprehensively varying the two focal elements of exposure (total exposure, and exposure to information with a targeted norm direction, user-norm information for example) to allow a systematic examination of the exposure-norm relation. After probing a number of possible linear and non-linear functions, we observed that repeated exposure, operationalized as numbers and percentages of comments containing the targeted norm direction, was positively associated with reality descriptive norm perceptions (in that corresponding norm direction) in a dose-response way. An important exposure threshold was found in the interactive relation between total exposure and percentage of exposure to the information with the targeted norm direction.

As a whole, all three studies aim at answering the same two over-arching questions: What is the role of repeated media exposure in the process of descriptive norm perception formation? How does each additional dose of exposure contribute to this process? Separately, the three studies engage in and speak to different lines of inquiry in the literature, address effects of different forms of media contents, tap into alternative mechanisms of descriptive norm perception formation, analyze at different levels, and apply different methods in quantifying the important concepts of exposure. In each of the following chapters, we present theoretical background and rationale, previous empirical evidence, research questions and hypotheses, methodological details, analyses and results, as well as discussion and conclusions separately for each individual study.

CHAPTER 2.

HOW REPEATED ROUTINE EXPOSURE TO MEDIA CONTENT AFFECTS DESCRIPTIVE NORM PERCEPTIONS: EVIDENCE OF DIRECT AND INDIRECT PATHWAYS FROM A NATIONAL LONGITUDINAL SURVEY

Introduction

For decades, communication scholars have put great effort towards answering the question of whether mass media affect their audiences; and if yes, how this influence operates. It is not hard to imagine how media contents that are intentionally designed to be persuasive, such as campaign messages, might have direct impacts on individuals' cognition and behavior changes. A more interesting and less intuitive question would be, how routine media exposure, media information without persuasive intent, , might affect them and in what way.

Information Scanning

Routine media exposure, also known as *scanning*, was defined as "information acquisition that occurs within routine patterns of exposure to mediated and interpersonal sources that can be recalled with a minimal prompt" (Niederdeppe et al., 2007). Therefore, scanning refers to the incidental exposure that has not been actively sought for, comes from different media and interpersonal channels in individuals' living environment, possibly offers mixed information (messages and counter-messages) for a topic, and receives a minimal degree of attention but is sufficient to be recalled later. Compared to active information seeking behavior, scanning is less likely to be the result of individual motivations and volitional controls. As random and sporadic as it may sound, in the health domain, accumulating empirical studies with national data observed a substantial amount of health-related scanning in the general population and consistently reported effects of cancer-related information scanning on knowledge, lifestyle or preventive behaviors, and cancer screening behaviors (Hornik et al., 2013; Kelly et al., 2010; Kelly, Niederdeppe, & Hornik, 2009; Nguyen et al., 2010; Shim, Kelly, & Hornik, 2006). While active seeking might be more influential than passive scanning if there is only one single episode of exposure, considering that scanning about most topics is more prevalent, and happens to many more individuals, on the aggregate-level, scanning might be more influential (Hornik et al., 2013; Niederdeppe et al., 2007; Shim et al., 2006).

Hornik et al. (2013) proposed that the underlying mechanisms through which information scanning affects personal health might either be 1) new information acquisition such that people learn costs and benefits associated with the behavior or even skills that are necessary to carry out the behavior from routine scanning; or 2) reinforcement of a descriptive norm such that repeated exposure from a range of different media sources might inflate individuals' perceptions about what is typically and commonly done among other people, and thus people react to this perception by adapting their cognitions and behaviors accordingly; or 3) reminding, such that repeated routine scanning might make the reasons to engage in or not engage in a behavior more salient and cognitively accessible at the time of decision making. While the first and last pathways tap more into the direct effects of scanning on health-related cognitions and behaviors, the second pathway describes a potential indirect mediating mechanism via changes in descriptive norm perceptions.

Scanning on Descriptive Norm Perceptions

Then how exactly does scanning affect descriptive norm perceptions? There are different theories and hypotheses trying to tap into this question. One possibility was based on a familiarity argument: things frequently seen are assumed to be widely known. A recent study (Kwan et al., 2015) showed, through experimental manipulation, that repeated incidental exposure to novel stimulus objects increased participants' perceptions about how widely these objects are known to other people in the population. In line with the classic mere-exposure research where researchers found that mere exposure to a stimulus category can affect individuals' attitudinal preferences even without conscious processing during the time of exposure (Zajonc, 1968), Kwan and colleagues (2015) argued that the repeated exposure to the stimulus created a sense of familiarity among the participants who then assume this must also be familiar to other people as well. In this way, the descriptive norm perceptions are inflated. Another explanation, particularly related to media scanning, was rooted in a well-known model in mass media communication research called the Influence of Presumed Media influence (IPI) (Gunther et al., 2006; Gunther & Storey, 2003). Derived from the Third-Person-Effect line of argument (Davison, 1983), the IPI model proposes that if people are exposed to some mass media content, they will assume that other people are also exposed to the same content; and more importantly they will assume that such exposure affects other people's cognitions and behaviors; then they will react and try to adapt to this subjective perception by changing their own cognitions and behaviors (Gunther et al., 2006; Tal-Or et al., 2010; Tsfati & Cohen, 2005).

While both of the hypotheses offer possible explanations for the potential mediating pathways between scanning and changes in descriptive norm perceptions, they both focus on individuals' subjective assumptions about other people, i.e., subjectively assumed familiarity and subjectively assumed media exposure and effects. Is it possible that repeated scanning across media channels can activate another process that involves real observations and interactions with other people instead of presumed influence? Both Katz and Lazarsfeld's two-step flow model (Katz, 1957; Katz & Lazarsfeld, 1955) and Rogers' diffusion of innovations theory (Rogers, 1962) throw light on this questions by arguing for the important role of social context on media effects. It could be that the more frequent scanning on a topic in media, the more likely that the interpersonal communication process will be activated such that people are more likely to bring these topics they hear from media to conversations with people in their social context, or people are more likely to memorize and recall occasions of interpersonal discussions about the topics. Through interpersonal conversations, meanings or interpretations might be provided, clarified or negotiated as people try to make sense of media messages together, and such interpretations might be crucial for their subsequent decision making; or social influencers who have been directly exposed to mass media content could relay or retransmit the information to others who have not been exposed to it yet; or conversations and discussions might lead to a discovery of descriptive norms about the topic or behavior within the group or for a larger population, which might affect how people interpret and react to that specific topic or behavior (Hornik, 2006; Hornik & Yanovitzky, 2003; Jeong et al., 2015).

Interpersonal Communication as A Mediator

The number of studies that have examined the role of interpersonal communication as a mediator is not trivial, but most of the prior studies have investigated this question in the context of persuasive media content, such as how exposure to the mass media campaign messages leads to relevant interpersonal discussions, which in turn affect people's cognitions and behaviors (Hafstad & Aaro, 1997; Hwang, 2012; Schuster et al., 2006). Some studies also distinguished the content of the interpersonal discussions and examined whether talking about the campaign or campaign messages themselves, versus talking about the target behavior of the campaign, such as quit smoking, will make any difference (e.g., Hendriks, van den Putte, de Bruijn, & de Vreese, 2014; Jeong et al., 2015; van den Putte, Yzer, Southwell, de Bruijn, & Willemsen, 2011). For example, with both cross-sectional and longitudinal evidence, Jeong and colleagues (2015) found that conversations about quitting smoking mediate anti-smoking campaign effects on quitting-related behaviors and conversations about the campaign ads have indirect effects on quitting-related behaviors by promoting conversations about quitting smoking. To our best knowledge, no prior study has tested the mediating mechanism through interpersonal communication between routine media exposure and descriptive norm perception changes. Therefore, along with looking at how scanning affects behavior directly and indirectly through descriptive norm perception changes, we would also like to further understand the underlying causal pathways by examining whether repeated media scanning about a topic would trigger people to talk with others about this topic in the first place, which then leads to descriptive norm perception changes, and ultimately behavior changes.

Conceptualizing the Extent of Scanning

One crucial issue related to the conceptualization of scanning in the context of the current study is the dimensions used to define the level or extent of scanning. For sporadic routine exposure about a topic to provoke interpersonal discussions and to influence descriptive norm perceptions, sufficient prominence of the topic might need to be warranted in the overall media environment. Presumably, repeated exposure through multiple media channels over time is needed before expecting to see any effects of scanning (Hornik et al., 2013; Hornik & Yanovitzky, 2003). In line with the above propositions, previous studies that empirically examined the influence of scanning have conceptualized the level of scanning along two dimensions: *breadth* and *depth* (Hornik et al., 2013; Kelly et al., 2009; Nguyen et al., 2010; Niederdeppe et al., 2007; Shim et al., 2006). To be specific, breadth of scanning refers to the total number of information sources encountered that mentioned the topic of interest, and depth of scanning refers to either the frequency of such encounters in total, or by source. The two dimensions are obviously not independent from one another, but may capture different aspects of scanning, since it is easy to imagine that an inference of high prevalence of behavior can come from minimal mentions but on many sources, as well as heavier mentions on one source. It is also common to take in to consideration of both dimensions in the assessment of level of scanning. For example, participants were first asked to recall the number of times they hear or come across information, without actively seeking for it, about the topic of interest from each of the media or interpersonal sources in a list. The frequencies of scanning episodes were then coded into categories (0 = *not at all*, 1 = *one or two times*, 2 = *three or more times*) for each source, and then a composite scanning score was created by either summing or averaging the categories across all types of sources (Hornik et al., 2013; Kelly et al., 2009). It is also worth noticing that previous scanning measures include both media sources and interpersonal sources to assess the extent of scanning in their overall communication environment (Niederdeppe et al., 2007). In the current study, due to our questions of interest, we separate the two sources of information to be media scanning and interpersonal communication and examined their associations both cross-sectionally and longitudinally.

While both breadth and depth of media scanning may influence the formation of descriptive norm perceptions, in the current study we only focus on examining the breadth construct, which is available in our data and is measured as the total number of media sources people passively encountered that mentioned the topic of interest. Although our own data did measure depth of scanning by asking the participants to indicate the total frequency of coming across information about e-cigarettes or vaping in the past 30 days, the frequency was not measured by each of the individual sources. In other words, the frequency of scanning people reported may include all types of channels, thus precluding us from separating the role of mediated and interpersonal communication. Therefore, the analyses presented in the current study will all focus on “breadth” as the measure of scanning.

E-cigarette Use among Youth and Young Adults

We investigate the question in the context of electronic cigarette use or vaping behavior. Electronic cigarettes (also called e-cigarettes) are battery-operated devices designed to deliver nicotine with flavorings and other chemicals to people in aerosol, simulating the visual, sensory, and behavioral aspects of smoking without the combustion of tobacco (Emery, Vera, Huang, & Szczypka, 2014; Orellana-Barrios, Payne, Mulkey, & Nugent, 2015; Riker, Lee, Darville, & Hahn, 2012). Some studies suggested that e-cigarettes may hold promise as a smoking-cessation tool (e.g., Siegel, Tanwar, & Wood, 2011), while others argued that vaping may cause nicotine addiction or act as a gateway to tobacco or even drug use (e.g., Riker et al., 2012). As the scientific evidence is far from certain, consensus about the public health benefits and risks associated with e-cigarette use has not been achieved yet. Despite the contentious debate, until recently vaping rapidly gained popularity, especially among youth and young adults (Hitchman, McNeill, & Brose, 2014; Noel, Rees, & Connolly, 2011). Indeed, as our own data suggested, which is described in more detail later, past-30-day use of e-cigarettes and of tobacco cigarettes among youth and young adult populations are quite similar (Table 2.1). Considering that the uncertainty and heated debates around vaping behavior, which is still a relatively novel behavior compared to traditional cigarette smoking, people's routine media exposure to e-cigarette related topics might consist of mixed messages across media sources. We suspect that interpersonal communication might be particularly meaningful and important under conditions fraught with ambiguity and novelty, as individuals might seek meanings and clarifications in their social context to better react to the messages and counter-messages they encounter in their environment, and such interactions might affect their descriptive norm perceptions about e-cigarette use within their social group or even for a larger population which might in turn affect their decisions to engage in the vaping behavior or not. Within this context, we ask whether repeated incidental exposure to e-cigarettes across different media sources, for example, celebrity use in TV shows or movies, outdoor ads on taxi tops, or e-cigarette users discussing their experiences of how to modify the device on YouTube, etc., might together trigger youth and young adults to talk about e-cigarettes or vaping with others, which may inflate their descriptive norm perceptions, and ultimately lead to e-cigarette use behavior.

The Present Study

The current study first examines the direct and indirect pathways through which routine exposure to media content related to e-cigarettes is to affect individuals' e-cigarette use behavior through changes in descriptive norm perceptions about e-cigarette use in the real world. Next, to further understand the mechanism of how descriptive norm perceptions are influenced in the first place, we explore whether repeated routine exposure to media content related to e-cigarettes would catalyze interpersonal communication about the same topic, and whether such conversations would lead to increases in individuals' prevalence perceptions of e-cigarette use. Our full model of proposed pathways is presented in Figure 2.1.

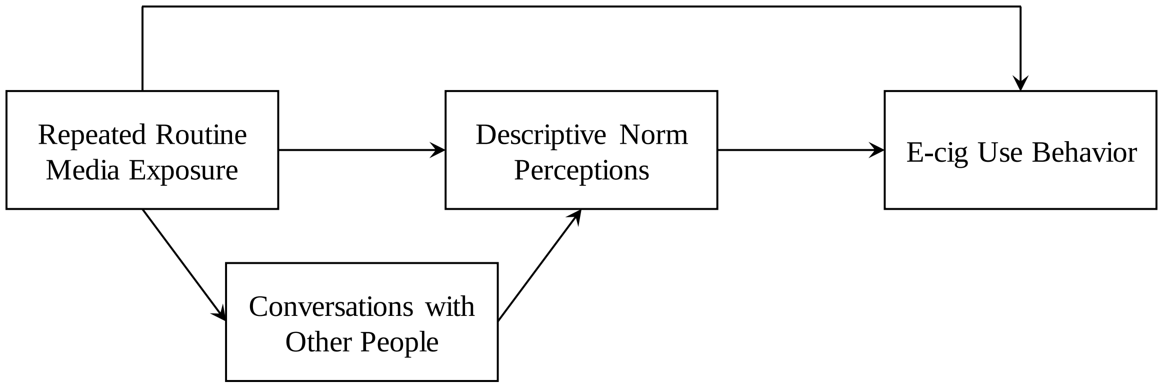

Figure 2.1. Full model of proposed pathways

Hypothesized Pathways

To decompose the full model, we first test the direct effect of routine media exposure on e-cigarette use behavior (See Figure 2.2, Hypothesis 1).

H1: The breadth of media scanning is positively associated with e-cigarette use.

We then examine the potential mediation pathway between media scanning and e-cigarette use behavior through descriptive norm perceptions. To be specific, we first examine the two essential direct effects in the mediation model (H2 & H3), which are the prerequisite steps for establishing the mediation model. If both pathways are significant, we then formally test the full mediation model to examine whether the indirect effect is significant (H4) (See Figure 2.2, Hypotheses 2 – 4).

H2: The breadth of media scanning is positively associated with descriptive norm perceptions about e-cigarette use.

H3: Descriptive norm perceptions is positively associated with e-cigarette use behavior.

H4: Descriptive norm perceptions mediate the relation between the breadth of scanning and e-cigarette use behavior.

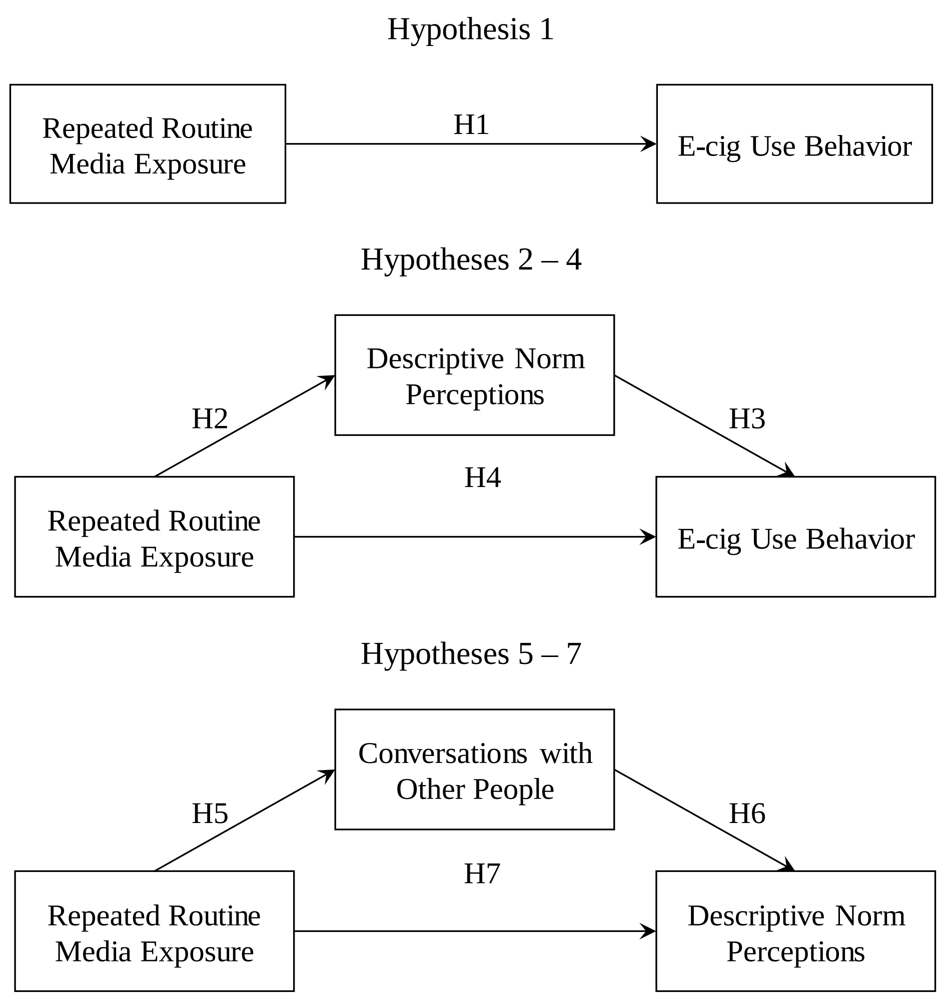

Figure 2.2. Proposed direct and indirect pathways by hypotheses

Finally, we examine whether talking with other people mediates the relation between media scanning and descriptive norm perceptions. If H2 above is supported, we further test the two hypothesized zero-order direct effects (H5 & H6) in the full mediation model, and then examine whether the indirect effect is significant with H7 (See Figure 2.2, Hypotheses 5 – 7).

H5: Increasing breadth of media scanning is associated with higher odds of talking about e-cigarettes with other people.

H6: Talking about e-cigarettes with other people is positively associated with descriptive norm perceptions about e-cigarette use.

H7: Talking about e-cigarettes with other people mediates the relation between the breadth of media scanning and descriptive norm perceptions about e-cigarette use.

All the above hypothesized pathways and mediation models are examined both cross-sectionally and longitudinally with a time lag of 6 months, which will be described in detail in the Method section.

Method

Participants

This study used data from a larger project that aimed at understanding how the current public communication environment about tobacco and e-cigarettes might affect youth and young adults' smoking and vaping related cognitions and behaviors, conducted by the Penn Tobacco Center of Regulatory Science (TCORS) and Annenberg School for Communication (Hornik & Lerman, 2014); Grant Number: P50-CA-179546-01)[1]. Data in this project are being collected on an ongoing basis using a nationally representative survey of 13- 25 year olds over the phone from June 2014 to June 2017. A panel of participants was recruited by Social Science Research Solutions (SSRS) from a partially

[1] https://prevention.nih.gov/tobacco-regulatory-science-program/research-portfolio/centers#UPenn

list-assisted, random digit dial (RDD) population of all landline telephone and cellphone numbers in the United States to provide a probability-based sample. The survey measures knowledge, beliefs, norms, intentions, and behaviors regarding tobacco products (including e-cigarettes) among youth and young adults, and also investigates their general media exposure as well as exposure to information about specific tobacco-related topics in the media. The American Association of Public Opinion Research response rate 3 for the cross-sectional interviews was estimated at 21%. About 35% of the participants who completed the interviews at time 1 (T1 hereafter) were successfully re-interviewed at time 2 (T2 hereafter) six months later. 13-15 year olds required parental consent for participating in the study, thus were the most willing to be called back, and had the highest retention rate (61%). The current study used 33 months of the T1 data from June 2014 to March 2017 (n = 11013), and 27 months of T2 re-interview data collected between December 2014 and March 2017 (n = 3212). All the T1 participants were used for cross-sectional analyses, and only participants who completed the interviews at both T1 and T2 were included in the lagged analyses. For all the analyses we conducted in the current study, the samples were weighted to the known current census population distributions (U.S. Census Bureau, 2016) on major demographic variables. Demographics characteristics and other descriptive statistics for both unweighted and weighted samples are presented in Table 2.1.

Measures

Routine Media Exposure. Before assessing the details of the routine media exposure about e-cigarettes, participants first answered an overall question about their scanning behavior: “In the past 30 days, did you come across information about vaping or using e-cigarettes online, in the media, or from other people even when you were not actively looking for it?” The responses were recorded on a dichotomous scale with 0 = *no* and 1= *yes*. Only those who responded *yes* to this question were asked questions about the extent of scanning. The breadth of scanning was assessed by asking the participants to indicate whether they came across information about e-cigarettes or vaping in the past 30 days on each of the following sources: 1) In the media like TV, radio, newspapers, magazines, or movies; 2) In outdoor ads like on billboards, in stores, or on taxis; 3) Online, like on social networking or other internet sites. Based on the above measures, we created a 4-category breadth of scanning measure by aggregating the number of above exposure sources for each person (0 = *no exposure*, 1 = *only scanned from one source*, 2 = *scanned from two sources*, and 3 = *scanned from three sources*). Among those who scanned, the average number of sources scanned out of a possible three used for scanning was 1.65 (*SD* = 0.97).

Interpersonal Conversations. Conversation with other people about e-cigarettes or vaping was assessed, similar to the other sources of routine media exposure variables introduced above, by asking people to indicate whether they came across information about e-cigarettes or vaping in the past 30 days while talking with other people (*yes*/*no*).

Descriptive Norm Perceptions. Descriptive norm perceptions about e-cigarette use or vaping were measured with two items, one tapping into descriptive norm perceptions of e-cigarette use among a more proximal social group, by asking the participants to indicate how many of their four closest friends vape or use e-cigarettes on a 5-point scale, ranging from *none* to *four*; and the other tapping into descriptive norm perceptions of e-cigarette use among a more distal social group, which asked participants to indicate how many people their age they would guess vape or use e-cigarettes on a 4-point scale, ranging from *none* to *most*. The two variables are correlated substantially at both T1 and T2 ($r = 0.35$, $p < .001$). We thus created an overall descriptive norm perception variable by averaging the two variables after standardization.

Current E-cigarette Use. Current e-cigarette use behavior was assessed by a standard measure asking participants whether they vaped or used e-cigarettes during the past 30 days on a dichotomous scale (0 = *no*, 1 = *yes*).

Confounders. All models were adjusted for potential confounders, including age, gender, race (*Hispanic*, *Non-Hispanic White*, *Non-Hispanic Black*, and *Other*), education level (*less than high school*, *high school*, *some college*, *college degree or more*), school performance (ranging from 1 = *Mostly F's* to 5 = *Mostly A's*), parents' education level (*less than high school*, *high school*, *some college*, *college degree*, *completed graduate school*) which was used as a proxy for social economic status, living with a vaper (*yes*/*no*), whether vaping or using e-cigarettes is allowed inside home (*yes*/*no*), and past 30-day cigarette use (*yes*/*no*). We also measured and controlled for individuals' sensation seeking tendency with a standard 4-item measure ranging from 1 = *strongly disagree* to 4 = *strongly agree*, Cronbach's $\alpha = 0.69$ (Stephenson, Hoyle, Palmgreen, & Slater, 2003). For longitudinal analyses, we also controlled for T1 measures of the corresponding outcome variable in the regression.

See Table 2.1 for details about the descriptive statistics of the key variables and confounder variables as mentioned above.

Data Analyses Considerations

We examined the hypotheses both cross-sectionally and longitudinally. To be specific, we first examined all the hypothesized pathways at the cross-sectional level with ordinary least square and logistic regression analyses controlling for confounders; during this stage, all the variables put into the regression analyses were measured at T1. If the two direct effects (*a* and *b* paths as in Baron & Kenny, 1986) involved in each of the mediation models were significant, we then carried out bootstrapping procedures (with 500 replications) to construct bias-corrected confidence intervals that help assess whether the indirect effects were indeed non-zero (Hayes, 2009; Hayes, Preacher, & Myers, 2011). This set of cross-sectional analyses helped us understand whether the effects we hypothesized happen more immediately.

With cross-sectional models, it is hard to establish causal ordering among the focal variables, as they are all measured at T1. We thus further conducted longitudinal analyses to establish the temporal order of our hypothesized effects using two waves of panel data. Specifically, we first fitted a series of lagged regression models in the following sequence: (1) routine media exposure at T1 predicting e-cigarette use behavior at T2 follow-up interview 6 months later (H1); (2) routine media exposure at T1 predicting descriptive norm perceptions at T2 (H2); (3) descriptive norm perceptions at T1 predicting e-cigarette use behavior at T2 (H3); (4) routine media exposure at T1 predicting interpersonal conversations about e-cigarettes at T2 (H5); (5) interpersonal conversations at T1 predicting descriptive norm perceptions at T2 (H6). All models adjusted for the demographics and confounder variables, as well as the corresponding outcome measure at T1.

Next, if the pairs of lagged relations involved in each of the mediation models showed significance in the regression analyses mentioned above, we then examined whether the causal order continued to hold true in full mediation models. Similar to the cross-sectional level mediation analysis, we performed bootstrapping procedures to confirm further whether mediation occurred at the longitudinal level. While three-waves of data may be at the best position to establish the full lagged causal chains, with the independent variable at T1 predicting the mediator at T2 which in turn lead to changes in the dependent variable at T3, our tests of longitudinal mediation hypotheses were limited in the current study by having only two waves of data. In order to reduce this concern, we examined lagged mediational pathways by using the mediator variable at both T1 and T2. If the indirect effect was significant regardless of which wave of the mediator variable was used, we were more convinced that mediation occurred longitudinally. All the mediation models also adjusted for the demographics and confounder variables, as well as the corresponding outcome measure at T1.

Finally, we also conducted sensitivity analyses (i.e., lagged regression analysis reversing predictor and outcome variables we examined above) to examine whether the observed longitudinal associations also operate in the reverse direction. If the causal direction of the effects was only observed in the proposed direction, our observed lagged relations were considered as carrying more weight as evidence for the hypothesized relationships; although even if there is evidence of reversed effects, our proposed causal order could not be rejected as the effects may operate reciprocally.

Results

Descriptive Data

Table 2.1 summarizes descriptive statistics of both cross-sectional and longitudinal samples we used for analyses, including the focal variables (breadth of routine media exposure, interpersonal conversations about e-cigarettes or vaping, descriptive norm perceptions, e-cigarette use behavior), as well as demographics and other confounder variables. We present summary statistics for both unweighted and weighted samples. All the analyses that follow applied weights to allow national representativeness of the results.

Table 2.1.

Descriptive Statistics of the Cross-sectional and Longitudinal Samples

	Unweighted		Weighted	
	Cross-sectional	Longitudinal	Cross-sectional	Longitudinal
Any scanning (%)	30.21	35.34	29.58	34.52
Traditional media scanning (%)	17.72	20.61	17.47	20.22
Outdoor media scanning (%)	13.97	16.06	13.83	15.39
Online media scanning (%)	18.17	20.55	17.79	19.69
Breadth of scanning (%)				
No exposure	73.49	69.15	74.06	69.75
Scanned from 1 source	9.50	11.30	9.18	11.75

	Unweighted		Weighted	
	Cross-sectional	Longitudinal	Cross-sectional	Longitudinal
Scanned from 2 sources	9.82	11.83	9.52	11.23
Scanned from 3 sources	6.82	7.32	6.87	6.98
Talking with other people (%)	16.24	18.43	16.42	18.54
Proximal norm perceptions (%)				
None	64.58	68.43	63.12	62.91
One	16.23	15.57	16.52	17.90
Two	9.52	8.03	9.97	9.9
Three	4.23	3.55	4.53	4.06
Four	4.88	4.20	5.19	4.87
Distal norm perceptions (%)				
None	11.33	9.99	11.56	8.42
A few	46.77	50.19	45.36	48.59
About half	26.99	26.90	27.18	28.23
Most	14.25	12.55	15.09	14.40
Current e-cigarette users (%)	10.41	8.28	11.37	12.07
Age (years; $M \pm SD$)	18.39 ± 3.61	17.18 ± 3.44	19.06 ± 3.80	18.65 ± 3.52
Female (%)	47.04	45.24	48.98	50.57
Race/ethnicity (%)				
Non-Hispanic White	50.21	56.44	51.21	52.23
Non-Hispanic Black	14.25	11.89	13.99	13.88
Hispanic	22.76	19.40	21.15	21.10
Other	12.06	11.92	12.81	12.32
Education (%)				

	Unweighted		Weighted	
	Cross-sectional	Longitudinal	Cross-sectional	Longitudinal
Less than high school	42.36	57.38	35.45	35.60
High school	22.62	15.41	28.95	29.02
Some college	22.80	16.91	25.87	26.61
College degree or more	11.13	9.81	8.64	8.33
School performance (%)				
Mostly F's	0.83	0.44	0.94	0.41
Mostly D's	1.60	1.84	1.88	2.08
Mostly C's	10.52	8.59	12.02	10.40
Mostly B's	40.20	37.02	41.20	40.08
Mostly A's	45.17	50.93	42.04	45.79
Sensation seeking ($M \pm SD$)	2.49 ± 0.52	2.46 ± 0.52	2.50 ± 0.53	2.51 ± 0.52
Current cigarette smokers (%)	12.23	7.63	15.59	15.12
Parental education (%)				
Less than high school	5.26	4.08	6.25	6.14
High school	19.72	16.84	23.38	23.25
Some college	14.54	13.08	17.01	17.27
College degree	28.36	28.14	24.10	22.49
Completed graduate school	22.95	27.68	19.41	22.03
Living with a vaper (%)	9.47	10.06	9.96	9.89
Vaping allowed inside home (%)	20.73	18.43	23.21	23.94

Note. Cross-sectional sample n = 11,013; longitudinal sample n = 3,212. Sample sizes reflect the overall samples. For some variables, percentages may not add up to 100 due to missing cases.

Table 2.2 and Table 2.3 show the zero-order correlations among the primary variables of interest at cross-sectional level and over-time respectively. Nearly all of these variables were significantly correlated at the bivariate level.

Table 2.2.

Zero-order Correlations of Focal Variables at the Cross-sectional Level

	1 (T1)	2 (T1)	3 (T1)	4 (T1)
1 – Media scanning (T1)	--			
2 – Interpersonal communication (T1)	.50	--		
3 – Descriptive norm perceptions (T1)	.17	.23	--	
4 – E-cigarette use behavior (T1)	.11	.20	.31	--

Note. The correlations were calculated based on the weighted sample, smallest n = 10,592. Pairwise Pearson's correlation coefficients are presented. All correlation coefficients presented in the table are significant at $p < .001$.

Table 2.3.

Zero-order Correlations of Focal Variables at the Longitudinal Level

	1 (T2)	2 (T2)	3 (T2)	4 (T2)
1 – Media scanning (T1)	.31	.23	.15	.11
2 – Interpersonal communication (T1)	.21	.26	.18	.15
3 – Descriptive norm perceptions (T1)	.12	.18	.55	.28
4 – E-cigarette use behavior (T1)	.04	.08	.22	.41

Note. The correlations were calculated based on the weighted sample, smallest n = 3,186. Pairwise Pearson's correlation coefficients are presented. Nearly all correlation coefficients presented in the table are significant at $p < .01$, except for the correlation between T1 behavior and T2 scanning ($p = 0.07$).

Hypotheses Testing

We next tested our hypotheses at both cross-sectional and longitudinal levels. Summaries of individual pathway testing results at both cross-sectional and longitudinal levels can be found in Table 2.4 below. Appendices A and B provide detailed information of the regression analyses results at the cross-sectional and longitudinal levels respectively. Table 2.5 presents mediation analyses results using bootstrapping procedures. All the analyses controlled for demographics and confounder variables as mentioned earlier; longitudinal analyses also controlled for the corresponding outcome variable measured at the first interview.

H1 predicted that increasing routine media exposure about vaping or using e-cigarettes is associated with e-cigarette use or vaping behavior. As can be seen from Table 2.4, at the cross-sectional level, we observed that, the breadth of scanning was significantly and positively associated with e-cigarette use. We then tested whether the pattern still held true with the longitudinal-level analysis, and the same pattern was observed, with a similar level of magnitude. Therefore, H1a was supported at both cross-sectional and longitudinal levels, such that breadth of routine media exposure significantly predicting e-cigarette use behavior both cross-sectionally and at six months later, with a substantial magnitude. Take the longitudinal effect as an example, an odds ratio of 1.26 (Table 2.4) suggests that 9% of those who did not scan at all used e-cigarettes at T2, while 18% of those who reported scanning from all three sources, reported e-cigarette use at T2.

Table 2.4.

Coefficients or Odds Ratios for Weighted Cross-Sectional and Longitudinal Regression Analyses that Test Proposed Pathways in Steps

Hypothesized Pathways	*B*	*OR*	95% CI
H1. Media scanning → E-cigarette use			
T1 → T1		1.23^{***}	1.14, 1.33
T1 → T2		1.26^{*}	1.05, 1.52
H2. Media scanning → Norm perceptions			
T1 → T1	0.12^{***}		0.09, 0.14
T1 → T2	0.04^{*}		0.00, 0.08
H3. Norm perceptions → E-cigarette use			
T1 → T1		2.38^{***}	2.16, 2.64
T1 → T2		2.00^{***}	1.52, 2.63
H5. Media scanning → Interpersonal conversations			
T1 → T1		3.10^{***}	2.91, 3.32
T1 → T2		1.38^{***}	1.20, 1.58
H6. Interpersonal conversations → Norm perceptions			
T1 → T1	0.42^{***}		0.37, 0.47
T1 → T2	0.11^{*}		0.01, 0.22

Note: CI = confidence interval; Sampling weights applied; $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

Table 2.5.

Indirect Effects in Weighted Cross-sectional and Longitudinal Mediation Analyses

Proposed Mediation Pathways	Indirect Effects		Total Effects
	Effect Size	BC CIs	Effect Size
H4. Media scanning → Norm perceptions → E-cigarette use			
T1 → T1 → T1	**.010**	.008 - .012	.022
T1 → T1 → T2	**.009**	.004 - .015	.025
T1 → T2 → T2	**.004**	.001 - .007	.018
H7. Media scanning → Interpersonal conversations → Norm perceptions			
T1 → T1 → T1	**.068**	.057 - .081	.114
T1 → T1 → T2	**.015**	.004 - .028	.035
T1 → T2 → T2	**.019**	.011 - .031	.035

Note: n = 2753 - 9601 (varies across analyses due to missing values in variables). BC CIs = Bias-corrected bootstrap confidence intervals. T1 = variable measured at first interview. T2 = variable measured at the re-contact interview. Indirect and total effect sizes are standardized. Nonzero indirect effects are bolded. These analyses report the effects of the compound path from the independent variable to the dependent variable through the mediator, adjusting for demographic variables and potential confounders at T1 as listed in regression result tables in Appendices A & B.

Hypotheses 2 through 4 predicted that descriptive norm perceptions would mediate the relation between routine media exposure and e-cigarette use behavior. We first tested the hypotheses at the cross-sectional level. As can be seen from Table 2.4, we observed that breadth of scanning was significantly associated with descriptive norm perceptions. Thus, H2 was supported. We then tested the second essential direct effect involved in the mediation model, descriptive norm perceptions on e-cigarette use behavior. We found that the descriptive norm perceptions variable was significantly associated with e-cigarette use behavior. H3 was supported. The subsequent mediation analysis testing the potential pathway between breadth of exposure to e-cigarette use behavior through descriptive norm perceptions about e-cigarette use was then performed using bootstrapping procedures with 500 replications. As can be seen from Table 2.5, the results revealed that the estimated bias-corrected 95% confidence intervals did not include zero, which served as evidence that the indirect effect was significant. Therefore, H4 was supported.

We next tested H2 – H4 at the longitudinal level. When we tested the temporal order of the variables that made up the mediation, we found a similar pattern: 1) breadth of routine media exposure at the first interview significantly predicted descriptive norm perceptions at the re-contact interview, controlling for T1 descriptive norm perceptions (H2 was supported); 2) descriptive norm perceptions at T1 significantly predicted subsequent e-cigarette use behavior at T2, controlling for T1 e-cigarette use behavior (H3 was supported). We thus conducted the longitudinal mediation test on the relation between breadth of media scanning and e-cigarette use behavior travelling through descriptive norm perceptions. Considering that the longitudinal mediation analysis was limited in the current study with only two waves of data, we examined the full mediation model by using the mediator, i.e., descriptive norm perceptions, at both T1 and T2. That is to say, we examined the mediation hypothesis with both causal pathways: media scanning (T1) – descriptive norm perceptions (T1) – e-cigarette use behavior (T2), and media scanning (T1) – descriptive norm perceptions (T2) – e-cigarette use behavior (T2). As shown in Table 2.5, the significant indirect effects suggested that descriptive norm perceptions at both T1 and T2, significantly mediated the relation between breadth of routine media exposure about e-cigarettes at T1 and e-cigarette use at T2. H4 was confirmed at the longitudinal level. To summarize, both cross-sectional level and longitudinal level analyses consistently suggested that encountering e-cigarettes or vaping related information in more media channels, would lead to a significant increase in prevalence estimation of e-cigarette use, which would then further result in a higher likelihood of e-cigarette use behavior, even with a time lag of six months.

Our next set of hypotheses (H5 – H7) aimed at further unpacking the underlying chains of influence by providing an explanation of how exposure to increased sources of media scanning about e-cigarette use or vaping would lead to increased descriptive norm perceptions. As shown in Table 2.4, cross-sectional analyses suggested that breadth of exposure is significantly and positively associated with interpersonal conversation with others about e-cigarette use or vaping. H5 was confirmed. In addition, having interpersonal conversations with others was also significantly associated with increases in descriptive norm perceptions about e-cigarette use. H6 was supported. A formal test of the full mediation model at the cross-sectional level confirmed that, as we predicted, interpersonal conversations about e-cigarette use or vaping significantly mediated the association between breadth of media scanning and prevalence perceptions about e-cigarette use (Table 2.5). H7 was supported.

We then tested the above hypotheses at the longitudinal level. As can be seen in Table 2.4, the two essential direct effects involved in the hypothesized mediation model were both significant, such that repeated incidental exposure to e-cigarette use or vaping information from multiple media channels at the first interview, was significantly more likely lead to higher odds of having interpersonal conversations about this topic six months later (H5 was supported), and in turn such conversations served as a significant predictor of increase in subsequent descriptive norm perceptions about e-cigarette use (H6 was confirmed). With both the direct lagged effects of breadth of routine media exposure on interpersonal conversations, and interpersonal conversations on descriptive norm perceptions, we further conducted longitudinal mediation tests to examine the prediction that breadth of media scanning at T1 affects descriptive norm perceptions about e-cigarette use at T2 through interpersonal conversations with others about this topic at T1 and T2. Bootstrapped mediation analyses results shown in Table 2.5 corroborated both the longitudinal mediational pathways. H7 was again supported at the longitudinal level.

Reverse Lagged Regression Analyses

Tests of the reverse longitudinal pathways suggested that descriptive norm perceptions at T1 predicted talking with others at T2 ($OR = 1.47$, $p < .001$), and the breadth of media scanning at T2 ($B = 0.08$, $p = .02$). Interpersonal conversations with others at T1 was also significantly and positively associated with the breadth of media scanning at T2 ($B = 0.18$, $p = .02$). However, e-cigarette behavior at T1 did not predict media scanning at T2. These significant reverse effects do not undermine any of the proposed pathways, and instead complete the whole picture of our full model by indicating that influence may go reciprocally among the scanning, interpersonal communication and descriptive norm perception variables, although not the behavior variable.

Discussion

While most previous studies generally agreed upon the effects of natural routine media exposure on behavior, the potential underlying pathways that lead to the observed effects have remained less explored. The current study contributed to the literature by demonstrating both the direct effect of media scanning about e-cigarette use on vaping behavior, and an indirect pathway through changes in descriptive norm perceptions about e-cigarette use in the real world, which ultimately lead to behavior changes, with both cross-sectional and longitudinal evidence among a nationally representative sample of youth and young adults. We also further showed that, increasingly passive encounters of e-cigarette related information across multiple media channels, including mass media, outdoor media, and online media are likely to give rise to higher odds of having interpersonal discussions about the topic with others, which in turn lead to inflated prevalence estimation of e-cigarette use behavior in the real world. The findings from the current study increased the granularity of our understanding towards the possible underlying causal chains of how routine media exposure reaches behavior decisions. These findings are noteworthy in several aspects.

Reinforced Norm Perceptions with Diverse Scanning Sources. We found that, regardless of either the intensity of scanning from each media source, or the level of specificity regarding the content of scanning (e.g., containing social norm information or not), increases in the mere number of scanning channels mentioning the behavior of interest suffice to bring substantial changes in behavior prevalence estimation in the real world. In other words, the perception that a variety of media channels act in concert in mentioning a behavior, particularly when one is not intentionally seeking for it, delivers an implicit descriptive norm signal that the behavior has gained substantial public prominence and is thus considered prevalent and popular. The diversity of different media sources lends credibility to one another that enhances such prevalence perceptions. This result is particularly meaningful under the current media landscape, where the numbers and types of media outlets have unprecedentedly expanded. Audiences are now constantly exposed to information from multiple sources of media outlets due to the evolving technology. Breadth of media scanning across channels, carries the potential for communicating normative information simply because multiple channels carry parallel information and are synergistic, complementing the quantity of information that is available. Breadth is one likely path to understand how "buzz" or popular public perceptions can be generated and consolidated. For health practitioners who hope to construct an environment that facilitates desirable behavior changes, holding total amount of exposure constant, an exposure "portfolio" that covers a diverse range of media channels, potentially of different communication modalities, media consumption characteristics, or target populations, etc., may together help create a shared sense of population-level behavior norm climate.

Interpersonal Processes Shape Media Effects. In addition, while admittedly there may be alternative pathways accounting for how routine incidental media exposure may affect descriptive norm perceptions, we observed clear evidence that interpersonal conversations positively mediated the relationship. Presumably, individuals who have more incidental encounters with the target behavior information across media sources, are more likely to either initiate conversations with others about the behavior or recall having heard about others talking about it in their social context. It is possible that, then such conversations have in turn increased the issue salience of the behavior in people's mental shortcuts (Bargh et al., 1996; Fiske & Taylor, 2013; Higgins, 1996; Tversky & Kahneman, 1982). When individuals are highly attentive to a behavior topic after talking with others, even the subtlest normative cues may be easily noticed, called to mind, and amplified. The operation of this mechanism is independent of the substantive content of the interpersonal conversations.

Alternatively, it could also be that through conversation exchanges, individuals discover that more people vape or use e-cigarettes than they previously assumed, or that they learn positive things about e-cigarette use and based on which they infer that more people must be using it. If this is the actual underlying mechanism that produces the direct and indirect effects we have observed, it may reflect an overall pro-e-cigarette-use public communication environment, where user-norm information prevails over non-user-norm information, and positive viewpoints outweigh negative ones. Moving forward, it would be a fruitful future direction to explore further the substantive content of both media scanning and interpersonal conversations, to understand whether it is the unique public communication environment surrounding e-cigarette use that mainly accounts for the increasing trend of descriptive norm perceptions. Our own data provides some initial evidence for the overall valence distribution of e-cigarette related information in the public communication environment, such that only 17% of the scanners reported scanning mostly negative information about e-cigarettes.

Although we do not have direct evidence to confirm which of the two mechanisms may have actually happened (or perhaps happened simultaneously), nevertheless, this set of results illustrated that interpersonal processes occurring in the individuals' immediate social context are crucial in terms of shaping people's descriptive norm perceptions. Therefore, the role of the more traditional interpersonal communication in the formation process of descriptive norm perceptions should not be underestimated. Health campaigns and interventions may benefit from leveraging the constructive effects of interpersonal communication processes and incorporating it as an integral part of the campaign goals.

Limitations and Future Directions. We recognize that the way the media scanning and the interpersonal conversation questions was asked may increase the likelihood of correlated errors, as these questions were asked side by side with a parallel structure and participants who responded *no* to the overall scanning or not question were assigned as non-scanners for all these variables. We are also aware that, on a substantive level, effects of the media scanning and interpersonal discussion sources are not easily distinguishable, thus it is hard to know whether interpersonal conversation is indeed a relatively distinct construct compared to the other media exposure variables, which may pose possible threats to inference. To reduce our concerns to the above questions, we first investigated whether the interpersonal conversation variable was contaminated by the media scanning variables if the former was asked after the latter. To answer this question, we first examined with the unweighted sample whether the distributions of answers to the interpersonal discussion variable were significantly different from each other if it was asked at the first (53.54% responded *yes*), second (53.42% responded *yes*), third (52.33% responded *yes*) or fourth place (56.02% responded *yes*) respectively. The Chi-square test results suggested that the answer distributions of the interpersonal conversation variable were not significantly different from one another when asked at different orders ($\chi^2(3) = 2.39$, $p = .50$). To understand whether the interpersonal conversation variable is a distinct measure and to provide evidence of its validity, we examined the test-retest reliability of the interpersonal conversation variable, and tested whether this measure has higher consistency over time compared to its association with the other media scanning variables (including mass media, outdoor media and online media) over time. We observed that those who reported having talked with others about e-cigarettes or vaping during the past 30 days at T1 were much more likely to report talking with others at T2 (39.59% versus 15.04% of those who reported not talking with others about the topic at T1; OR= 3.70, 95% CI = 3.04, 4.51). The over-time correlation between the T1 and T2 interpersonal conversation variables was substantial and significant (r = 0.24), which was higher compared to either the average correlation between T1 interpersonal conversation and the three T2 media scanning variables (r = 0.15) or the average correlation between T2 interpersonal conversation and the three T1 media scanning variables (r = 0.17). The over-time correlations of the three pairs of media scanning variables (T1 and T2 mass media scanning: r = 0.24; T1 and T2 outdoor media scanning: r = 0.25; T1 and T2 online media scanning: r = 0.29) were also higher compared to their over-time correlations with the interpersonal conversation variable as shown above. The interpersonal conversation measure is thus considered having solid support for its validity. Nevertheless, future studies should assess this construct with a question structure that can better separate the influence from the other media scanning variables, and a battery of items to further increase the reliability of the assessment, as well as to allow us better distinguish whether after repeated media scanning, people initiate the thread of e-cigarette related conversations in their social circle, or are just more aware of this topic when passively receiving information from interpersonal discussions.

In addition, while we consider the use of longitudinal data in our analyses as one of the major strengths of our study, we also acknowledge that the two-wave panel data are not at the best position to test longitudinal mediation pathways. Even though we obtained consistent results using the mediator variables at both T1 and T2, which gave us more confidence in our conclusions, future studies are recommended to use three-wave panel data and replicate whether the significant mediation pathways still hold true when the mediator is not assessed at the same time with either the independent or the dependent variable.

We would also like to point out some potentially promising lines of future research following from the current study. First, we were not able to examine the other dimension of repeated exposure, i.e., total frequency of e-cigarette related information scanning, regardless of media sources, that describes the depth of information about e-cigarettes an individual encountered in the media environment, as we did not have the cleanest measure for the depth construct. While breadth deals with the diversity of information sources, depth captures the amount of exposure individuals are exposed to for each source, or summed across all sources, and can be large because of intense use of one source or moderate use of multiple sources (Hornik et al., 2013). Future studies are encouraged to explore, when there is a measure that can more accurately capture the depth of media scanning, whether breadth and depth of scanning may carry similar or different implications to descriptive norm perception and behavior changes.

In addition, even though comparing to other more active forms of media exposure such as information seeking, media scanning is often considered less purposive, however, sometimes it could still be a result of people's more purposeful choices. People may embed themselves in a more information rich environment by leaving TV as a background noise more, or subscribing to magazines and newspapers, or turning to NPR while driving to work in the morning, etc.; all these media consumption habits and patterns are sometimes intentional preferences, but have been incorporated into a routine and normal course of life (Johnson, Case, Andrews, Allard, & Johnson, 2006; Niederdeppe et al., 2007). In other words, media scanning may not be completely passive as it seems to be at the face level. Therefore, future studies are encouraged to take into consideration of how individual differences in general media use patterns may affect the extent to which media scanning shapes descriptive norm perceptions and behavior choice decisions.

Concluding Remarks

The results from the current study advanced our understanding of how routine media exposure affects behavior choices by illuminating a potential causal chain through interpersonal communication and descriptive norm perception changes. We show robust evidence for the proposed pathways with both cross-sectional and longitudinal results, using a nationally representative youth and young adults sample. While previous studies focused on the interplay between mass and interpersonal communication processes within more targeted contexts such as exposure specifically pertinent to messages in a mass media health campaign, we demonstrate that repeated routine acquisition of media information about a topic can also effectively change prevalence perceptions and behavior decisions through triggering more interpersonal conversations or a more acute awareness and better recall of interpersonal conversations about the topic. These results illustrate the important role of repeated scanning across a diverse range of media sources in shaping descriptive perceptions, and highlight the substantial impacts of interpersonal discussions in people's immediate social context, as the next step ensuing mass media consumption, in providing opportunities for shared interpretation of media content, that can ultimately lead to subsequent changes in cognitions and behavior choice decisions.

CHAPTER 3.

HOW DO ONLINE COMMENTS AFFECT PERCEIVED DESCRIPTIVE NORMS OF E-CIGARETTE USE? THE ROLE OF EXPOSURE DOSAGE, QUASI-STATISTICAL SENSE, AND NEGATIVITY BIAS

Introduction

Human beings are equipped with antennae that quiver to every subtle change in their social environment; they sense what is typical and desirable in their surroundings and form normative perceptions, which greatly shape and guide their behaviors (Noelle-Neumann, 1993). Cialdini and colleagues (1990) referred to the normative perceptions of what is commonly done among other people as *descriptive norm perceptions*. In line with social learning theory (Bandura, 1985) and social comparison theory (Festinger, 1954), descriptive norm perceptions motivate action by informing people about what is likely to be effective or adaptive in specific situations. Descriptive norm perceptions have long been considered a potent tool for influencing cognition and behavior change, despite the fact that people's subjective perceptions of descriptive norms rarely match the actual distribution of the behaviors in their environment (Borsari & Carey, 2003; Cruz et al., 2000; Neighbors et al., 2006; Prentice & Miller, 1993; Sandstrom & Bartini, 2010); still, such normative perceptions they form based on their own subjective experiences matter more than the actual norms in guiding their decisions and behaviors (Rimal & Real, 2003; Tankard & Paluck, 2016). Therefore, influencing people's descriptive norm perceptions is considered one effective way to bring in behavior change.

Previous literature identified three sources of information that people use to understand social norms – summary information about a group, individual behavior cues, and institutional signals about the behavior. While the last source could be utilized to tap into perceptions of both how common or desirable a behavior is considered, the first two sources are most frequently employed to convey descriptive norm information (Tankard & Paluck, 2016). Summary information refers to the prevalence statistics people usually get from census, survey results, newspaper reports, or educational campaigns, and is considered the most straightforward way to deliver descriptive norm information. In fact, most of previous studies in the realm of social norms manipulate descriptive norm perceptions by directly providing summary information in the messages, such as "*almost 75% of guests who are asked to participate in our new resource savings program do help by using their towels more than once*" (Goldstein, Cialdini, & Griskevicius, 2008). While such descriptive norm information often times reflects the actual behavior norm in the environment, it does not approximate the typical way in which individuals form their own subjective perceptions of behavior distribution based on their own experiences; however, such subjective perceptions are all that matters for effective behavior change.

Individual behavior cues, which refer to behaviors (or lack thereof) performed by surrounding salient reference groups or media mentions or portrayals of the behaviors observed by individuals, convey the descriptive norm information in a relatively implicit way, but may be the most typical sources that allow individuals to perceive and gauge behavior prevalence based on what they have observed and inferred by themselves (Lapinski & Rimal, 2005; Tankard & Paluck, 2016). The subjective perceptions of behavior choice distribution formed in this way might be quite powerful in affecting people's cognitions and behaviors. Some scholars argued that out of fear of isolation, human beings have developed an almost instinctual *quasi-statistical sense* that automatically collects and infers distribution information about opinions and behaviors in the community or society they are embedded in through direct observation, media exposure and interpersonal discussion. In other words, behaviors practiced by other individuals around people or portrayed in the media serve as cues and evidence for them to form the quasi-statistical picture about the reality (Deutsch & Gerard, 1955; Noelle-Neumann, 1993; Scheufele & Moy, 2000).

Currently, ever-evolving web technologies expand the means that individuals employ to obtain behavioral information by facilitating user participatory features such as online user-generated comments (Walther & Jang, 2012). This also opens new research avenues in the pursuit of understanding how social influence is exercised in the virtual space. Accumulating evidence, across a diverse range of topic domains, has suggested the powerful impacts of online comments in changing individuals' perceptions, such that people's attitudinal judgments tend to follow the direction where they believe the dominant opinion wind blows, despite the fact that people who leave online comments are oftentimes anonymous strangers, and only consist of a small and non-representative sample of opinions (Salganik, Dodds, & Watts, 2006; Shi, 2016; Shi, Messaris, & Cappella, 2014; Walther, DeAndrea, Kim, & Anthony, 2010). For example, Walther et al. (2010) found that if people perceived that the opinion climate in the comment board was positive towards an anti-marijuana ad, they tended to give higher evaluation on the ad compared to when they believed the opinion climate was negative for the same ad. However, most of the existing literature focused on how valence perceptions (i.e., positive vs. negative) affect individuals' attitudinal judgments. To our best knowledge, there has been no study that examined whether people could observe individual behavior cues and infer the distribution of the descriptive norm of the behavior (i.e., behavior prevalence) from online comments. The current study attempts to fill the gap by experimentally manipulating the distribution of individual behavior cues mentioned in the online comment board, and examines whether people could perceive the direction of the dominant norm within the online comment board and how such quasi-statistical picture they form might affect their descriptive norm perceptions about the behavior in the real world.

Specifically, in terms of the behavior of interest, the current study investigated the question in the context of electronic cigarette use or vaping behavior. Electronic cigarettes (also called e-cigarettes) are battery-operated devices designed to deliver nicotine with flavorings and other chemicals to people in vapor, simulating the visual, sensory, and behavioral aspects of smoking without the combustion of tobacco (Emery et al., 2014; Orellana-Barrios et al., 2015; Riker et al., 2012). Some studies suggested that e-cigarettes may hold promise as a smoking-cessation tool (e.g., Siegel, Tanwar, & Wood, 2011), while others argued that vaping may cause nicotine addiction or act as a gateway to tobacco or even drug use (e.g., Riker et al., 2012). As the scientific evidence is far from certain, no consensus about the benefits and risks associated with e-cigarette use has been achieved yet. Despite the contentious debate, it rapidly gained popularity after its introduction to the U.S. market in the year of 2007 (Hitchman et al., 2014; Noel et al., 2011). Considering the uncertainty and heated debates surrounding the vaping behavior and that individuals' likelihood of following what most others do is usually heightened under conditions of ambiguity (Kim, Kim, & Niederdeppe, 2015; Rimal, Lapinski, Cook, & Real, 2005), individuals' estimation of the behavior prevalence in the public might be particularly susceptible to the prevalence information they obtain from a more immediate environment. Therefore, we propose that:

H1: People are able to correctly perceive and infer the constructed behavior prevalence of e-cigarette use based on the distribution of individual behavior cues on the online comment board.

H2: The constructed behavior choice distribution within the online comment board affects people's descriptive norm perceptions about e-cigarette use in the real world, such that,

a) Those who read predominantly more comments that contain user norms (i.e., commenters themselves or people they know use e-cigarettes) on average have significantly higher descriptive norm perceptions about e-cigarette use in the real world, than those who read predominantly more comments that contain non-user norms (i.e., commenters themselves or people they know *don't* use e-cigarettes);

b) Compared to those who do not read any comments, those who read predominantly more comments that contain user norms on average have significantly higher descriptive norm perceptions about e-cigarette use in the real world;

c) Compared to those who do not read any comments, those who read predominantly more comments that contain non-user norms on average have significantly lower descriptive norm perceptions about e-cigarette use in the real world.

Considering that the descriptive norm information as implicated in the distribution of the behavioral cues might be too implicit for people to infer, the current study also explored two variations in experimental manipulation that might potentially make the normative cues more salient, and thus more likely to affect descriptive norm perceptions about the reality. The first factor we considered was the dose of exposure. Both communication theories and accumulating empirical evidence from various media campaigns have pointed to the importance of having sufficient level of exposure to messages before expecting any changes in perceptions, beliefs, and attitudes (Gerbner, 1998; Hornik, 2002). Multiple exposure to consistent messages is effective in enhancing the acceptance of beliefs, values, norms, and conceptions of reality that are in line with the messages by increasing the opportunity for learning and memorizing, as well as the likelihood of availability of the information at the time of judgment (Bargh et al., 1996; Higgins, 1996; Potter, 1993; Tversky & Kahneman, 1982). Therefore, we propose that:

H3: Doubling the exposure dosage of the comments facilitates the formation of the descriptive norm perceptions about e-cigarette use in the real world.

The second variation to the manipulation we considered was to add visual behavioral cues to increase the visual prominence of the stimulus. According to the Focus Theory of Normative Conduct (Cialdini et al., 1990), people learn norms from salient behaviors and actions that stand out and easily catch their attention. People's perceptions and decisions are more likely to be swayed with the presence of visual behavior in their close environment (Cialdini, 2003; Mcshane, Bradlow, & Berger, 2012). In the computer-mediated environment, one way to increase the salience of the behavior stimulus would be to demonstrate the behavior using avatars, the digital representations of people, including but not limited to graphical icons (cartoon humans, nonhumans), profile pictures (real human photos), interactive bots etc.; in fact, most online networking websites provide cue-rich platforms for users to communicate in an environment that is mixed with both textual and visual cues, and find that such features effectively facilitate online social interaction (Boyd & Ellison, 2007; Nowak & Rauh, 2005; Westerman, Tamborini, & Bowman, 2015). Therefore, in the current study, we planned to add anonymous cartoon human profile icons to all the comments, and for user-norm comments, a vaper profile icon will be adjacent to each of the comments (i.e., vaping behavior added to the cartoon human profile icon), and for non-user-norm and no-norm comments, no vaping behavior will be added to the profile icon. As such, we hypothesize that:

H4: Adding visual behavioral cues to the comments facilitates the formation of the descriptive norm perceptions about e-cigarette use in the real world.

Method

Participants

A total of 702 U.S. adults were recruited through Amazon Mechanical Turk (MTurk), an online crowdsourcing service offered by Amazon. MTurk allows researchers to put up short tasks (a.k.a., “Human Intelligence Task,” or “HIT”) and place qualification restrictions that specify who can participate in the study to ensure quality results. Accumulative evidence shows that participants recruited through MTurk are more representative of the U.S. population than in-person convenience samples – which is the modal sample used in most of the experimental studies in social science – and can replicate previous important experimental works that used internet-based panels or national probability samples (Berinsky, Huber, & Lenz, 2012; Buhrmester, Kwang, & Gosling, 2011). Following prior practices (Peer, Vosgerau, & Acquisti, 2014), we restricted participation to MTurk workers with high reputation (above 97% approval ratings and had been approved more than 100 times) to ensure the credibility and reliability of their responses. Additionally, to be eligible for the study, a participant also had to be 18 years or older, and did not respond "yes" to a "foil" question[2]. Eleven participants who took the survey with excessively long (3 *SD* or more above the mean) or short (3 *SD* or more below the mean) completion time were excluded from the sample for analysis (final N = 691). Fifty-nine percent of the participants were female, and the sample included 79.3% Non-Hispanic White, 6.7% Non-Hispanic African American, 4.9 % Asian/Pacific Islander, 5.9% Hispanic/Latino, and 0.4% Native American. The mean age of the participants was 38.06 (*SD* = 12.23), ranging from 18 to 75, most of them had finished high school (97.8%) and 62.81% had finished college. Slightly more than half of the participants (56.2%) had smoked 100 cigarettes or more in their lifetime, and 44.6%

[2] The "foil" question, i.e., whether they have been vaccinated against Ebola virus in the U.S., was used to screen out participants who try to fake their identity or answers in order to get in the survey by responding "yes" to every question. Participants who responded "yes" to this question were screened out regardless of other responses.

have ever used an e-cigarette, even one or two puffs. Most of the participants in the final sample had heard of vaping or using e-cigarettes before the study date (95.4%).

Study Design and Procedures

This study adopted a 3 normative cues (10 comments vs. 20 comments vs.10 comments plus visual cues) X 2 norm directions (High-prevalence vs. Low-prevalence) + 1 (no comment control) between-subject design. The experiment used an online Qualtrics-based survey, distributed through Mturk. Participants were told the purpose of the study was to ask their opinions about some short online materials related to health issues. They were first screened for eligibility by age and the "foil" question. Eligible participants were then randomly assigned to one of the seven experimental conditions. They all first read a short news article about e-cigarettes. The treatment groups then went on to read 10 or 20 (depending on conditions) user-generated comments, while the control group directly moved to the outcome measure assessment pages. After exposure to the stimulus materials, all participants clicked to advance the browser to be assessed by a set of measures on descriptive norm perceptions about e-cigarette use, demographic variables, other covariates and manipulation check questions. Finally, participants in the treatment conditions were also given a chance to leave their own comments.

Stimulus Materials

News article. The news article was created by modifying real news articles from the online websites of top news outlets including *New York Times*, *Wall Street Journal*, and *Huffington Post*. Considering that the news article serves as a cover story for the experimental manipulation and was viewed by all subjects across conditions, the article was modified so that no normative information was mentioned at all, and the valence or tone towards e-cigarette use was held balanced (i.e., no dominant favorable or unfavorable overall viewpoint towards e-cigarettes use). The participants were told that the short news article about e-cigarettes was selected from one of the top news outlets to increase the credibility of the material (See Appendix C for the script and display of the news article).

Comments. Twenty-two comments, each reflecting one unique topic or theme about e-cigarettes, were collected from actual comments appearing on online websites of *New York Times*, *Wall Street Journal*, and *Huffington Post* as responses to e-cigarette related news articles. In order to control for the potential influence of comment valence, half the comments collected contained negative topics or themes about e-cigarette use (e.g., e-cigarettes are ineffective cessation tools, e-cigarettes contain carcinogens, or they are gateways to drug use, etc.), and the other half were positive about e-cigarette use (e.g., e-cigarettes have a diverse range of flavors, vaping looks cool, or vaping is less harmful compared to smoking, etc.). We then modified each of these comments into three versions that contained either e-cigarette user descriptive norm, non-e-cigarette-user descriptive norm or absence of e-cigarette use descriptive norm, while keeping the remaining content in the comments exactly the same. Comments were defined as e-cigarette user descriptive norm ("user-norm" hereafter) if they contained explicit indication that an individual or a group of individuals (either the commenters themselves or people they know) are using or have used e-cigarettes; Non-e-cigarette-user ("non-user-norm" hereafter) comments were the ones that contained clear indication that an individual or a group of individuals (either the commenters themselves or people they know) are *not* using or had not used e-cigarettes; Absence of e-cigarette use descriptive norm ("no-norm" hereafter) refers to no mention about e-cigarette use behavior in the comments. For example, for the comment topic that talks about e-cigarette use as a gateway to drug use, the no-norm comment would be just "*What I worry about is that ecigs might increase the likelihood that people will go on to something really bad, like cigarettes, or drugs!!*", user-norm comment added behavior indication following the no-norm comment "*Still, I know lots of people who vape*," and non-user-norm comment added "*I don't know anyone who vapes*." See Appendix C for more details of the 66 comments, i.e., 22 topics with three versions, which served as the comment pool of the current study.

To increase the ecological validity of the study and address potential case-category confound problems (Jackson, 1992; Jackson & Jacobs, 1983), following prior practices (Shi, 2016; Shi et al., 2014), we developed a comment allocation algorithm that ensured the comments each participant saw were randomly drawn from the comments pool, randomly ordered, and balanced in valence. The descriptive norm expressed in the comments were mixed at a 7: 2: 1 ratio based on the conditions they were assigned, i.e., High-prevalence conditions had 70% user-norm comments, 20% non-user-norm comments, and 10% no-norm comments; Low-prevalence conditions had 70% non-user-norm comments, 20% user-norm comments, and 10% no-norm comments. For example, for a participant in the 10 comments High-prevalence condition, the algorithm would first randomly select four positive topics from the positive topics pool, four negative topics from the negative topics pool, and two neutral topics from the neutral topics pool; seven topics would then be randomly chosen from the 10, and the user-norm version of the comments would be used for the seven topics; for the rest of the three topics, two would be randomly chosen and the non-user-norm version of the comments would be used; and the last comment would be no-norm. Finally, the order of these 10 comments was randomized before they were presented to the participant.

In order to examine the potential influence of exposure dosage, we also had the 20 textual cues conditions, where participants read 20 comments (i.e., two pages with 10 comments on each) with the same structure as those in the 10 comments condition (i.e., randomly drawn from the comments pool, randomly ordered, balanced in valence, and had a ratio of 7: 2: 1 according to the conditions they were assigned). In addition, to see whether visual cues would enhance the descriptive norm manipulation, we also had the 10 textual cues with visual cues conditions, where participants read 10 comments with the same structure as those in the 10 textual cues only conditions, with a vaper avatar image appending to each of the user-norm comments to increase the salience of vaping behavior indication in the comments. non-user-norm and no-norm comments had usual anonymous avatar images attached to the comments as in the other conditions.

Figure 3.1 below lists all the experimental conditions. Appendix D shows two sample stimulus pages for the 10 comments High-prevalence condition and 10 comments plus visual cues High-prevalence condition respectively.

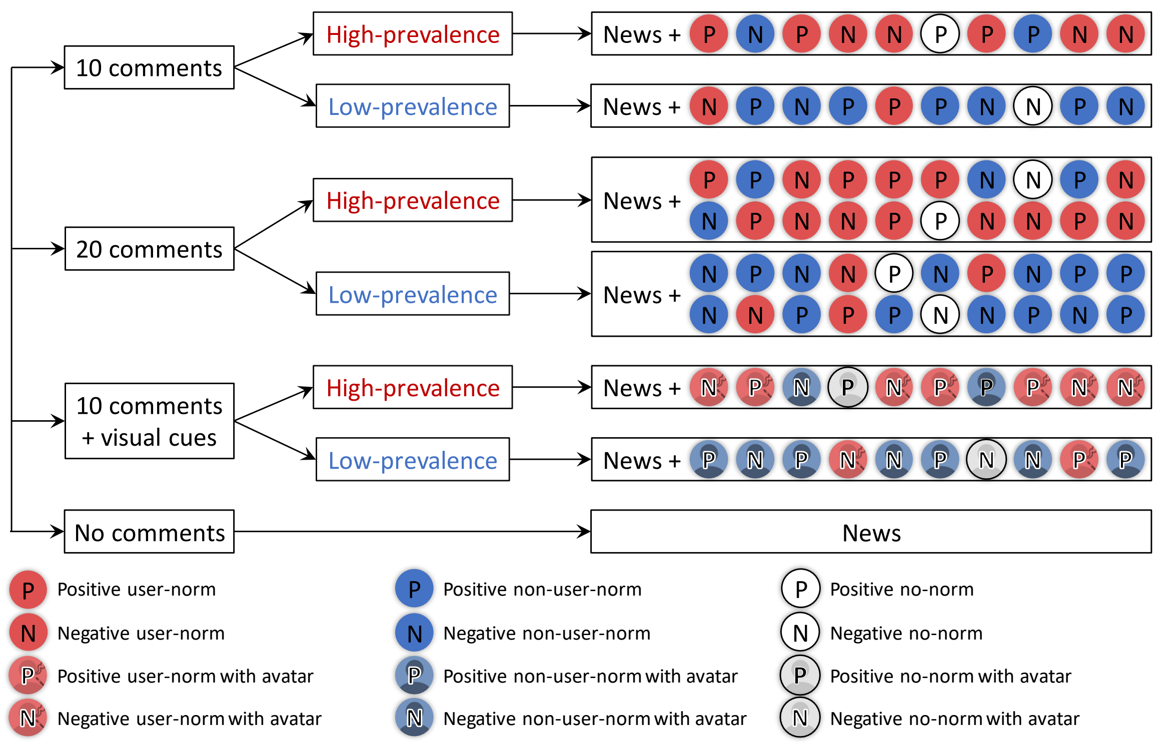

Figure 3.1. Study design and an example of stimuli composition for each condition

Measures

Dependent Variable.

Reality descriptive norm perceptions. Descriptive norm perceptions about e-cigarette use in the real world were assessed with two sets of questions, immediately after the participants finished reading the materials. The first set of questions consisted of seven items that asked the participants to gauge the prevalence of e-cigarette use behavior among different reference groups, ranging from (a) people in the U.S.; (b) people who are residents of their city; (c) people in their neighborhood; (d) people who are similar to them; (e) people their age; (f) people who are important to them; (g) and their four closest friends. Response options for the first six questions range from “1 – *none*” to “6 – *almost* *all*.” The last item was measured on a five-point scale, ranging from “1 – *none*” to “5 – *four*.” The items yielded moderately high reliability (Cronbach’s α based on standardized seven items = .88).

The descriptive norm perceptions were also measured with a scale that asked the participants to indicate how much they agree or disagree with a five-point Likert-type scale ranging from “1 – *strongly disagree*” to “5 – *strongly agree*” on the following statements about e-cigarette use: (a) “*In the U.S., many people vape or use e-cigarettes*”; (b) “*Vaping or using e-cigarettes is not very common in the U.S.*”; (c) “*Most people my age vape or use e-cigarettes*”; (d) “*Vaping or using e-cigarettes is not at all popular in the U.S.*”; (e) “*Most people that I know vape or use e-cigarettes*”; (f) “*A high percentage of the population in the U.S. vape or use e-cigarettes*.” After reverse coding the second and fourth items, higher scores on the five-point scale indicated higher descriptive norm perceptions (Cronbach’s α based on standardized six items = .86).

The two scales (after standardization) are significantly correlated ($r = 0.59$, $p < .001$). We then combined the set of the standardized 13 items and observed the highest reliability (Cronbach’s $\alpha = 0.91$) compared to each of the sets alone and that removing any of the single items reduced the magnitude of the Cronbach’s α, indicating that the 13 items reliably capture the same underlying construct, i.e., descriptive norm perceptions, despite the fact that they were measured in slightly different ways and question formats. The standardized 13 items were then averaged to create an overall descriptive norm perception scale which served as the outcome variable in the analysis.

Manipulation Check Variable.

Constructed descriptive norm perceptions. Perceptions of behavior choice distribution on the online comment boards were assessed by asking the participants in the treatment groups to think about the comments following the news, and rate the following statements on a five-point scale, ranging from "*strongly disagree*" to "*strongly agree*": 1) *They were posted mostly by vapers or commenters who know others who vape*; 2) *They were posted mostly by non-vapers or commenters who don't know others who vape* (r = 0.75, $p < .001$). The average score of the two items (after standardization) was used as the constructed norm perceptions variable in our analysis.

Secondary Outcome Variable.

***Valence perceptions*.** While the valence of the news article and the comments was intentionally constructed to hold a neutral or balanced opinion tone towards e-cigarette use, it is still possible that the experimental manipulation may affect the valence perceptions. We thus also measured valence perceptions by asking the participants to indicate, respectively, whether the news article (for all groups) and the comments (for treatment groups only) they read were: 1) in favor of e-cigarette use, or 2) against e-cigarette use on a five-point scale ranging from "*strongly disagree*" to "*strongly agree*" (r = 0.65, $p < .001$ for the two news valence measures; r = 0.62, $p < .001$ for the two comments valence measures). We then created two valence perceptions variables, news valence and comments valence separately by averaging the two items measuring each. Considering that the no-comments news-only control condition gives us the cleanest estimation of valence perceptions of the news article as no comments were presented to this group, the news valence perceptions within this group could also serve as a manipulation check on whether the news article was perceived as relatively neutral, as we intended.

Results

Manipulation Check

A manipulation check was conducted first to understand whether our experimental manipulation worked successfully as intended. For treatment groups, we found that participants in the High-prevalence conditions were more likely to agree that the comments they read were posted mostly by vapers or commenters who know others who vape (M = 0.61, SE = 0.04) compared to those in the Low-prevalence conditions (M = -0.61, SD = 0.05), F (1, 562) = 407.18, p < .001, Cohen's d = 1.70). This result shows that the direction of descriptive norms via online comment manipulation was successful, and that people are capable of perceiving and inferring the dominant constructed descriptive norms based on observation of the individual behavior cue distribution; H1 was supported. Table 3.1 presents the mean perceived constructed descriptive norms in each condition. In addition, participants in the news-only control condition rated the news as having a relatively balanced view towards e-cigarette use (M = 3.08, SD = 0.81), and was not significantly different from the midpoint (i.e., 3) of the scale (t(126) = 1.15, p = 0.25), indicating that the valence of the news article was perceived as balanced towards e-cigarette use.

Hypothesis Testing

Our major hypothesis (H2) predicted that the manipulated norm directions of the online comments mock-ups affect viewers' descriptive norm perceptions or prevalence estimation about e-cigarette use in the real world such that, despite the variations of the actual comments appearing in the mock-ups, High-prevalence conditions (i.e., predominantly more user-norm comments) lead to perceptions of higher behavior prevalence compared to both the Low-prevalence and the no-comment news-only control conditions, and Low-prevalence conditions (i.e., predominantly more non-user-norm comments) lead to lower prevalence perceptions compared to the control condition. Mean reality descriptive norm perceptions for each of the seven individual conditions are also summarized in Table 3.1. One-way analysis of variance (ANOVA) was conducted with a three-category experimental condition variable (i.e., High-prevalence combined, Low-prevalence combined, and news-only control) as the independent variable and the reality descriptive norm perceptions as the dependent variable. A significant overall effect was observed, F (2, 688) = 4.56, p = .01, η^2 = .01. Planned contrasts comparing reality descriptive norm perceptions indicated that the three High-prevalence conditions on average (M = 0.01, SE = 0.03) produced no significant difference with the three Low-prevalence conditions (M = -0.06, SE = 0.03; F (1, 688) = 2.22, p = .13), and marginally significant difference with the news-only control condition (F (1, 688) = 3.33, p = .07); however, a significant difference was observed between the Low-prevalence and the news-only control conditions, such that participants in the three Low-prevalence conditions on average had significantly lower descriptive norm perceptions about e-cigarette use (M = -0.06, SE = 0.03) compared to the control group (F (1, 688) = 9.00, p < .01). The hypothesis was partially supported.

Table 3.1

Mean Perceived Constructed and Reality Norms of E-cigarette Use across Conditions

Individual Conditions	Sample Size	Constructed Norms	Reality Norms
	n	*M* (*SE*)	*M* (*SE*)
1. High-prevalence 10 comments	97	0.60 (0.07)	−0.00 (0.05)
2. High-prevalence 20 comments	92	0.68 (0.06)	0.05 (0.06)
3. High-prevalence 10 comments + visual	93	0.53 (0.06)	−0.02 (0.05)
4. Low-prevalence 10 comments	97	−0.54 (0.08)	−0.01 (0.07)
5. Low-prevalence 20 comments	98	−0.55 (0.09)	−0.14 (0.05)
6. Low-prevalence 10 comments + visual	87	−0.75 (0.08)	−0.03 (0.05)
7. No-comment news-only control	127	--	0.11 (0.05)

Note: Means and standard errors were calculated based on standardized items.

Our next set of research hypotheses asked whether increasing the dose of exposure (i.e., 20 comments conditions compared to 10 comments conditions) or adding a visual behavior cue (i.e., 10 comments plus vaper avatar conditions compared to 10 comments conditions) would help facilitate participants inferring the constructed descriptive norms about e-cigarette use from the comments frequency distributions thus produce higher (for High-prevalence conditions) and lower (for Low-prevalence conditions) reality descriptive norm perceptions compared to the no-norm news-only control condition. If double dosage and visual cues both help form reality descriptive norm perceptions as intended, we would also like to know whether one way works better than the other. Considering examination of the above questions involves multiple pairs of comparisons among the seven individual conditions, we first performed an omnibus test to understand whether there is any significant difference among conditions, and if yes, we then further conducted pair-wise comparisons among the seven conditions, applying the Bonferroni correction to control the family-wise error rate. One-way analysis of variance (ANOVA) was conducted with a seven-category experimental condition variable (i.e., each category represents one of the seven individual conditions) as the independent variable and the reality descriptive norm perceptions as the dependent variable. An overall significant effect was observed, F (6, 684) = 2.21, p = .04, η^2 = .02. Pair-wise comparisons across conditions with Bonferroni correction found that the significant difference was only observed between the 20-comments Low-prevalence condition and the no-norm news-only control condition, such that the Low-prevalence condition with a double dose of exposure produced significantly lower descriptive norm perceptions compared to the control condition (p = .01). This result indicated that the observed significant difference between the Low-prevalence conditions and the control condition, as we observed earlier while examining H2, was driven by the 20-comments Low-prevalence condition. A post-hoc test also revealed that, the mean difference of descriptive norm perceptions between the 20-comments High- and Low-prevalence conditions were also substantial, such that when Bonferroni correction was not applied, the 20-comments High-prevalence condition produced significantly higher descriptive norm perceptions compared to that of the 20-comments Low-prevalence condition (p = .02). These results highlighted the importance of exposure dosage in facilitating the formation of people's descriptive norm perceptions. Figure 3.2 below displays significant differences in reality descriptive norm perceptions among conditions discussed above.

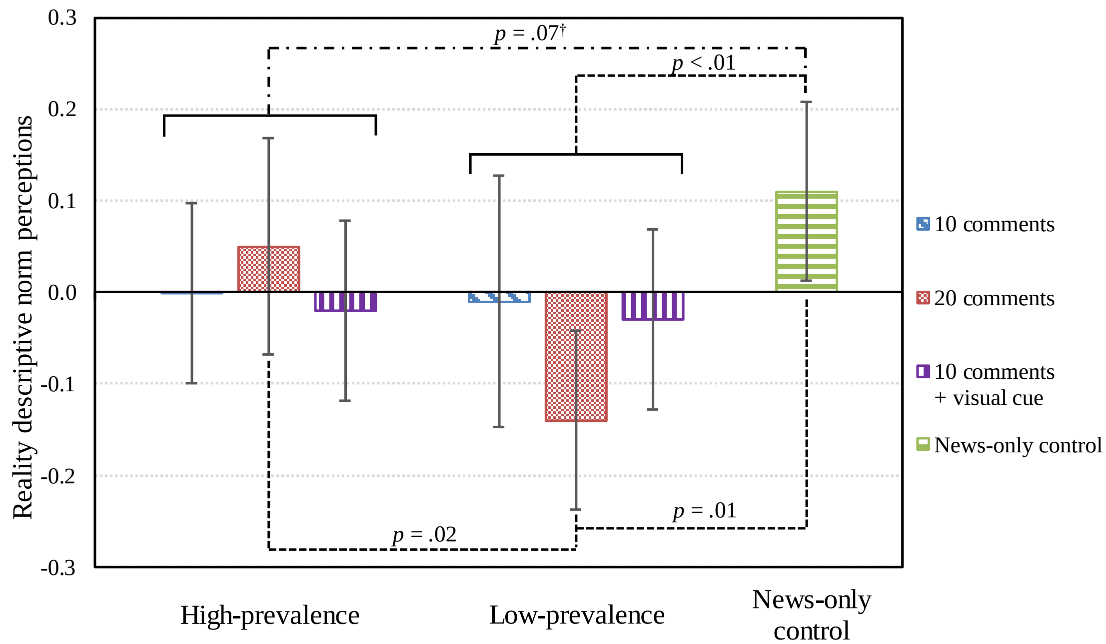

Figure 3.2. Mean reality descriptive norm perceptions across experiment conditions

Note: Error bars represent 95% CIs. The reality descriptive norm perception measure is an average of the 13 standardized norm items. The significant differences among conditions as suggested by analyses above was marked with corresponding p-values. Low-prevalence conditions yielded significantly lower scores compared to the news-only control condition. High-prevalence conditions also produced lower scores compared to the control condition but the difference was marginal. When looking at the individual conditions, the 20-comments Low-prevalence condition produced significantly lower scores compared to the news-only control with Bonferroni correction applied. When Bonferroni correction was not used, the 20-comments High-prevalence condition was also observed to have significantly higher prevalence estimation than 20-comments Low-prevalence condition.

Interestingly, an analysis of variance comparing across the High-prevalence, Low-prevalence and news-only control conditions revealed that participants rated the perceived valence of the news article differently across conditions, F (2, 688) = 4.33, p =

.01. Table 3.2 presents the mean perceived news valence for each of the seven individual conditions. Post-hoc contrasts indicated significant differences in valence perceptions between High-prevalence (M = 2.98, SE = 0.05) and Low-prevalence conditions (M = 2.84, SE = 0.05; F (1, 688) = 4.05, p = .04), as well as Low-prevalence and the control condition (F (1, 688) = 7.66, p < .01), such that participants in the three High-prevalence conditions and the control condition perceived the news article as having a more favorable viewpoint towards e-cigarette use compared to the three Low-prevalence conditions. We also examined participants' perceptions of the comments valence towards e-cigarette use among the treatment groups. We observed similar patterns as in the news valence manipulation check: participants in the three Low-prevalence conditions (M = 2.46, SE = 0.05) tended to perceive the comments overall as having a less favorable viewpoint towards e-cigarette use compared to the three High-prevalence conditions (M = 3.43, SE = 0.04; F (1, 562) = 220.88, p < .001). The mean comments valence perceptions across conditions are also summarized in Table 3.2. The pattern we observed here might speak to the potential spill-over effects of norm manipulation on valence perceptions, even though we intentionally constructed the valence towards e-cigarette use in both the news article and the comments to be balanced in all conditions. We will discuss this issue further in the discussion section.

Table 3.2

Mean Valence Perceptions towards E-cigarette Use across Conditions

Conditions	Sample Size	News Valence	Comments Valence
	n	*M* (*SE*)	*M* (*SE*)
1. High-prevalence 10 comments	97	3.11 (0.08)	3.43 (0.08)
2. High-prevalence 20 comments	92	2.96 (0.08)	3.38 (0.07)
3. High-prevalence 10 comments + visual	93	2.85 (0.08)	3.49 (0.07)
4. Low-prevalence 10 comments	97	2.81 (0.09)	2.51 (0.08)
5. Low-prevalence 20 comments	98	2.82 (0.09)	2.45 (0.08)
6. Low-prevalence 10 comments + visual	87	2.89 (0.09)	2.41 (0.08)
7. No-comment news-only control	127	3.08 (0.07)	--

Note: The mean scores and standard errors of the two variables were calculated based on the raw scores. News valence and comments valence were measured on 5-point scales ranging from “strongly disagree” to “strongly agree,” with higher scores indicating more positive valence perceptions.

Discussion and Future Directions

Descriptive social norms have long been utilized to promote positive behavior changes, and the very first step would be to find ways that can effectively affect people’s subjective perceptions of norms. Therefore, a better understanding towards how individuals perceive and form such perceptions is crucial. Following this line of inquiry, the current study examined whether people’s descriptive norm perceptions could be shaped through their subjective experiences or observations of behavior prevalence in the online comments.

We found that people were able to correctly identify the numerical majority of the behavior choice based on the comments they read, such that people in the High-prevalence conditions recalled that more vapers (or people who know vapers) than non-vapers left comments in their conditions, while those in the Low-prevalence conditions recalled that more non-vapers (or people who know non-vapers) left the comments. The current study is among the first efforts that has demonstrated the formation of descriptive norms through less explicit manipulation of norm directions with constructed distributions of individual behavior cues. One issue worth noticing with this design is that the ratio of the norm direction dominance was set to be 7 (dominant norm): 2 (the opposite norm): 1(no-norm) following prior practices, however whether this ratio would affect normative perceptions differently compared to other ratios (say 6:3:1) was not apparent to us. In addition, classic conformity studies informed us (Asch, 1955; Tanford & Penrod, 1984a) that, conditions with unanimous opinions (i.e., 10:0:0) versus those with dominant opinions (e.g., 9:1:0 or 8:2:0) have very different impacts on descriptive norm perceptions such that as long as the opinions in the group are not unanimous, the normative pressures created by the majorities are substantially reduced. Testing across a range of potential thresholds, either defined by ratios or pure numbers, would be an interesting and fruitful next step, which could further our knowledge in understanding how the "quasi-statistical organ" works, and what is the optimal condition of the descriptive norm perception formation.

In addition, we also observed that the descriptive norm perceptions formed through their subjective experiences within a more immediate environment (i.e., online comment board) significantly influenced their estimation of the overall behavior prevalence in the real world, such that when people perceive that predominantly more commenters do not practice the behavior, their estimation of the behavior prevalence in the public is significantly lowered. On one hand, this finding illustrated the clear influence of the constructed numerical majority perceived from online user-generated comments on people's cognitions, and suggested potential avenues for social change in the online environment; this is particularly striking especially considering that people who leave the comments online are usually anonymous, do not represent any salient social reference groups, and are not representative of the population in the real world. On the other hand, the fact that this effect was observed in Low-prevalence conditions when compared to the no-norm control condition might indicate that, *negativity bias* potentially exists in the formation of normative impressions, such that negation of performing the behavior significantly decreased the normative perceptions of the behavior prevalence. Such effect was consistent with prior literature where the negative valence was also found to have more potent power in changing people's attitude, evaluation, and decision making (Cacioppo, Gardner, & Berntson, 1997; Ito, Larsen, Kyle, & Cacioppo, 1998; Shi, 2016). However, considering that even though not statistically significant when controlling for family-wise error with Bonferroni adjustment, we still observed substantial difference between the 20-comments High- and Low-prevalence conditions ($p < .05$ when Bonferroni correction was not applied), we do not want to reject the possibility that the effects might also exist in the double-exposure High-prevalence condition too soon. Further investigation is warranted to interrogate deeper into this issue.

In addition, among the three different ways to present normative cues, only the double exposure conditions where the participants read 20 comments with the same fixed ratio significantly changed participants' descriptive norm perceptions towards e-cigarette use prevalence in the real world. Considering that individual behavior cues might be less obvious compared to summary information in delivering the descriptive norm cues, this finding speaks to the importance of ensuring sufficient exposure to normative cues before expecting individuals to accurately sense the behavior distribution, which would then further influence their overall behavior prevalence estimation.

An interesting and unexpected pattern we observed was a potential spill-over effect of perceived descriptive norms on valence perceptions, such that while overall participants tended to perceive that the news article and comments had a relatively balanced viewpoint towards e-cigarette use, however when compared across conditions, participants in the Low-prevalence conditions tended to perceive both the news and comments overall as having a less favorable viewpoint towards e-cigarette use, even though we intentionally constructed the comment valence to be balanced in each condition. This finding might indicate that descriptive norm information might have implicitly conveyed individuals' behavioral preference or attitudinal climate information too, and accumulation of such preference information influenced participants' perception of valence distribution of the comments, regardless of the valence of the comment topic itself.

Finally, we would like to acknowledge some of the limitations of the current study. First of all, we found that among the conditions with different norm directions, the control condition (i.e., the no-norm condition) yielded the highest descriptive norm estimation. This finding is a little unexpected and less intuitive as we hoped that the control condition would produce lower, or at least equal level of descriptive norm estimation, as participants in this condition were only exposed to a norm-free valence-neutral short news article about e-cigarettes without additional user-norm information provided by comments. Close scrutiny of our instructions prior to the news page, we found that for the purpose of a reasonable cover story, we described the news article as "a short news article about e-cigarettes selected from one of the top news outlets," and we suspect that the information about a top news outlet might have given participants an institutional signal, which seems to suggest that the popularity or prominence of this topic has already reached the level where mainstream top news outlets would like to report on it (Hodgson, 2006; Silverblatt, 2004; Tankard & Paluck, 2016). This might have inflated the level of descriptive norm estimation in the control condition. Therefore, combing this issue with the fact that non-user-norm comments might be particularly influential (i.e., the "negativity bias" we mentioned before) even the 20% of non-user-norm comments included in the High-prevalence conditions might have significantly decreased the prevalence estimation. This might explain why we observed higher descriptive norm perceptions in the control condition than in High-prevalence conditions. This set of results suggested that, as next steps, the institutional signal hint should be removed from the instruction, and different variations of ratios that are key to norm direction manipulation should be varied to further increase our confidence in making conclusions based on the effects we observe from the study results. Answers to research questions such as whether a High-prevalence condition that consists of 100% user-norm comments could yield higher descriptive norm perceptions would help us better explore and understand the negativity bias we observed in the current study. Finally, considering that we only examined a single behavior, i.e., e-cigarette use, the findings might not be generalized to other behaviors. Therefore, in order to establish the robustness of the current findings, future studies are encouraged to examine across a diverse range of behaviors that are potentially of different nature compared to vaping.

Concluding Remarks

Engaging in the lines of the classic Asch conformity study and Noelle-Neumann's theory of public opinion formation, the present study experimentally manipulates the exposure dosage of norm information about e-cigarette use, with an aim to understand how group pressure is exercised in the virtual space through individuals' observation of the behavior distribution as manifested in the online user-generated comments. The results suggested that individuals were able to infer the implicit norm information embedded in the online comments, based on which they changed their perceptions about the reality. We also found that negation of performing a behavior weighed more heavily in norm perception changes about the behavior. The potential spill-over effects of norm manipulation on valence perceptions also pointed to future research avenues that look into the dynamics between normative and attitudinal perception changes. The current study provides novel evidence of individuals' quasi-statistical sense that gauges behavior distribution in their immediate environment, identifies crucial factors that triggers and catalyzes the formation of descriptive norm perception, and sheds light on how to harness the power of social influence to bring in desirable behavior changes at the societal level in the digital age.

CHAPTER 4.

A MECHANISM OF DESCRIPTIVE NORM PERCEPTION FORMATION: AN EXPERIMENTAL INVESTIGATION ON TWO BEHAVIORS SURROUNDED WITH UNCERTAINTY

Introduction

The results of the pilot study suggested several intriguing patterns that warrant further exploration. Therefore, in the current study, we delve deeper into investigating the mechanism of descriptive norm perception formation at the following fronts.

First of all, in the pilot study, in order to make sure that participants all went through a similar process, such that any observed difference could only be attributed to the comments manipulation, we asked participants in the control condition (i.e., news-only control) to read the same news article the participants in the treatment conditions did. However, as suggested by the pilot study results, the highest descriptive norm perceptions were observed in this condition. Therefore, in the current study, to further understand whether the newspaper article (and the instruction associated with it) may have unintentionally conveyed an institutional signal which may have affected descriptive norm perceptions, we replicated the pilot study with an additional no-message control condition, where participants' descriptive norm perceptions about e-cigarette use were assessed directly without being exposed to any reading materials, thus serving as a baseline or benchmark estimate. We also removed language in the instruction that referred to the news article as coming from "top news outlets" to further minimize the possibility of any unexpected effects. Specifically, we seek to understand whether a news-only condition produces significantly different prevalence estimation compared to the baseline, and whether the difference in estimation has a consistent pattern (e.g., descriptive norm perceptions in the news-only condition being always higher than that of the no-message control condition). Second, in addition to replicating the pilot study with e-cigarette use as the target behavior, we also applied the same design to a different behavior, i.e., checking for Genetically Modified Food (GMO hereafter) label on a food product. We examined whether the results we observed still hold for the GMO label checking behavior; and if not, what the possible boundary conditions are in directing how the mechanism of descriptive norm perceptions formation operates. Particularly, we would like to examine whether the previously observed results including “negativity bias” and “spill-over” effect still exist when a different target behavior is under investigation.

In the next section, we first introduce the theoretical rationale of how the second behavior was selected, and propose hypotheses and research questions based on both theoretical propositions and empirical observations from the pilot study.

Normative Influence as a Function of Behavioral Attributes

Behavior change theories such as the Theory of Reasoned Action (TRA) and accumulating empirical evidence have argued for the need to take into consideration the different nature of behaviors before expecting to select the most effective path of influence, as the underlying attributes of the behavior of interest might determine the relative importance of the antecedents (i.e., attitude, social norms, and self-efficacy) in influencing intention and behavior change (Fishbein & Ajzen, 2011; Godin & Kok, 1996;

Johnston & Dixon, 2008; McEachan, Conner, Taylor, & Lawton, 2011). Researchers investigating the influence of social norms also noted that some behaviors are more susceptible to normative influence while the others are more strongly driven by other psychological antecedents such as attitudinal control or efficacy expectancy (Kim et al., 2015; Lapinski & Rimal, 2005; Mollen, Rimal, & Lapinski, 2010; Rimal & Lapinski, 2015; Rimal et al., 2005; Rivis & Sheeran, 2003).

Lapinski and Rimal (2005) proposed that the behavioral attribute of ambiguity is likely an important determinant of the relative importance of normative influence. The authors defined ambiguity as "*a situation in which the appropriate course of action is unclear to the actor*" (pp. 139 – 140). Under such a condition, as people seek information from their surrounding environment for assistance in interpretation, descriptive norm serves its primary function by helping people understand the appropriate mode of conduct (Cialdini et al., 1990; Darley & Latane, 1968).

At least three types of closely related behaviors are characterized by the attribute of ambiguity. First of all, novel behaviors are likely to be fraught with ambiguity and uncertainty, as they are unfamiliar, have no apparent course of action, and people have yet to acquire a sense of controllability over such behaviors with an established behavior-consequence association. Secondly, behaviors that are high in scientific uncertainty are also susceptible to normative influences. With no solid scientific consensus achieved, mixed contradictory information makes behavioral choices difficult. While the scientific understanding of such behaviors may change over time in response to new evidence, aggregate public perceptions of uncertainty and ambiguity involved in the behaviors may change relatively slowly (Kim et al., 2015). Such perceptions may lead to increasing dependence on the choices of the crowd, with an aim to maximally avoid potential risks that the individuals may have to face alone. Finally, the impact of normative information is perhaps most influential when people lack access to more diagnostic information about consequences of the actual choices of the behaviors (i.e., hard to verify or falsify), have perceptions of low competence on judgments of truth, but in the meantime are desiring to be accurate due to high relevance (R. S. Baron, Vandello, & Brunsman, 1996; Weaver, Garcia, Schwarz, & Miller, 2007). Such behaviors could include but are not limited to private behaviors.

The above considerations served as the major criteria when we initially examined the vaping or e-cigarette use behavior in the pilot study, which seemed to fit the major criteria for an expected normative influence. These criteria were applied again in the current study to guide our selection of the second target behavior, which, for reasons outlined next, was thought to be even more likely to be influenced by normative information.

Checking for GMO Labels on Food Products

Genetically modified foods (GM foods), sometimes called genetically engineered foods, are foods produced from genetically modified organisms (GMO) that have had changes introduced into their DNA using the methods of genetic engineering (WHO, 2017a). GM foods were commercialized and introduced to the U.S. market more than 20 years ago (James & Krattiger, 1996), and ever since have been a subject of intense debate in food science and in public domains, as foods are crucially relevant to everyone's daily life.

Despite the fact that scientific consensus has already been reached with abundant research evidence suggesting that currently available GM foods pose no greater risk to human health compared to their conventional food counterparts (WHO, 2017b), public opinion in the U.S. still remains quite diverse towards the health consequences of GM foods. According to a survey conducted by Pew (Pew Research Center, 2016), a sizeable majority (39%) think GM foods are worse for health compared to traditional non-GM foods, while 48% believe there is no difference between the two types of foods, and only 10% think GM foods can bring health benefits. As we mentioned earlier, while the factual basis of science can evolve over time, changes in aggregate public perceptions take time; however, when it comes to behavioral decisions, individuals' own beliefs and perceptions play the most decisive role. The heightened ambiguity surrounding GM foods in the American public is also reflected in the mismatch between their own estimation of GM foods consumption and the actual availability of GM foods in the U.S. food market. According to the estimates provided by the United States Department of Agriculture (USDA, 2016), currently some 90% of soybeans, cotton, corn and other major crops in the U.S. are genetically modified, and more than 70% of processed foods on the shelves of grocery stores contain GMO ingredients. With such high prevalence of GM foods available in the market, it is almost impossible to totally avoid them. However, findings from a recent survey Annenberg Science Knowledge (ASK, 2016) indicated that more than one third (34%) of Americans reported they had consumed GM foods "not much" or "none at all" during the past week, while another 34% said they ate "a great deal" or "some," and the remaining 32% said they do not know.

Some advocate that this situation could be effectively solved by mandatory labeling of GM foods, which requires companies to put labels on the food product packaging to indicate whether the food contains GMOs, is free from GMOs, or is partially produced with GMOs. There was no nation-wide mandatory labeling in the past, with some states issuing their own labeling standards (e.g., in 2014, the Vermont legislature passed the first state law to require labels on all foods with genetically engineered ingredients) or some companies voluntarily labeling their products. The types of available labels also vary – they are either in the format of plain texts, or smartphone-readable QR codes, or toll-free phone numbers, or links to internet websites that would provide customers information related to the presence or absence of GMO ingredients in the food products. Only on July 14, 2016, legislation approved by Congress required, for the first time, that food products in the United States containing genetically modified ingredients carry identifying labels (National Bioengineered Food Disclosure Standard, 2016). Interestingly, prior to passage of the new law, when people were asked whether labeling of GM foods was already mandated by laws, a substantial proportion (28%) responded "yes," and 54% responded "not sure" (ASK, 2016).

In terms of the GMO label checking behavior, Pew (Pew Research Center, 2016) found that 25% of adults reported that they always checked for such labels every time they shop, 25% checked sometimes, while 17% did so "not too often," and 31% never looked for GM labeling. Then, what is the likely effect of people checking for GMO labels on purchases? The answer to this question intertwines with people's perceptions towards GM foods consumption. If they perceive GM foods as generally more positive or beneficial than traditional foods, the goal of label checking is to make sure they buy GM foods; in contrast, if they perceive GM foods as generally more negative or less safe, they check the labels to avoid them. However, considering that the largest proportion of the population shows uncertainty towards the safety of GM foods, in aggregate, checking for GMO labels should be producing a suppressing effect on purchases. ASK (2016) found that nearly half of Americans reported that they would be "much less likely" or "somewhat less likely" (49%) to purchase a food product after learning that it contains GMO ingredients; only 6% responded that learning the product has GMO ingredients would increase their purchase intention. Pew (Pew Research Center, 2016) also found that concerns of health consequences seemed to drive people's label checking behavior with the goal of avoiding such foods, such that those who considered GM food consumption as unsafe were more likely to check for labels (35%), while only 9% of those who considered it safe would bother to check.

In the current study, we decided to choose checking for GMO labels on food products as the target behavior of Study 2. This decision was made mainly based on the following considerations. First of all, GMO label checking is a relatively new and unfamiliar behavior with no obvious course of action compared to some other more established behaviors (e.g., smoking), and even though shopping is a public behavior, checking for the labels on the food packaging could be considered as semi-private, as people often do not know what other shoppers are looking for in a food package even when they stand close to each other. Therefore, it is considerably harder to have accurate diagnostic information about the actual prevalence of this behavior in the population, compared to behaviors that are more visible. Label checking is also antecedent to purchase and consumption behaviors, thus the decision to check the GMO labels on food products is not highly tied to the perceived obscurity and scientific uncertainty associated with the consequences of eating GM foods. Second, although the consumption or purchase behaviors of GM foods taps more directly into the public contention surrounding the benefits and risks associated with GM foods, those behaviors may invite unintended ceiling effects in the estimation of the behavior prevalence, as a sizeable proportion (32%) of people was even unsure about whether they have performed these behaviors at all, according to ASK (2016). Our own data, which will be described in detail later, also corroborated this concern by showing that almost 42% of the participants in our sample were unsure about whether they purchased GM foods or not during the past week. Based on their own experiences, it is likely that they would assume others also purchase or consume GM foods more often than they intend to, simply because they are not sure whether the foods they buy contain GMO ingredients or not, thus inflating the prevalence estimation unduly. Checking for GMO labels on foods, on the other hand, is a behavior that people clearly know whether they have done it or not, and it also has important direct impacts on purchase and consumption decisions. We thus considered checking for GMO labels an appropriate target behavior for our second experiment in the current study.

The Present Study

In the present investigation, we first replicate the pilot study with the same target behavior, i.e., vaping or e-cigarette use, but with a slightly different design. With the e-cigarette replication study (Study 1), we seek to understand: 1. Whether the results we observed in the pilot study still hold; 2. Whether the news article changes descriptive norm perceptions from the baseline; 3. What implications our experimental manipulation may have on behavioral intentions. We next apply the experimental design to a different behavior, checking for GMO labels in food products (Study 2), which also taps into issues that are fraught with uncertainty and ambiguity and are going through heated debates in the American public, but has a very different nature and characteristics compared to those that are specific to the e-cigarette vaping behavior. With Study 2, we hope to examine whether the patterns in the e-cigarette study could be generalized to a different target behavior; and if not, what factors may have come into play, and what conclusions we can draw from the findings of both studies to enlighten future research directions.

Hypotheses and Research Questions

First and foremost, based on what we have examined and observed in the pilot studies, we propose the following hypotheses regarding the constructed and reality descriptive norm perceptions:

H1: Participants in High-prevalence conditions on average have significantly higher estimations of behavior prevalence within the online comment boards compared to those in the Low-prevalence conditions.

H2: Participants in High-prevalence conditions on average have significantly higher reality descriptive norm perceptions compared to those in the Low-prevalence conditions.

Considering that in the pilot study, significant difference between conditions was only observed when the total exposure is high (i.e., 20-comments), to further understand whether total exposure dosage (10 comments vs. 20 comments) may affect the magnitude of reality descriptive norm perceptions differently, we also propose to examine R1 and R2.

R1: Do participants in the 20-comments High-prevalence condition on average have significantly higher reality descriptive norm perceptions compared to those in the 10-comments High-prevalence condition?

R2: Do participants in the 20-comments Low-prevalence condition on average have significantly lower reality descriptive norm perceptions compared to those in the 10-comments Low-prevalence condition?

Next, we would like to understand whether the intended valence-neutral norm-free news article can significantly change reality descriptive norm perceptions from the baseline, and what the direction of such change might be. We thus propose:

H3: Participants in the news-only condition have significantly higher reality descriptive norm perceptions about using e-cigarettes / checking for GMO labels on food products compared to those of the no-message baseline control condition.

If H3 is supported, all the comparisons involving the control condition would be conducted with the news-only and the no-message baseline control conditions as the reference group respectively. If H3 is rejected, we follow what we did in the pilot study, such that these contrasts would be conducted only against the news-only control condition. It is worth noting here that, compared to the no-message baseline control condition, the news-only condition enjoys greater ecological validity, considering the typical juxtaposition of news article and the comments accompanying it on news websites in the real-world settings. Therefore, comparing treatment groups against news-only control group can help us better gauge the effects of norm manipulation through online comments above and beyond news consumption. However, if the two control conditions do show significant patterns in reality descriptive norm perceptions, then it would be more appropriate to compare treatment groups against both conditions separately.

To further explore the potential negativity bias in the formation of normative perceptions as we observed in the pilot study, we also examine H4 and H5 below. Rejection of H4 and confirmation of H5 would provide further evidence that supports the negativity bias hypothesis.

H4: Participants in High-prevalence conditions on average have significantly higher reality descriptive norm perceptions compared to those in the control condition(s).

H5: Participants in Low-prevalence conditions on average have significantly lower reality descriptive norm perceptions compared to those in the control condition(s).

To further explore the potential “spill-over” effects of norm manipulation on valence perceptions, as we observed in the pilot study, we examine H6 – H8 below. Confirmation of the three hypotheses would provide further evidence that supports the “spill-over” effects hypothesis.

H6: Participants in Low-prevalence conditions on average tend to perceive the news article as having a less positive viewpoint towards using e-cigarettes / checking for GMO labels on food products compared to that of the news-only control condition.

H7: Participants in High-prevalence conditions on average tend to perceive the news article as having a more positive viewpoint towards using e-cigarettes / checking for GMO labels on food products compared to that of the news-only control condition.

H8: Participants in High-prevalence conditions on average tend to perceive the comments overall as having a more positive viewpoint towards using e-cigarettes / checking for GMO labels on food products compared to that of the Low-prevalence conditions.

In addition to the hypotheses and research questions we have examined in the pilot study, in the current study we also aim to explore whether our experimental manipulation could also produce any impact on behavioral intentions, and through which pathways. We propose the following hypotheses:

H9: Experimental manipulation of behavior choice distribution on the online comment boards has a direct effect on intention to use e-cigarettes / check for GMO labels, such that participants in High-prevalence conditions on average have significantly higher intentions compared to those in the Low-prevalence conditions.

H10: Experimental manipulation of behavior choice distribution on the online comment boards has an indirect effect on intention to use e-cigarettes / check for GMO labels mediated through reality descriptive norm perceptions, such that participants in High-prevalence conditions on average have significantly higher reality descriptive norm perceptions, which in turn lead to significantly higher intentions, compared to those in the Low-prevalence conditions.

Finally, we would like to compare multiple linear regression models to formally test whether adding the experimental manipulation variable can explain significantly more variance in the dependent variable, i.e., reality descriptive norm perceptions, above and beyond the demographics and other potentially influential factors. We therefore hypothesize:

H11: The full model (experimental manipulation variable included) fits the data significantly better than the reduced model (experimental manipulation variable not included).

Study 1 – Using E-cigarettes

Method

Study design and procedures. The design of the current study replicated most of the pilot study, with three major changes. First of all, considering the importance of baseline prevalence estimation towards the target behavior, and also for the purpose of understanding how reading a no-norm newspaper article may affect individuals' descriptive norm perceptions from the baseline, in the current study, while still keeping the news-only control condition, we added a no-message control condition where participants are not exposed to any reading material but are directly assessed for descriptive norm perceptions towards the target behavior. Secondly, considering that conditions with visual cues did not significantly affect people's normative perceptions in the pilot study, and the underlying mechanism of how visual cues would increase the possibility for people to pick up normative cues is less relevant to the main research questions and hypotheses we proposed here, in the current study we only keep the first four treatment conditions, which varied the total exposure (10 vs. 20 comments) and normative directions (High-prevalence vs. Low-prevalence). Lastly, in the pilot study, to ensure that the comment board mock-ups presented to the participants were of good ecological validity, in each of the treatment conditions, we had incorporated 10% comments that have no normative indications (i.e., no-norm comments). However, considering that no-norm comments are not crucial in addressing the main research questions, in the current study we used only comments that have either user-norm or non-user-norm indications, and no longer incorporated no-norm comments in the treatment conditions. Therefore, for the treatment groups in our current design, while the proportions of comments with the opposite minority normative direction would still be kept as 20%, the comments of the dominant normative direction will be 80%, instead of 70% as in the pilot study.

To sum up, the current study adopted a 2 total exposure (10 comments vs. 20 comments) X 2 norm directions (High-prevalence vs. Low-prevalence) + 1 (news-only control) + 1 (no-message baseline control) between-subject design. For all respondents, 40% of the comments held positive views towards using e-cigarettes / checking for GMO labels on food products and 40% expressed negative views while 20% were neutral. The valence dimension (positive vs. negative) was independent of the norm direction dimension (user-norm vs. non-user-norm) in the comments. As in the pilot study, the current study also used online Qualtrics-based surveys, distributed through Mturk. Eligible participants were randomly assigned to one of the six experimental conditions.

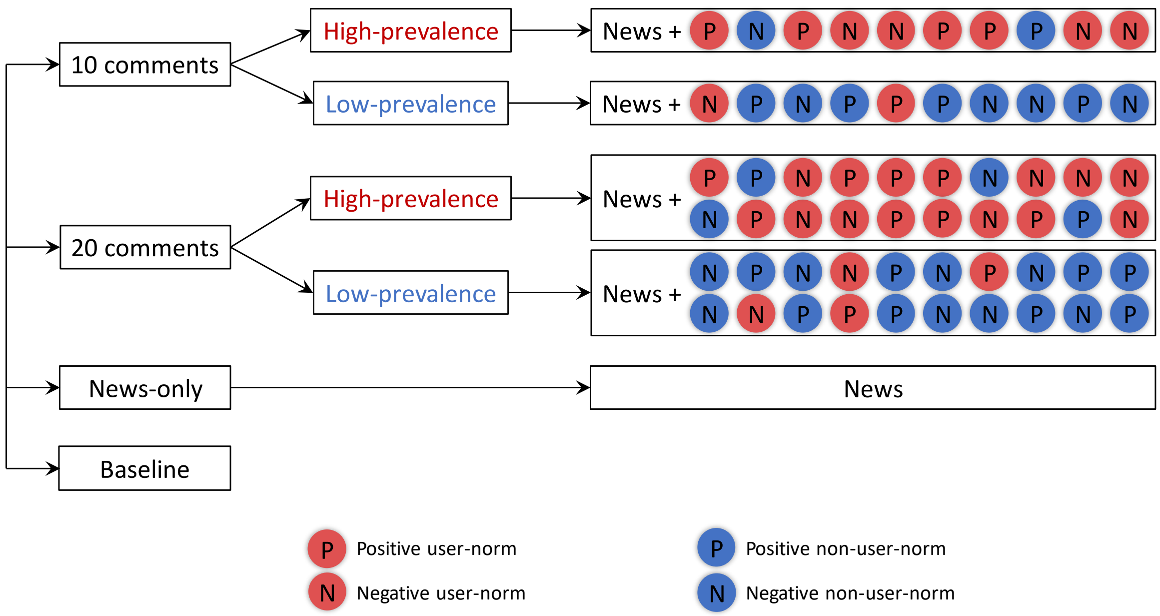

Figure 4.1. Study design and an example of stimuli composition for each condition

Participants in the treatment and the news-only control conditions first read a short news article about e-cigarettes (with no normative information and balanced in tone towards the behavior), while those in the no-message baseline control condition were directly brought to the outcome measure assessment pages without being exposed to any reading materials. The treatment groups then went on to read 10 or 20 (depending on conditions) user-generated comments, while the news-only control group skipped the comments and were assessed for their descriptive norm perceptions towards the behavior and other outcome measures. Participants in the High-prevalence treatment conditions were exposed to 80% comments that contained user-norm information and 20%

comments that contained non-user-norm comments, and vice versa. After exposure to the stimulus materials, the participants in the treatment groups were directed to the outcome measures pages, answering questions assessing their descriptive norm perceptions and intentions towards vaping e-cigarettes. We also included an open-ended question for participants in the treatment and news-only control conditions to allow feedback or thoughts from the participants. Demographics and other covariates measures were assessed at the end. Figure 4.1 presents the experimental conditions and an example of comment presentation for each condition.

Participants. According to the results of the pilot study, the overall effect of norm manipulation is quite small, with $\eta^2 = .02$ or Cohen's *f* of about 0.14 (J. Cohen, 1988; Rosenthal, 1991). Based on power analysis using G*Power 3.1 (Faul, Erdfelder, Buchner, & Lang, 2009; Faul, Erdfelder, Lang, & Buchner, 2007), a minimum total sample size of 403, i.e., approximately 67 participants in each of the six conditions, is required to achieve statistical power of .80 in detecting the small effect. To better ensure adequate power for detecting even smaller effects, and to facilitate direct comparison with the pilot study results, the current study went beyond the minimum and recruited approximately 100 participants for each of the conditions.

A total of 601 U.S. adults were recruited through MTurk. Similar to the pilot study, the participants were high-quality Mturk workers (above 97% approval ratings and had been approved more than 100 times), age 18 or older, and passed the screening test of the "foil" question as described in the pilot study. Ten participants who took the survey with excessively long (3 *SD* or more above the mean) or short (3 *SD* or more below the mean) completion time were excluded from the sample for analysis (final $N = 591$). About half of the participants were female (49.58%), and the mean age of the sample was 35.21 ($SD = 11.43$, range = 18 – 79). Most of them had finished high school (90.86%) and approximately half (48.22%) had finished college. A majority of the participants were Non-Hispanic White (71.40%), 7.11% Non-Hispanic African American, 9.31% Non-Hispanic Asian/Pacific Islander, 7.61% Hispanic/Latino, and 4.57% more than one race. Most of the participants had heard of vaping or using e-cigarettes before the study date (95.60%), and about half of the sample had ever used an e-cigarette, even one or two puffs (49.41%). Slightly more than half of the participants (53.64%) had smoked 100 cigarettes or more in their lifetime. The majority of the participants in the treatment groups (79.08%) either sometimes or often read comments left by previous viewers on news websites ($M = 3.11$, $SD = 0.79$, on a 1-4 scale with anchors "*never,*" "*seldom,*" "*sometimes*" and "*often*"); however, only about a quarter of the participants in the treatment groups (25.26%) would sometimes or often post their own comments on news websites ($M = 1.97$, $SD = 0.83$, on the same 1-4 scale).

Stimulus Materials. The news article and the same set of comments from the pilot study were used in the current study, with some modifications. Specifically, as we speculated earlier in the pilot study, mentioning that the news article was adapted from a top news outlet such as *New York Times* or *Washington Post* may unintentionally deliver an institutional signal such that the topic described in the news article must be so prominent and prevalent in the society as to attract the attention of top news sources, thus leading to inflated descriptive norm perceptions. Therefore, in the current study, while we still used the same news article stimulus (i.e., the valence or tone towards e-cigarette use was held balanced, and no normative information was mentioned), we modified the instruction on the news page so that wordings such as "*top news outlet*" were removed. We also used the same set of comments stimuli from pilot study, after making modifications to items that may contain implicit normative information. See Appendix C for the news article and the comments pool used in the current study. Particularly, in the notes section of the comments pool table, we further describe in detail the changes we made to some previous comments stimuli, and why the changes were necessary. As in the pilot study, we also developed a comment allocation algorithm to ensure that the comments each participant saw were balanced in valence (four positive topics randomly drawn from the positive pool, four negative topics randomly drawn from the negative pool, and two neutral topics randomly drawn from the neutral pool), and were mixed at 8:2 ratio based on the conditions they were assigned , i.e., High-prevalence conditions had 80% user-norm comments, and 20% non-user-norm comments; Low-prevalence conditions had 80% non-user-norm comments, and 20% user-norm comments. The algorithm also made sure that the order of the comments was randomly scrambled before being presented to each participant.

Measures.

Constructed descriptive norm perceptions. For the manipulation check, we used the same set of two questions as in the pilot study to assess how participants in the treatment groups would perceive the behavior choice distribution through comments, i.e., whether the comments they viewed were posted mainly by vapers or commenters who know others vape. The two items (after reverse coding the second item) were highly and significantly correlated with each other ($r = .75$, $p < .001$). The average score of the two items (after standardization) was used as the constructed norm perceptions dependent variable in our analysis.

Reality descriptive norm perceptions. Following our practice in the pilot study, our focal dependent variable, the reality descriptive norm perceptions about e-cigarette use in the real world, was assessed with two sets of questions. The first set of questions, which included seven items asking the participants to gauge the prevalence of e-cigarette use behavior among different reference groups yielded moderately high reliability in the current study (Cronbach's $\alpha = .84$ based on the standardized seven items). The second set of questions, which consisted of a scale that asked participants to indicate how much they agree or disagree with six statements about e-cigarette use prevalence, also produced moderately high reliability (Cronbach's $\alpha = .84$ based on the standardized six items). The average scores of the standardized items from the two question sets were significantly and positively correlated ($r = 0.70$, $p < .001$), indicating the suitability of combining the two sets of items. We then combined the standardized 13 items and observed the highest reliability (Cronbach's $\alpha = .90$) compared to each of the sets alone. Removing any of the single items would also result in reduced magnitude of the Cronbach's α. Therefore, the standardized 13 items were then averaged to create an overall scale which served as the measurement of the focal outcome variable, i.e., reality descriptive norm perceptions, in our analysis.

Intention. To examine whether the subtle descriptive norm manipulation could have any effect on behavioral intentions, the participants were asked to indicate how likely they will vape or use an e-cigarette, even one or two puffs, at any time in the next six months on a 4-point Likert scale ranging from "*definitely will not*," "*probably will not*," "*probably will*," to "*definitely will*." Higher scores indicate greater intentions to conduct the behavior. On average, participants had moderately low intention to use e-cigarettes in the next six months (M = 1.87, SD = 1.00), with about half of the sample responding with the answer "*definitely will not*" (49.24%).

Valence perceptions. To understand how the participants perceive the valence or tone towards e-cigarette use in both news article and comments, we asked the participants to indicate whether the news article and the comments are in favor of or against e-cigarette use on a 5-point scale ranging from "*strongly disagree*" to "*strongly agree*." Substantial correlations were observed for both news valence and comment valence perception measures (r = 0.58, p < .001 for the two news valence measures; r = 0.69, p < .001 for the two comments valence measures). We then created two valence perceptions variables, news valence and comments valence separately by averaging the two items measuring each.

See Appendix E for details on question wordings, question sequence, programming instructions, and skip patterns used in Study 1.

Results

Testing for random assignment. To ensure that there were no differences between the experimental groups with respect to age, gender, education, race/ethnicity, topic familiarity, e-cigarette use status, established smoking status, comments reading and posting habits, we conducted one-way analysis of variances (ANOVAs) with condition as the independent variable. These analyses suggested that there were no significant differences among conditions, with *p*-values ranging from 0.42 – 0.94.

Manipulation check. We first examined whether the behavior choice distributions on the online comment boards were perceived differently between High-prevalence and Low-prevalence conditions as we intended. Mean constructed norm perceptions for each condition are summarized in Table 4.1. Participants in the two High-prevalence conditions ($M = 0.60$, $SE = 0.04$) on average had higher constructed norm perceptions (i.e., were more likely to agree that the comments they read were posted mostly by vapers or commenters who know others who vape) compared to that in the Low-prevalence conditions ($M = -0.58$, $SE = 0.06$), and the difference was significant and fairly large (F (1, 388) = 270.22, $p < .001$, Cohen's $d = 1.62$). H1 was supported. In terms of valence perceptions, participants in the news-only condition rated the news article as relatively balanced ($M = 3.12$, $SD = 0.79$), and not significantly different from the midpoint (i.e., 3) of the scale ($t(99) = 1.52$, $p = 0.13$).

Table 4.1

Mean Perceived Constructed and Reality Norms of E-cigarette Use across Conditions

Conditions	Sample Size	Constructed Norms	Reality Norms
	n	*M* (*SE*)	*M* (*SE*)
1. High-prevalence 10 comments	96	0.52 (0.07)	0.11 (0.07)
2. High-prevalence 20 comments	97	0.68 (0.05)	0.07 (0.07)
3. Low-prevalence 10 comments	102	−0.39 (0.09)	−0.09 (0.06)
4. Low-prevalence 20 comments	97	−0.78 (0.07)	−0.17 (0.07)
5. News-only Control	100		0.10 (0.07)
6. Baseline Control	99		−0.01 (0.06)

Note: Means and standard errors were calculated based on standardized items.

Hypothesis testing. We next examined whether the experimental manipulation could affect individuals' descriptive norm perceptions or prevalence estimation of e-cigarette use in the real world. Mean reality descriptive norm perceptions for each condition are also summarized in Table 4.1. As predicted, the two High-prevalence conditions produced significantly higher reality descriptive norm perceptions (M = 0.09, SE = 0.05) than that of the two Low-prevalence conditions (M = -0.13, SE = 0.05; F (1, 585) = 10.96, p < .01; Cohen's d = 0.33). H2 was supported. There was no difference in reality descriptive norm perceptions varying total exposure dosage (R1 and R2) when comparing high and low conditions within the same norm direction (two High-prevalence conditions: F (1, 585) = 0.17, p = .68; two Low-prevalence conditions: F (1, 585) = 0.62, p = .43).

H3 predicted that reading the news article about e-cigarettes affects participants' reality descriptive norm perceptions such that participants in the news-only condition have significantly higher reality descriptive norm perceptions towards vaping compared to those in the no-message baseline control condition. While the average descriptive norm perceptions in the news-only condition were slightly higher than those in the baseline condition as shown in Table 4.1, results from the planned contrast indicated that there was no significant difference between the two conditions (F (1, 585) = 1.33, p = .25). H3 was rejected.

To further understand whether there is a negativity bias in the formation process of normative perceptions, the next set of hypotheses proposed to examine whether the High-prevalence conditions and the Low-prevalence conditions have significantly different reality descriptive norm perceptions compared to the control condition. Considering that the news-only condition was not different compared to the no-message control condition with respect to reality norm perceptions, we contrasted the treatment groups against the news-only condition, following our practice in the pilot study. Planned contrasts revealed that the reality descriptive norm perceptions in the High-prevalence conditions were not significantly different from the news-only condition (F (1, 585) = 0.00, p = .97). Low-prevalence conditions, however, were observed to have produced significantly lower reality descriptive norm perceptions compared to the news-only control condition (F (1, 585) = 7.67, p < .01, Cohen's d = -0.33). The rejection of H4 and confirmation of H5 dovetailed with what we found in the pilot study, and provided further evidence to corroborate the "negativity bias hypothesis." Figure 4.2 below displays significant differences in reality descriptive norm perceptions among conditions as suggested by the planned contrasts.

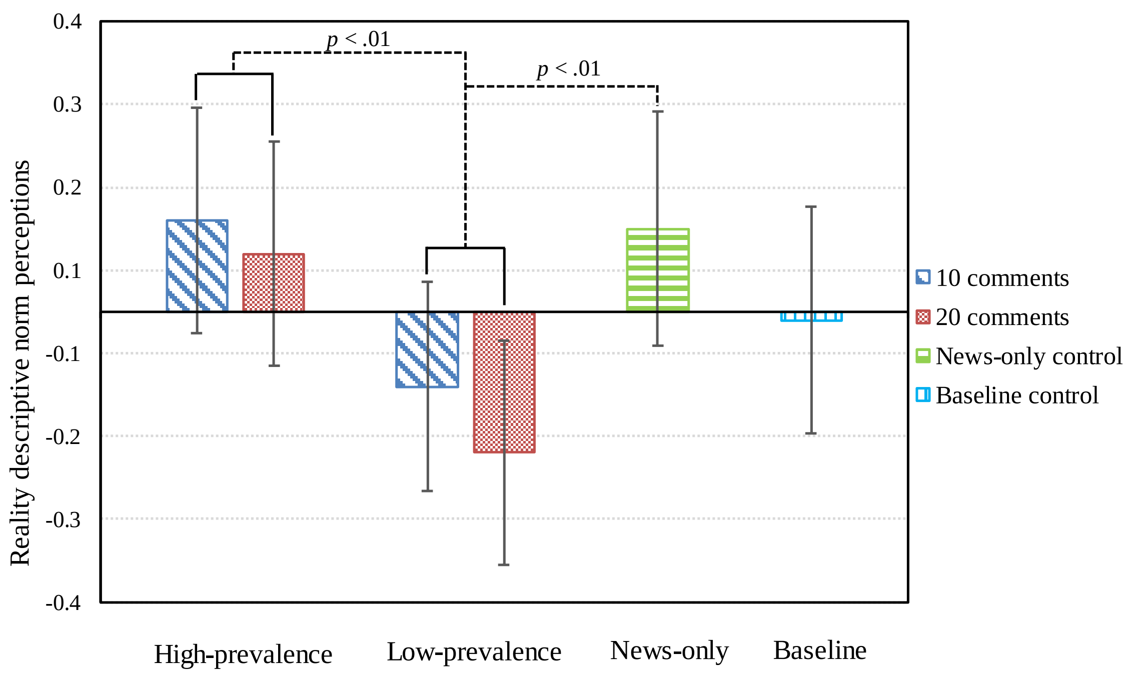

Figure 4.2. Mean perceived e-cigarette use reality norms and significant contrasts

Note: Error bars represent the 95% CIs. The reality descriptive norm perception measure is an average of the 13 standardized norm items. Significant differences as suggested by planned contrasts were marked with corresponding p-values. The high-prevalence conditions had significantly higher prevalence estimation than that of the low-prevalence conditions. The low-prevalence conditions also produced significantly lower prevalence estimation compared to the news-only control condition.

With respect to valence perceptions, to further explore the potential "spill-over" effects as we observed in the pilot study, the next set of hypotheses predicted that experimental manipulation on norm directions would affect valence perceptions accordingly. Table 4.2 summarized mean values for the news valence perception variable in each condition. The results from planned contrasts showed that, compared to the news-only condition, those in the Low-prevalence conditions (*M* = 2.82, *SE* = 0.06) on average tend to perceive the news article as having a less positive viewpoint towards vaping (F (1, 487) = 7.90, $p < .01$, Cohen's $d = -0.35$). H6 was supported. Those in High-prevalence conditions (*M* = 2.99, *SE* = 0.06), on the other hand, did not differ significantly in perceptions of news valence towards e-cigarette use (F (1, 487) = 1.51, $p = .22$) compared to those in the news-only control condition. H7 was rejected. We then examined whether treatment conditions with different norm directions may affect the overall valence perceptions of comments differently. As hypothesized, participants in High-prevalence conditions (*M* = 3.36, *SE* = 0.06) had significantly more positive valence perceptions of comments compared to that of the Low-prevalence conditions (*M* = 2.41, *SE* = 0.06), and the difference was larger than one standard deviation (F (1, 388) = 119.70, $p < .001$, Cohen's $d = 1.10$). H8 was confirmed. The patterns we observed from the above results were highly consistent with what we observed in the pilot study, which provided further evidence for the "spill-over" effects.

In addition to the research questions we examined in the pilot study, we also explored in the current study whether our experimental manipulation could affect intention towards vaping or e-cigarette use through both direct and indirect pathways. Mean values for the intention variable across conditions were also summarized in Table 4.2. The planned contrast comparing means of the behavioral intention in the two High-prevalence conditions (*M* = 1.90, *SE* = 0.07) and the two Low-prevalence conditions (*M* = 1.75, *SE* = 0.07) showed that there was no significant difference in intention between conditions with the two norm directions (F (1, 585) = 2.11, p = .15). H9 was rejected. An overall omnibus test also suggested that no significance in intention was detected among any of the conditions (F (5, 585) = 1.21, p = .30). The results indicated that norm manipulation had no direct impact on intention to use e-cigarettes.

Table 4.2

Mean Valence Perceptions and Intention towards E-cigarette Use across Conditions

Conditions	Sample Size	News Valence	Comments Valence	Intention
	n	*M* (*SE*)	*M* (*SE*)	*M* (*SE*)
1. High-prevalence 10 comments	96	3.00 (0.10)	3.36 (0.09)	1.91 (0.11)
2. High-prevalence 20 comments	97	2.97 (0.08)	3.35 (0.09)	1.89 (0.10)
3. Low-prevalence 10 comments	102	2.88 (0.09)	2.49 (0.09)	1.73 (0.09)
4. Low-prevalence 20 comments	97	2.76 (0.09)	2.33 (0.09)	1.77 (0.09)
5. News-only Control	100	3.12 (0.08)		2.04 (0.12)
6. Baseline Control	99			1.87 (0.10)

Note: The mean scores and standard errors of the three variables were calculated based on the raw scores. News valence and comments valence were measured on 5-point scales ranging from “strongly disagree” to “strongly agree,” with higher scores indicating more positive valence perceptions. Intention was measured by a 4-point Likert scale ranging from “definitely will not” to “definitely will.” Higher scores indicate greater intentions to vape or use e-cigarettes in the next six months.

To test our expectation that reality norm perceptions would mediate the effects of condition on vaping intention, such that participants in the High-prevalence conditions on average have significantly higher reality descriptive norm perceptions, which in turn lead to significantly higher intentions, compared to those in the Low-prevalence conditions.

This test was implemented by running a mediation model with the bootstrapping procedure, which is a nonparametric resampling procedure that has high power, does not impose the assumption of normality of the sampling distribution, and is generally considered superior to the product-of-coefficients strategy (Hayes, 2009; Hayes & Preacher, 2014; Preacher & Hayes, 2008). To assess whether the indirect effects were significantly different from zero, bias-corrected 95% confidence intervals were constructed using bootstrapping with 500 replications. The results suggested that in the full model (as shown in Figure 4.3), while norm manipulation conditions (High- vs. Low-prevalence) remained an insignificant predictor of vaping intentions, $b = 0.02$ ($\beta = 0.01$), $p = .83$, the indirect effect through reality norm perceptions was significant (indirect effect = 0.13, 95% *CI* [0.05, 0.22]). Normal theory tests of the indirect effect provided identical conclusions ($p < .01$). H10 was confirmed[3].

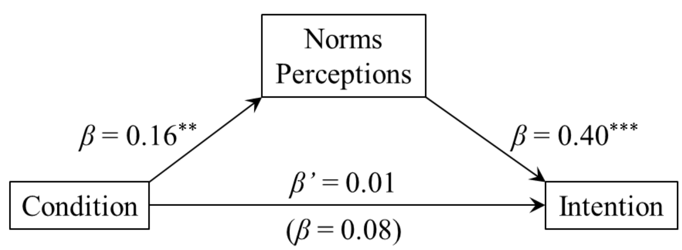

Figure 4.3. Indirect experimental effects on intention through reality norm perceptions

Note: Standardized path coefficients βs are shown in the figure. Condition variable was coded as 1 = High-prevalence conditions, 0 = Low-prevalence conditions. Reality descriptive norm perceptions and intention

[3] It is important to note here that intention is also a significant predictor of reality descriptive norm perceptions ($\beta = 0.39$, $p < .001$). The significant reverse pathway does not reject the current model, but it is also possible that the apparent mediation effect may also be consistent with another model. The relationship between reality descriptive norm perceptions and intentions is observational and not experimentally induced, and we do not have evidence for a direct experimental effect on intentions. The causal order between intentions and norms cannot be assumed, although it is typical to assume that norms precede intentions.

were both treated as continuous variables. On the path from condition to intention, the parenthetical value β represent the direct effect without controlling for the mediator, and the value β' outside parentheses represent the effect when the mediator is included in the model. Asterisks indicate significant coefficients (**$p < .01$, ***$p < .001$).

Finally, to understand whether our experimental manipulation contributed to explaining the variation in reality descriptive norm perceptions above and beyond demographics and other potentially influential factors, two multiple linear regression models (reduced vs. full) were conducted to examine whether the experimental manipulation significantly improved the model fit. As shown in Table 4.3, we first examined the reduced model (Model 1) where participants' age, gender, race/ethnicity, education levels, ever e-cigarette use status, topic familiarity (i.e., whether they had heard of vaping or using e-cigarettes before), and established cigarette use status were included in the regression. We then conducted the full model analysis (Model 2), where the experimental condition variable was added on top of all the predictor variables in Model 1. Considering that the 10-comment and 20-comment conditions did not differ significantly within each norm direction (i.e., High-prevalence and Low-prevalence), we collapsed conditions of the same norm direction, and used a 4-category experimental condition variable (High-prevalence, Low-prevalence, Baseline control, and News-only control which served as the reference category) in the analysis. The maximum likelihood ratio test comparing the two nested models suggested that adding the condition variable significantly improved the model fit (χ^2 (3) = 13.65, $p < 0.01$), further confirming that our experimental manipulation which varied the behavior choices distribution using online comments was indeed capable of changing people's descriptive norm perceptions in the real world, even when other potential sources of influence were taking into consideration.

In addition, the results of the multiple regressions also indicated that age, gender, education levels, ever e-cigarette use status and topic familiarity were predictive of reality descriptive norm perceptions such that populations that are younger, female, less educated, have ever tried e-cigarette use, and haven't heard about e-cigarette use before, are more likely to have higher prevalence estimation of e-cigarette use. H11 was confirmed.

Table 4.3

Multiple Regression Models in Predicting Perceived Reality Norms of E-cigarette Use

Predictor Variables	Model 1			Model 2		
	B	*SE*	*β*	*B*	*SE*	*β*
Experimental conditions [a]						
High-prevalence				0.03	0.07	0.02
Low-prevalence				−0.18*	0.07	−0.13*
Baseline control				−0.05	0.09	−0.03
Age	−0.01***	0.00	−0.23***	−0.01***	0.00	−0.23***
Gender (1 = Female)	0.17***	0.05	0.13***	0.17**	0.05	0.13**
Race/ethnicity [b]						
Hispanic	0.19*	0.10	0.08*	0.20*	0.10	0.08*
African American	0.09	0.10	0.04	0.10	0.10	0.04
Asian/Pacific Islander	−0.10	0.09	−0.05	−0.12	0.09	−0.05
More than one	0.13	0.01	0.04	0.12	0.12	0.04
Education [c]	−0.06***	0.02	−0.13***	−0.05**	0.02	−0.11**

Predictor Variables	Model 1			Model 2		
	B	*SE*	*β*	*B*	*SE*	*β*
Ever vaping (1 = Yes)	0.32***	0.06	0.24***	0.32***	0.06	0.24***
Ever heard of vaping (1 = Yes) [d]	−0.44***	0.12	−0.13***	−0.43***	0.12	−0.13***
Smoked ≥100 cigs (1 = Yes)	−0.00	0.06	−0.00	0.00	0.06	0.00
Adjusted R^2		0.173			0.188	

Note. *N* = 590. *B* = Unstandardized regression coefficients; *SE* = Standard errors of *B*; *β* = Standardized regression coefficients. * $p < .05$, ** $p < .01$, *** $p < .001$.
[a] News-only control condition is the reference category.
[b] Non-Hispanic White is the reference category.
[c] Education was measured as a 14-category ordinal variable ranging from "*Less than 6th grade*" to "*Graduate or professional school degree (MA, PhD, MBA, MD, JD, etc.)*." It was entered as a continuous variable in the two regression models.
[d] Ever heard of vaping was measured with three categories "*yes*," "*no*" and "*not sure*." We combined "no" and "not sure" to create a dichotomous variable, with 0 representing "no" and 1 representing "yes," to enter in the two regression models.

Discussion

The results in the current study mirrored what we observed in the pilot study. To summarize, we confirmed that people were capable of correctly sensing the numerical majority of the behavior choices based on the comments they read, despite the subtleness of the normative cues conveyed in this way. More importantly, through changes in this constructed descriptive norm perception, their prevalence estimation about e-cigarette use in the real world was also significantly influenced correspondingly. By adding an additional no-message news-only control condition in the current study, we were able to show that, even though reading the news article did increase the reality norm perceptions slightly, such change was not statistically significant. This finding relieved our concern that the institutional signal manifested through the form of attention from the mainstream news may affect the experimental manipulation in the pilot study unexpectedly. We also observed, again, that compared to the news-only control condition, Low-prevalence conditions had significantly lower reality norm perceptions, while no difference was found between the High-prevalence conditions and the control, replicating the "negativity bias" pattern in the pilot study. One difference worth noting though, is that while we observed that only the double exposure (i.e., 20 comments) Low-prevalence condition seemed to have produced significant effects in the pilot study, in the current study, we observed that 10-comments and 20-comments Low-prevalence conditions were not significantly different from each other (p = .43). Post-hoc tests also showed that even when examining the two Low-prevalence conditions separately, both the 10-comments condition (Cohen's d = -0.28, p = .04) and the 20-comments condition (Cohen's d = -0.38, p = .01) had significantly lower reality descriptive norm perceptions compared to that of the news-only control condition. This difference may be related to the increased behavior dominance ratio (8:2) we used in the current study compared to that in the pilot study (7:2:1), further suggesting the importance of systematically exploring how the total exposure dosage and the behavior dominance ratio may work together in influencing people's normative perception formation, which we examine in the next Chapter. The pattern of the "spill-over effects" also dovetailed with the findings of the pilot study. In a nutshell, the replication hypotheses were almost all corroborated in the current study.

In addition, the current study also expanded our understanding towards how affecting perceived norms within a more immediate environment (online comment boards in our case) may ultimately lead to changes in people's behavioral intention. We found that, while our experimental manipulation was not directly associated with intention to vape, the effect travelled through the indirect pathway via reality descriptive norm perception changes. The significant influence of constructed descriptive norm perceptions on reality descriptive norm perceptions as we observed in both the pilot study and the current study, the strong association between reality norm perceptions and behavioral intention, as suggested both by conventional behavior theories and our empirical evidence here, as well as the significant perceived constructed norms – perceived reality norms – intention change pathway, converge to suggest an important implication, that focusing on changing norm perceptions within a more immediate, local environment, may benefit future behavior change interventions using normative appeals.

Study 2 – Checking for GMO food labels

Method

Study design and procedures. The second experiment methodologically replicated Study 1. However, instead of focusing on vaping or e-cigarette use behavior, the target behavior in the second study is checking for GMO food labels. Participants in the current study went through the same procedures, and were randomly assigned to one of the six experimental conditions as demonstrated earlier in Figure 4.1.

Participants. A total of 602 U.S. adults were recruited through MTurk. Nine participants were excluded from the sample for analysis due to excessively long or short completion time (more than 3*SD* above or below the mean), resulting a final sample of N = 593 participants. Of these participants, 50.59% were female, and the average age of the sample was 37.22 years (*SD* = 12.26). The sample included 77.07% Non-Hispanic White, 6.24% Non-Hispanic African American, 7.08% Non-Hispanic Asian/Pacific Islander, 5.23% Hispanic/Latino, and 4.05% with more than one races. Most of them had finished high school (97.81%) and 61.05% had at least a college or equivalent degree. A majority of the participants in the treatment groups (74.42%) either sometimes or often read comments left by previous viewers on news websites (M = 2.98, SD = 0.82, on a 1-4 scale with anchors "*never*," "*seldom*," "*sometimes*" and "*often*"); however, 81.65% reported that they never or seldom posted their own comments on news websites (M = 1.81, SD = 0.78, on the same 1-4 scale).

Considering that GMO related topics are often fraught with uncertainty and misconceptions, we also asked several topic-related questions to gauge people's perceptions and behavior status concerning GM foods consumption and GMO label checking. The results indicated that almost all participants (96.29%) had heard of GM foods and 81.51% had heard of GM food labels before the study date. Of those who responded that they had heard of GM foods before, about half of them (47.29%) thought that scientists do not yet have a clear understanding about the health effects of GM foods, while 32.92% thought that scientists do have a clear understanding and the rest, 19.79%, were unsure, suggesting a lack of consensus perception about the scientific certainty of the GM foods among the participants. Such a diverse perception pattern was also observed when they were asked to rate their own opinions on whether eating GM foods is generally safe or unsafe on a 5-point scale (ranging from "*very unsafe*" to "*very safe*"), such that while about half of them (49.04%) thought GM foods consumption is either "*probably safe*" or "*very safe*," a substantial proportion of the sample (34.50%) also held the opinion that eating GM foods is either "*probably unsafe*" or "*very unsafe*." Behavior-wise, interestingly, while more than one third (34.6%) of the participants reported that they purchased GM foods in the past week and 23.6% reported that they did not, a large proportion of the sample (41.8%) was unsure whether they purchased GM foods or not during the past week.

Stimulus Materials. Following the same procedures in the pilot study and study 1, we also modified real news articles from top news outlets to create a news article that talked about GM foods and GMO labels in general but remained valence-neutral and norm-free towards GMO label checking behavior. Similarly we also collected actual comments appearing on online news websites, and chose 22 themes or topics related to GM foods (nine positive themes: "*less risk*," "*not the worst thing in food*," "*environmentally friendly*," "*future of agriculture*," "*scientists' endorsement*," "*off-season food availability*," "*less expensive*," "*health benefits*," and "*reduce world hunger*"; nine negative themes: "*unsafe*," "*harm ecosystem*," "*long-term effects*," "*agricultural monopolization*," "*lack of genetic variation*," "*glyphosate*," "*no economic value*," "*allergies*," and "*create superweeds*"; four neutral themes: "*free choice*," "*lack of knowledge to judge*," "*two sides*," and "*different voices*."). We then developed the label checking norm and non-checking norm versions based on the no-norm version of each theme. We applied the same comment allocation algorithm we used in the prior experiments to ensure that the comments each participant saw were balanced in valence (four positive themes, four negative themes, and two neutral themes, all randomly selected from the pool of themes described above), were mixed with 8:2 or 2:8 ratio of checking norm and non-checking norm comments, based on the conditions they were assigned, and were presented in a random order.

Measures.

Constructed descriptive norm perceptions. Similar to Study 1, we used two questions to assess whether participants would be able to perceive the numerical majority in behavior choices as expressed in the comments, i.e., whether they perceived that the comments were posted mostly by people who check for GMO labels or those who know others that check them, or the other way around. The two items (after reverse coding the second) were significantly correlated with each other ($r = .69$, $p < .001$). We then averaged the two items (after standardization) to serve as the constructed descriptive norm perceptions variable in our analysis.

Reality descriptive norm perceptions. To assess our focal dependent variable, people's descriptive norm perceptions towards GMO label checking behavior in the real world, we used the same two sets of questions as in the pilot study and in Study 1. The first set of items ($N = 7$) asked participants to estimate behavior prevalence among different reference groups. Take the reference group "people in the U.S." for example, we asked "*If you had to guess, how many people in the U.S. have checked for GMO labels to see whether a food product contains any GMO ingredients at least once when shopping for groceries in the past week?*" Compared to Study 1 where we assessed the prevalence estimation of e-cigarette use in general, in the current study, we decided to frame these questions with more clarity in terms of the behavioral goal (i.e., *to see whether a food product contains any GMO ingredients*). This decision was made based on the consideration that the interpretation of the behavioral goal could be to check either a product *contains* or *is free from* GMO ingredients. In addition, considering that checking for product labels is a relatively frequent and easy behavior to perform during grocery shopping, leaving the behavior frequency and time frame ambiguous may lead to an unintended ceiling effect, i.e., people estimate that everyone does so every now and then. Therefore, we also specified behavior frequency and time frame (i.e., *at least once when shopping for groceries in the past week*) for the GMO label checking behavior questions. The items yielded moderately high reliability with Cronbach's $\alpha = 0.85$ based on the standardized seven items. We also measured descriptive norm perceptions by asking the participants to indicate how much they agree or disagree with statements about the prevalence of GMO label checking ($N = 6$) on a 5-point Likert-type scale. We applied the same statement structures used in the predecessor studies to the six GMO label checking related statements by replacing "*vape or use e-cigarettes*" with "*check for GMO labels to see whether a food product contains any GMO ingredients*." After reverse coding the second and fourth items, higher scores on the 5-point scale indicated higher descriptive norms perceptions (Cronbach's $\alpha = 0.88$ based on the standardized six items).

Based on the observations that the two sets of items (after standardization) were highly correlated ($r = 0.67$, $p < .001$), and that combining all 13 standardized items yielded the highest reliability (Cronbach's $\alpha = 0.91$) with removal of any single item resulting in reduced Cronbach's α, the standardized 13 items were then averaged to create an overall reality descriptive norm perception variable which served as the focal outcome variable in the analysis.

Intention. We also asked the participants to indicate how likely they would check for GMO labels to see whether a food product contains any GMO ingredients during their next visit to a grocery store, with the same 4-point Likert scale used in Study 1. Higher scores indicate greater intention to check for GMO labels. Participants' intentions regarding checking for GMO labels were quite divided (M = 2.46, SD = 0.87), with about half of them responding with the answer "*definitely will not*" and "*probably will not*" (50.59%), and the other half "*definitely will*" and "*probably will*" (49.41%).

Valence perceptions. To assess valence perceptions, we asked the participants in the treatment conditions and the news-only condition to indicate whether the news article and the comments were mostly in favor of or against checking for GMO labels on foods on a 5-point scale ranging from "*strongly disagree*" to "*strongly agree*." Substantial correlations were observed for both news valence and comment valence perception measures (r = 0.42, p < .001 for the two news valence measures; r = 0.43, p < .001 for the two comments valence measures). We then created news and comments valence perceptions variables separately by averaging the two items measuring each.

See Appendix G for details on question wordings, question sequence, programming instructions, and skip patterns used in Study 2.

Results

Testing for random assignment. One-way ANOVAs were conducted to examine whether systematic differences existed among the experimental groups with respect to age, gender, education, race/ethnicity, topic familiarity, previous GM foods purchase behavior, perceived scientific uncertainty towards GM foods, perceived safety of GM foods consumption, comments reading and posting habits. The results confirmed that the random assignment to conditions was successful, with *p*-values ranging from 0.10 – 0.81.

Manipulation check. We first examined whether participants in the High-prevalence and Low-prevalence conditions had significantly different perceptions of the behavior choice distributions as reflected through the online comments. Mean constructed descriptive norm perceptions for each condition were summarized in Table 4.4. Planned contrasts confirmed that, participants in the two High-prevalence conditions (M = 0.56, SE = 0.05) on average were more likely to agree that the comments they read were posted mostly by people who check for GMO labels or those who know other people that check them (F (1, 383) = 230.79, p < .001, Cohen's d = 1.53), compared to those in the Low-prevalence conditions ((M = -0.55, SE = 0.06). Therefore, H1 was supported. In terms of valence perceptions, participants in the news-only condition rated the news article as having a relatively more positive viewpoint towards GMO label checking compared to the midpoint of the scale (M = 3.46, SD = 0.70, t(101) = 6.69, p < .001). We discuss limitations associated with this result and future directions in later sections.

Table 4.4

Mean Perceived Constructed and Reality Norms of Checking GMO Labels across Conditions

Conditions	Sample Size	Constructed Norms	Reality Norms
	n	*M* (*SE*)	*M* (*SE*)
1. High-prevalence 10 comments	96	0.53 (0.07)	0.07 (0.07)
2. High-prevalence 20 comments	96	0.60 (0.07)	0.11 (0.07)
3. Low-prevalence 10 comments	98	-0.42 (0.09)	-0.10 (0.07)
4. Low-prevalence 20 comments	97	-0.69 (0.07)	-0.07 (0.08)
5. News-only Control	102		-0.07 (0.07)
6. Baseline Control	104		0.06 (0.07)

Note: Means and standard errors were calculated based on standardized items.

Hypothesis testing. We next examined our focal hypothesis H2 which predicted that participants in High-prevalence conditions on average have significantly higher reality descriptive norm perceptions compared to that in the Low-prevalence conditions. Mean reality descriptive norm perceptions for each condition were also summarized in Table 4.4. As predicted, results from the planned contrast showed a significant difference between High- and Low-prevalence conditions (F (1, 587) = 6.25, p = .01, Cohen's d = 0.25). The two High-prevalence conditions produced significantly higher reality descriptive norm perceptions (M = 0.09, SE = 0.05) than the two Low-prevalence conditions (M = -0.08, SE = 0.05). H2 was confirmed. There was no difference in reality descriptive norm perceptions varying total exposure dosage (R1 and R2) when comparing conditions within the same norm direction (two High-prevalence conditions: F (1, 587) = 0.10, p = .75; two Low-prevalence conditions: F (1, 587) = 0.12, p = .73).

To make sure that reading the news article would not change individuals' reality descriptive norm perceptions from the baseline, we next compared the news-only control and the no-message baseline control condition. While the average descriptive norm perceptions in the news-only condition were slightly lower than those in the baseline condition as shown in Table 4.4, however, results from the planned contrast indicated that the difference was not statistically significant (F (1, 587) = 1.65, p = .20). H3 was rejected. Any following analyses involving control conditions will then be examined only against the news-only condition.

The next set of hypotheses are aimed at examining the potential "negativity bias" in the formation of normative perceptions. While we observed this pattern in both the pilot study and Study 1, considering they focused on the same behavior, i.e., vaping or using e-cigarettes, we would like to examine whether such an effect would still hold true in a very different behavior context. We first tested H4, which predicted that High-prevalence conditions on average have significantly higher reality descriptive norm perceptions compared to the control condition. The planned contrast suggested that the difference between the High-prevalence and the news-only control conditions was marginal, F (1, 587) = 3.51, p = .06. H4 was not supported. When comparing between Low-prevalence and the news-only control conditions, no significant difference was observed either, F (1, 587) = 0.04, p = .84. H5 was rejected. This set of results indicated that the "negativity bias" pattern was not replicated in the current study where the target behavior was checking for GMO labels. We provide further discussion on this result later. Figure 4.4 displays significant planned comparisons of reality norm perceptions among conditions as discussed above.

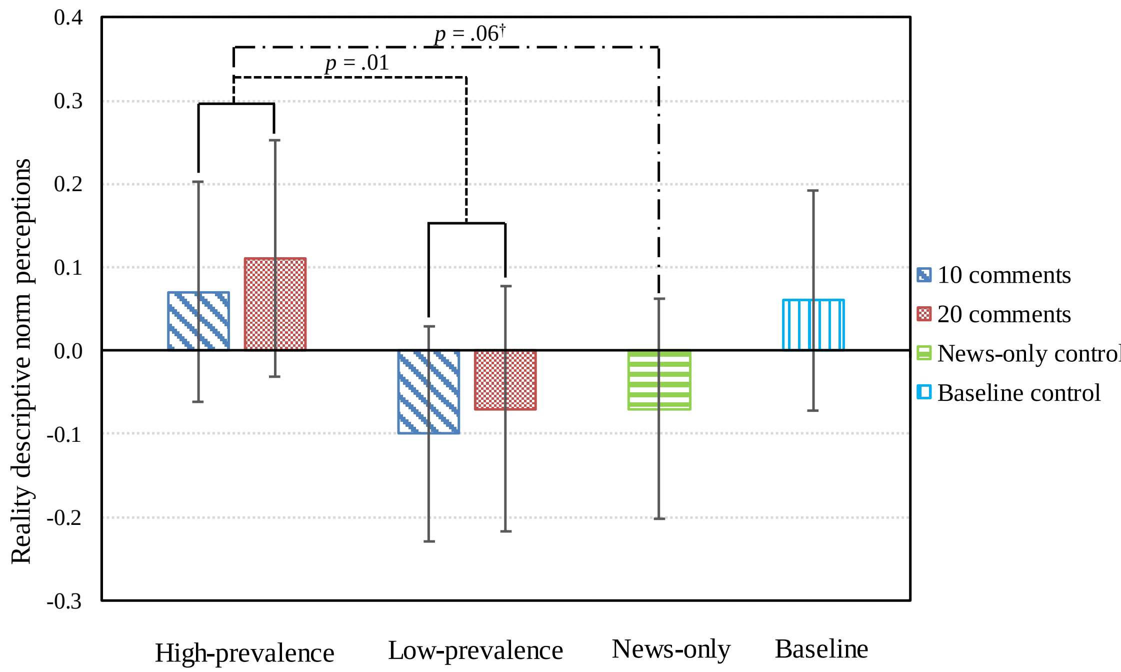

Figure 4.4. Mean perceived GMO label checking reality norms and significant contrasts

Note: Error bars represent 95% CIs. The reality descriptive norm perception measure is an average of the 13 standardized norm items. The significant difference as suggested by planned contrasts was marked with the corresponding p-value. The high-prevalence conditions had significantly higher prevalence estimation than the low-prevalence conditions, and the news-only condition (though the latter comparison was marginally significant).

To examine the potential "spill-over" effects within a different behavior context, we then examined whether the experimentally constructed norm perceptions using online comments could affect people's perceptions about the valence stance of the news article and the comments overall towards the GMO label checking behavior. Table 4.5 summarized news and comments valence perceptions for each condition. Results from the planned contrasts suggested that, first, participants in the Low-prevalence conditions ($M = 3.41$, $SE = 0.05$) did not have significantly different perceptions about news valence compared to that in the news-only condition, $F(1, 484) = 0.35$, $p = .55$. H6 was rejected. Second, no difference was observed either when comparing the High-prevalence conditions ($M = 3.53$, $SE = 0.05$) with the news-only condition, $F(1, 484) = 0.67$, $p = .41$. H7 was not supported. Finally, when the valence perceptions of comments were compared between the High- and Low-prevalence conditions, we observed a significant difference between the two conditions with substantial magnitude ($F(1, 383) = 62.81$, $p < .001$, Cohen's $d = 0.81$), such that participants in High-prevalence conditions on average tended to perceive the comments overall had a more positive viewpoint towards checking for GMO labels on food products ($M = 3.65$, $SE = 0.05$), compared to those in the Low-prevalence conditions ($M = 3.06$, $SE = 0.06$). H8 was supported. Combing evidence above, we consider the "spill-over" effects to be partially supported. The perceptions of news valence were not different across conditions – participants in all conditions seemed to perceive the news article as having a relatively positive viewpoint towards checking for GMO labels; this was further corroborated by a post-hoc overall test across all conditions ($F(4, 484) = 0.77$, $p = .55$). However, on the other hand, comments valence perceptions were affected by the experimental manipulation in the same way as we observed in both the pilot study and Study 1.

Table 4.5

Mean Valence Perceptions and Intention towards Checking GMO Labels across Conditions

Conditions	Sample Size	News Valence	Comments Valence	Intention
	n	*M* (*SE*)	*M* (*SE*)	*M* (*SE*)
1. High-prevalence 10 comments	96	3.52 (0.07)	3.63 (0.07)	2.44 (0.09)
2. High-prevalence 20 comments	96	3.55 (0.08)	3.67 (0.07)	2.45 (0.08)
3. Low-prevalence 10 comments	98	3.40 (0.08)	3.13 (0.09)	2.56 (0.09)
4. Low-prevalence 20 comments	97	3.42 (0.07)	2.98 (0.07)	2.23 (0.09)
5. News-only Control	102	3.46 (0.07)		2.52 (0.08)
6. Baseline Control	104			2.58 (0.08)

Note: The mean scores and standard errors of the three variables were calculated based on the raw scores. News valence and comments valence were measured on 5-point scales ranging from "*strongly disagree*" to "*strongly agree*," with higher scores indicating more positive valence perceptions. Intention was measured by a 4-point Likert scale ranging from "*definitely will not*" to "*definitely will.*" Higher scores indicate greater intentions to check for GMO labels during their next visit to a grocery store.

The next set of hypotheses asked whether our experimental manipulation could affect people's intention towards checking for GMO labels to see whether a food product contains any GMO ingredients during their next visit to a grocery store, and through which way. Mean values for the intention variable for all conditions were summarized in Table 4.5. The planned contrast comparing means of the behavioral intention in the two High-prevalence conditions (M = 2.44, SE = 0.06) and the two Low-prevalence conditions (M = 2.39, SE = 0.07) showed that there was no significant difference in intention between conditions with the two norm directions (F (1, 587) = 0.31, p = .58).

H9 was rejected. The results indicated that there was no direct effect of norm manipulation on intention to check GMO labels.

We then tested whether reality norm perceptions mediate the effects of norm manipulation on intention, such that participants in the High-prevalence conditions on average have significantly higher reality descriptive norm perceptions, which in turn led to significantly higher intentions to check for GMO labels during their next visit to a grocery store, compared to that in the Low-prevalence conditions. We ran the mediation model using bootstrapping procedures with 500 replications. If the bias-corrected 95% confidence intervals surrounding the indirect effects do not include zero, we conclude that the indirect effect is statistically significant. The results showed that, similar to what we found in Study 1, after controlling for the mediator, the norm manipulation remained insignificant in predicting intentions to check for GMO labels, $b = -0.05$ ($\beta = -0.03$), $p = .55$. However, the indirect effect of norm manipulation through reality norm perceptions was found to be significant (indirect effect = 0.10, 95% *CI* [0.04, 0.19]). Normal theory tests of the indirect effect provided identical conclusions ($p = .02$). The full model is shown in Figure 4.5. H10 was confirmed[4].

[4] As we noted earlier, the relationship between reality descriptive norm perceptions and intentions is observational and not experimentally induced. Similar to what we observed in Study 1, intention is also a significant predictor of reality descriptive norm perceptions in Study 2 ($\beta = 0.39$, $p < .001$), indicating that the mediation model may not be the only model that is consistent with the data.

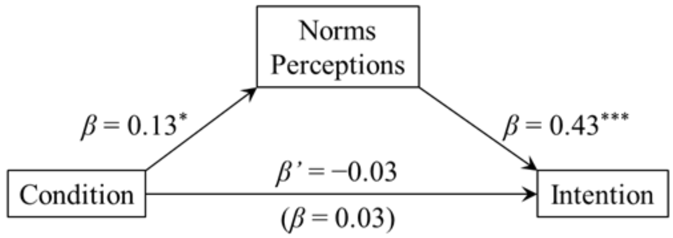

Figure 4.5. Indirect experimental effects on intention through reality norm perceptions

Note: Standardized path coefficients βs are shown in the figure. Condition was coded as 1 = High-prevalence conditions, 0 = Low-prevalence. Reality descriptive norm perceptions and intention were both treated as continuous variables. On the path from condition to intention, the parenthetical value β represents the direct effect without controlling for the mediator, and the value β' outside parentheses represent the effect when the mediator is included in the model. Asterisks indicate significant coefficients (*$p < .05$, ***$p < .001$).

Finally, H11 predicted that our experimental manipulation contributed to explaining significantly more variation in reality descriptive norm perceptions in addition to the demographics and other relevant variables. To test the hypothesis, we ran two multiple regression models, without (Model 1) and with (Model 2) the experimental condition variable, and examine whether the second model significantly improved the model fit. Specifically, in Model 1, we included participants' age, gender, race/ethnicity, education levels, whether they had purchased any GM foods in the past week, topic familiarity (i.e., whether they had heard of GM food labels before), perceived scientific uncertainty, and perceive safety of GM foods consumption. The results of Model 1 are shown in Table 4.6. We then conducted the full model analysis (Model 2), where the experimental condition variable was added on top of all the predictor variables in Model 1. Following our practice in Study 1, considering that the 10-comment and 20-comment conditions did not differ significantly within each norm direction (i.e., High-prevalence and Low-prevalence), we collapsed conditions of the same norm direction, and used a 4-category experimental condition variable (High-prevalence, Low-prevalence, Baseline control, and News-only control which served as the reference category) in the analysis. The maximum likelihood ratio test comparing the two nested models was significant (χ^2 (3) = 9.84, p = 0.02), suggesting that adding the condition variable significantly improved the model fit. H11 was supported. In addition, the results of the multiple regressions also indicated that gender, perceived scientific uncertainty of the health effects of GM foods, and perceived safety of GM foods consumption were predictive of reality descriptive norm perceptions such that females, people who perceived the health effects of GM foods as more uncertain and the consumption of GM foods as less safe were more likely to have higher prevalence estimation of GMO label checking behavior.

Table 4.6

Multiple Regression Models in Predicting Perceived Reality Norms of GMO Label Checking

Predictor Variables	Model 1			Model 2		
	B	*SE*	*β*	*B*	*SE*	*β*
Experimental conditions [a]						
High-prevalence				0.17^*	0.08	0.12^*
Low-prevalence				−0.03	0.08	−0.02
Baseline control				0.11	0.10	0.06
Age	−0.00	0.00	−0.02	0.00	0.00	−0.03
Gender (1 = Female)	0.10^*	0.04	0.11^*	0.10^*	0.04	0.11^*
Race/ethnicity [b]						
Hispanic	−0.06	0.13	−0.02	−0.06	0.13	−0.02

Predictor Variables	Model 1			Model 2		
	B	*SE*	*β*	*B*	*SE*	*β*
African American	−0.05	0.12	−0.02	−0.05	0.12	−0.02
Asian/Pacific Islander	−0.10	0.12	−0.03	−0.11	0.12	−0.04
Native American	0.17	0.50	0.01	0.19	0.50	0.02
More than one	0.25	0.15	0.07	0.26	0.15	0.07
Education [c]	0.01	0.02	0.02	0.01	0.02	0.02
Heard of GMO label						
Yes	0.06	0.08	0.03	0.07	0.08	0.04
Not sure	−0.16	0.14	−0.05	−0.13	0.14	−0.04
GM foods purchase [d]						
Yes	−0.06	0.08	−0.04	−0.07	0.08	−0.05
Not sure	−0.09	0.08	−0.07	−0.11	0.08	−0.08
Perceived uncertainty						
Yes	0.14*	0.07	0.10*	0.14*	0.07	0.10*
Not sure	−0.00	0.08	−0.00	−0.01	0.08	−0.01
Perceived Safety	−0.13***	0.03	−0.22***	−0.14***	0.03	−0.22***
Adjusted R^2		0.062			0.073	

Note. N = 568. *B* = Unstandardized regression coefficients; *SE* = Standard errors of *B*; *β* = Standardized regression coefficients. * $p < .05$, ** $p < .01$, *** $p < .001$.

[a] News-only control condition is the reference category.

[b] Non-Hispanic White is the reference category.

[c] Education was measured as a 14-category ordinal variable ranging from "*Less than 6th grade*" to "*Graduate or professional school degree (MA, PhD, MBA, MD, JD, etc.)*". It was entered as a continuous variable in the two regression models.

[d] Topic familiarity, i.e., ever heard of GMO food labels, was measured with three categories "yes," "no" and "not sure." Considering that the "no" and "not sure" categories both accounted for substantial proportions (13.03% and 5.46%), we thus did not combine the two categories as we did in Study 1. "No" is the reference category.

[e] GM foods purchase in the past week, was measured with three categories "yes," "no" and "not sure." Considering that the "no" and "not sure" categories both accounted for substantial proportions (23.61% and

41.82%), and that the two categories may have different implications on reality norm perceptions, we treated them as separate categories in the regression. "No" is the reference category.
[f] Perceived scientific uncertainty of the health effects of GM foods ("*From what you've heard or read, would you say scientists have a clear understanding towards the health effects of GM foods*"), was measured with three categories "yes," "no" and "not sure." Considering that the "no" and "not sure" categories both accounted for substantial proportions (47.29% and 19.79%), and that the two categories may have different implications on reality norm perceptions, we treated them as separate categories in the regression. "No" is the reference category.
[g] Perceived safety of GM foods consumption ("*In your opinion, is eating GM foods generally safe or unsafe?*"), was measured with a 5-point Likert scale, ranging from 1=*very unsafe* to 5=*very safe*. It was entered in the regressions as a continuous variable.

Discussion

Study 2 successfully replicated the pilot study and Study 1 with respect to the focal hypotheses, i.e., people can perceive and infer the constructed descriptive norms about the target behavior based on the distribution of individual behavior cues on the online comment board, and most importantly, the direction of the perceived norms within this more immediate environment, can in turn affect their descriptive norm perceptions about the reality accordingly. Additionally, we also found that the constructed descriptive norm perceptions affected individuals' intention to check for GMO labels indirectly through the reality norm perception changes. However, there was also some inconsistency observed in the current study.

First of all, the manipulation check suggested that the news article and the comments were perceived as relatively more positive towards checking for GMO labels. Second, the "negativity bias" pattern we observed in the two e-cigarette use studies was not replicated, such that while High-prevalence and Low-prevalence conditions had significantly different reality norm perceptions, Low-prevalence conditions did not differ significantly from the news-only control condition; on the contrary, the difference in normative perceptions between the High-prevalence and news-only conditions is approaching significance ($p = 0.06$). Third, the "spill-over" effects of norm manipulation on valence perceptions were partially supported such that only the valence perceptions of comments showed the same pattern, but not the news valence perceptions.

One observation across the results above suggested that the news-only control condition was involved in all the inconsistencies. We thus examined some potential concerns associated with the news article by looking at the normative perceptions and valence perceptions generated by the article respectively. We observed that the news article was rated as relatively more positive towards GMO label checking behavior. Even though we tried to equally present both the positive and negative sides associated with GM foods and GMO labels as much as possible, with the single article used as the stimuli in the current study, we cannot rule out the possibility that some language used in the article may have been unexpectedly interpreted by the participants as favoring the target behaviors, or some of the evidence we presented in the article was perceived as strongly advocating for the behavior. An alternative explanation is that, no matter how novel or uncertain an object or a behavior seems to be, they do not exist in isolation; instead they are embedded in a relatively thick web of associations with other objects or behaviors. The target behavior itself, checking for GMO labels in our case, may happen to fit into certain schematic categories that trigger people to intuitively think of it as a beneficial behavior. If this is the case, no matter how careful the valence is controlled in the article, people's pre-existing schema may naturally bring in valenced interpretations. However, we have no evidence to confirm either of the speculations.

With respect to the norm perceptions induced by the news article, we observed that, although the news-only condition did not differ significantly from the no-message baseline control condition, after reading the news article, people's prevalence estimation about the GMO label checking behavior was decreased slightly. A close scrutiny of the news stimuli used in the current study led us to speculate that the last paragraph "*With so much debate, the development of national GMO labeling standards has been very slow. Some food companies have already started to voluntarily label their food products as either containing GMOs, or free from GMOs, or partially produced with GMOs, while other companies feel labeling is too much trouble*" (see details of the news stimuli in Appendix F) may have lowered people's normative perceptions. Considering that according to the ASK study (2016), a large proportion of people either thought the labeling of GM food was already mandated by nation-wide laws, or unsure about the regulatory status of labeling (82%), the information about the slow development of the national labeling standard may have lowered the prevalence estimation of GMO label checking behavior by making people think that there were not many food products already labeled as containing GMO on the market. Considering that with the current design, the news article sets the anchoring normative perceptions in the first place, we acknowledge that the use of a single article may be problematic. Future studies should consider solving the potential case-category confounding issue by using a pool of news articles with pre-tested labels of valence and normative perceptions for each, and ensuring that the news each participant sees is randomly drawn from the pool, balanced in valence and normative perceptions.

General Discussion

A post-hoc overall test combining two datasets. Given the results from the two studies, we suspect that if we conduct a more powerful test combining the two datasets, we may be able to observe more convincing evidence that the experimental manipulation produces the same effects across both behaviors. To confirm our speculation, considering that both studies have identical designs and measures as well as comparable sample sizes, we merged the two datasets to perform a post-hoc but more formal and powerful test that examined whether the experimental manipulation in the two datasets which targeted different behaviors produce the same or different patterns in affecting reality descriptive norm perceptions. To be specific, the regression model is summarized as follows:

$$\text{Reality Norm}_i = \beta_0 + \beta_1 \times \text{Condition}_i + \beta_2 \times \text{Behavior}_i + \beta_3 \times \text{Behavior}_i \times \text{Condition}_i + \varepsilon_i$$

Where *Reality Norm* is the continuous reality descriptive norm perceptions variable created by averaging the 13 standardized items measured in each of the studies, *Condition* is a 4-category experimental condition variable (High-prevalence, Low-prevalence, News-only control, and Baseline control which served as the reference category), and *Behavior* is a binary variable with 1 = *vaping or e-cigarette use*, and 2 = *GMO label checking*. We specifically focused on the interaction term in the regression. The results of an omnibus test of the interaction between conditions and behaviors indicated no statistical significance (F (3, 1176) = 1.30, p = .27), suggesting that our experimental manipulation did affect reality descriptive norm perceptions in a consistent way, regardless of behaviors. It is worth noting that the interaction between the news-only condition and the behavior variable was only marginally significant (β = -.10, p = .09), suggesting no differential effect of news on descriptive norm perceptions was found between the two behaviors. We also looked at the main effects of the experimental manipulation after excluding the behavior variable and the interaction term, we again confirmed that the experimental manipulation affected reality norm perceptions in the way such that High-prevalence conditions produced significantly higher reality descriptive norm perceptions compared to that in the Low-prevalence conditions (F (1, 1180) = 16.79, $p < .001$). These tests further corroborate the idea that our experimental manipulation, which constructed behavior choice distributions using online comment boards, affected descriptive norm perceptions about reality in an effective, expected and consistent way, and were observed across two different behaviors.

In addition to reinforcing the main findings of the current study, we also share thoughts and reflections based on inspecting the result patterns of both studies, as well as concerns or limitations that may shed light on future research endeavors in this area.

Online comments affect perceptions about social reality. Although online comments seem to lack some of the important features that make traditional word-of-mouth so influential, nevertheless, in the current study, repeated exposure to such user-generated contents demonstrated a clear influence on people's normative perceptions about social reality. Regardless of the non-representative, atypical nature of the online commenters sample, people still tend to make unwarranted generalizations from these samples to populations (Hamill, Wilson, & Nisbett, 1980; Shi, 2016; Walther et al., 2010). Perhaps one of the most striking observations was that, with the absence of the physical appearance of the commenters and the non-coercive atmosphere of the online comment boards we created, we still observed significant changes in normative perceptions; this may suggest that it is highly likely that the participants' descriptive norm perceptions have been truly affected with private acceptance of the constructed norms, rather than just public compliance, which is often the case in off-line lab experiments (Cialdini & Trost, 1998). In addition, while outcome variables in most of the prior classic conformity studies (Asch, 1951, 1955, Sherif, 1935, 1936) focused on judgments of some aspects of an object that had objective "ground truth" answers (e.g., the length of the lines in Asch studies, and the movement direction and distance of a stationary light in an otherwise dark room in Sherif studies), our findings revealed that the online comments induced norms can effectively change cognitions, in both norm directions, even when the outcome is behavior choice, on which we did not impose objective correctness. This further demonstrates the powerful influence of comments-induced normative perceptions.

Incongruence Bias. Related to the last point, it is noteworthy that the constructed descriptive norm perceptions with comments seemed to be so influential that they may have overridden the anchor norm perceptions set by reading the news article, when the directions of news-induced and comments-induced norms were incongruent. When closely inspecting the result patterns of the two studies (as shown in Figures 4.2 and 4.4), an interesting inconsistency emerged: while comparing the treatment conditions to the news-only control condition, only the Low-prevalence conditions showed significant differences in the estimation of the vaping prevalence (Figure 4.2); however, when the target behavior was checking for GMO labels, only the High-prevalence conditions showed differences in prevalence estimation (Figure 4.4)[5]. These observed opposite patterns ruled out our prior hypothesis of a generalizable "negativity bias" in the formation of descriptive norm perceptions; in fact, both High- and Low-prevalence conditions can produce significantly different descriptive norm perceptions compared to that in the news-only condition.

Even though in neither study was the news-only condition significantly different from the baseline control condition, nonetheless, the direction of each news-only condition was different: for vaping, it produced somewhat more increased descriptive norm perceptions; for GMO label checking, it produced somewhat more decreased descriptive norm perceptions. While these effects were not significant, they provide some basis for speculation about why the Low-prevalence conditions affected normative perceptions about vaping but the High-prevalence conditions affected normative perceptions about GMO label checking. We summarize this speculation under the term: *incongruence bias*.

"Incongruence bias" describes the pattern such that individuals trusted the norm perceptions formed with subjective experiences (through constructed norm perceptions in our case) more than the normative perceptions they inferred from the news article, when the directions of news-induced and comments-induced normative perceptions were incongruent. Take Study 1 as an example, when participants only read the news article

[5] Although the difference of reality descriptive norm perceptions in the High-prevalence and news-only condition was marginally significant (p = .06), considering that we detected a significant difference between the High- and Low-prevalence conditions (p = .01), and the latter (M = -0.08) had essentially the same level of descriptive norm perceptions as in the news-only condition (M = -0.07), we consider the evidence of difference between High-prevalence and news-only conditions clear. The marginally significant effect may be due to power issue, because the news-only condition had only half the sample compared to the merged low and high prevalence conditions.

(i.e., in the news-only condition), according to Figure 4.2, their descriptive norm perceptions about e-cigarette use were slightly increased compared to the baseline, though the difference was not significantly different. The descriptive norm perceptions of the participants in the Low-prevalence conditions, however, after reading the comments and perceiving the e-cigarette use norm was low on the comment board, corrected the slightly increased norm perceptions which were anchored by reading the news earlier, to be significantly lower than those who only read the news article. In the treatment conditions that had a congruent direction of normative perceptions with the news article (i.e., the High-prevalence conditions in Study 1), reading comments neither enhanced the anchor norm perceptions set by the news article significantly, nor dissolved the effect of news article by driving the normative perceptions down.

In other words, people seem to trust the normative perceptions constructed with subjective experience and through their own efforts more. Such perceptions affect their judgment about reality above and beyond the information conveyed by news. If the news-induced norms and the comments-induced norms are incongruent, people are more likely to treat their own perceived norms (i.e., comments-induced norms), regardless of the potential problems associated with the sources of behavior cues, as the ground truth, and produce even more discrepant normative perceptions against the anchor set by the news article. Such a phenomenon is very similar to what was observed previously when discrepant sentiment positions were expressed in news and the comments accompanying the news. Lee and Jang (2010) found that when exposed to user-generated comments opposing the position that was advocated in a news article, readers inferred public sentiments based on several unknown others' comments, and thought the actual public sentiment was more discrepant from the news article's position than did those who read only the article. Lee (2012) further argued that people do not normally have an objective standard to evaluate whether media content has any bias, and they tend to infer and trust the "public opinions" they hear from interpersonal settings. Such "interpersonally generated reality" (Eveland & Shah, 2003) may serve as distorted standards in the evaluation of media coverage, and may add to the discrepancy between the stance of the news, and the stance of the "public opinions" they generated from online comments posted by others. Empirical evidence from exemplification research also to some degree corroborates this idea by demonstrating that people's cognitions are more influenced by isolated specific examples narrated by vivid others, than by structural, summarized accounts of the issue and its diverse consequences, and exemplars are often intuitively regarded as being representative (Brosius & Bathelt, 1994; Daschmann, 2008; Gibson & Zillmann, 1994; Ziegele & Weber, 2015; Zillmann, 1999; cf. Betsch, Renkewitz, & Haase, 2013; Peter & Brosius, 2012).

The "incongruence bias" we assumed here remains speculative until the norm direction of news articles is systematically manipulated on top of the current design and the interactive effects between directions of news-induced norms and comments-induced norms can be directly examined, which could be a worthwhile future direction following on the line of the current research. It is also very interesting to examine whether adding normative information in the news article with base-rate information derived from scientific analysis or from public opinion polls could exercise more a powerful influence compared to normative perceptions generated by comments.

In addition to manipulating the norm directions expressed in the news article, it is also important to examine across a diverse range of behaviors, because an alternative explanation, which is independent of any effects that can be produced by the news article, for the observed opposite patterns, could be that the behavior attributes may have created a ceiling or floor that limits the room of normative perception changes with respect to different norm directions. For example, if e-cigarette use is deemed as a relatively unhealthy behavior, greater room for changes may favor the Low-prevalence conditions; in the similar vein, if checking for GMO labels is generally regarded as a benign behavior that won't produce more harms than benefits, then High-prevalence conditions have a higher likelihood to induce significant changes in norms.

Limitations and future directions. As we were initially interested only in the effects of comments-induced norms, we only used one news article in the treatment and control conditions in both Study 1 and Study 2. We also tried to make the news articles as valence-neutral and norm-free as possible. However, manipulation checks showed that the news article, particularly the one in Study 2, was perceived as more positive towards checking for GMO labels than it intended to be. While it is possible that individuals may interpret even the most neutral article as either positive or negative with their own existing schema towards the target behavior described in the article (i.e., "vaping is like smoking, so the news should hold a negative stance," or "checking labels to get more informed cannot be a bad thing, so it is natural that the news should hold a positive viewpoint”), it is also likely that some language used in the article stimuli were perceived as valenced, or some information that was mentioned in the article was perceived as novel knowledge and incurred unexpected valence perceptions. We have no evidence in the current study to speak to either of the possibilities, but either way the use of a single article as the news stimuli in the study design should be considered as a limitation in the current study. Particularly, considering that the effects we observed in the treatment conditions are in fact combined or interactive effects of news and comments consumption, it is even more important that future studies utilize multiple news stimuli to solve the case-category confounding issue as we did for the comments stimuli in the current study. Combining with what we mentioned earlier, the use of a pool of news articles varying valence positions and norm directions can also facilitate exploration of important research questions that could not be addressed with a single news article design in the current study.

Concluding Remarks

Although research on social norms has remained a central and fruitful line of inquiry in communication as well as social psychology, and accumulating evidence has substantially enriched our understanding particularly towards the effects of social norms on cognitions and behaviors, little is known about how people construct estimates of prevalence and internalize normative perceptions in the first place. However, it is crucial to unpack this process, as in many real-life scenarios, people form erroneous prevalence estimates and adjust their behaviors to be aligned with the misidentified norms (Noelle-

Neumann, 1993; Prentice & Miller, 1993; Shelton & Richeson, 2005; Weaver et al., 2007).

On a theoretical level, this work contributes to our knowledge about this construction process by elucidating an underlying mechanism of how people's normative perceptions about social reality come into being through their acute sense and identification of a behavior choice distribution in a more immediate environment. Such behavior prevalence perceptions formed through their subjective experiences and "quasi-statistical sense" are insensitive to the sources (as well as the credibility and representativeness associated with the sources) from which they derive, and are used by them as credible anchors to infer real-world behavior prevalence. This observation is consistent with findings from previous research where even repetitive exposure to a single voice can sound like a chorus and create an illusion of consensus within the broader social group (Weaver et al., 2007). Based on the empirical findings in our study, we also proposed future lines of inquiry that tap into the dynamics of news-induced and comments-induced normative perceptions, and how they together may contribute to enriching our understanding in the formation process of social influence in the evolving media landscape.

On a practical level, the findings from this work provide a promising path of influence to health interventions that employ normative appeals. Now we understand that perceived norms acquired through subjective experiences can effectively influence reality norm perceptions, which may in turn contribute to driving behavior changes, a priority goal for health campaigns or interventions utilizing normative appeals is to effectively develop desirable perceived norms within a relatively more immediate environment, and help people achieve a common understanding of the world, or shared reality. In addition, the increasingly participatory and interactive web media platforms, such as social media or different sorts of online user-generated comment boards, have greatly expanded the means through which individuals can more easily get exposed to opinions and behavioral information of others, beyond their strong social ties (Walther & Jang, 2012). These new features of the current media environments also provide unprecedented opportunities to help achieve the goal of norm perceptions construction. For example, one potential application of the study findings would be to design health interventions by constructing online social groups with carefully designed behavior choice distribution. Applying the experiment setup in real-life settings, online social discussion groups can be constructed with intended behavior prevalence distribution based on measures of individuals' real baseline behavior status, to promote the ultimate desirable behavior changes among the within-group behavior choice minorities.

CHAPTER 5.

EXPOSURE DOSAGE ON DESCRIPTIVE NORM PERCEPTION FORMATION: HOW MUCH MUST I HAVE BEFORE I CONFORM?

Introduction

One of the critical questions left unanswered in the pilot study was whether the number (i.e., 10 and 20) and the distribution of normative message exposure (i.e., 7:2:1) we specified, reflected the overall picture of the underlying mechanism of reality descriptive norm perception formation. Are 10 comments not enough to trigger the formation of prevalence perception? Is 70 percent the best definition of "critical mass"? What is the "tipping point" that spurs the "quasi-statistical organ" to form a sense of prevailing dominance in behavior choices? Which aspect of an exposure threshold is more important: the percentage of messages with different normative directions? The total number of message exposures? Or potentially some combination of both? Is it important that all the normative message exposure is unanimous in normative directions? We observed in Chapter 4 that when specifying the dominant behavior distribution ratio as 8:2, participants in the same norm direction conditions but with different total exposure (i.e., 10 vs. 20 comments) form reality descriptive norms with a similar magnitude and in the same expected direction. This result further suggested that the behavior distribution ratio (i.e., percentage of messages with different normative directions), and/or total number of exposures may independently or jointly affect the likelihood and magnitude of descriptive norm perception formation. Therefore, in the current study, we would like to systematically investigate the exposure threshold question, aiming at delineating a more comprehensive picture of how different components of repeated exposure may affect the formation process of descriptive norm perceptions, and what minimum dosage of exposure is needed for the process to happen.

Before we dive deep into investigations of the exposure – norm relations, we would like to first confirm whether some crucial findings we observed in the previous studies still hold in the current design, where the exposure dosage was varied across different levels. In particular, we would like to understand whether High-prevalence conditions on average still produce significantly higher constructed and reality descriptive norm perceptions, as well as more positive valence perceptions, compared to that of the Low-prevalence conditions. In addition, we would also like to examine whether reading the news article would change the reality descriptive norm perceptions from the baseline. Finally, considering that we have observed a potential "incongruence bias" in the previous studies, we would like to examine in the current study whether High-prevalence, Low-prevalence and all treatment conditions combined are significantly different from the control condition(s) and in which way. To sum up, we hypothesize that:

H1: Participants in High-prevalence conditions on average are more likely to agree that the comments they read were posted mostly by vapers or commenters who know others who vape, compared to those in the Low-prevalence conditions.

H2: Participants in High-prevalence conditions on average have significantly higher reality descriptive norm perceptions compared to those in the Low-prevalence conditions.

H3: Participants in High-prevalence conditions on average tend to perceive the news article as having a more positive viewpoint towards the target behavior compared to those in the Low-prevalence conditions.

H4: Participants in High-prevalence conditions on average tend to perceive the comments overall as having a more positive viewpoint towards the target behavior compared to those in the Low-prevalence conditions.

H5: Reality descriptive norm perceptions are not significantly different between the news-only and no-message baseline control conditions.

If H5 is supported, the analyses conducted to examine R1 – R3 would involve the news-only condition; if H5 is rejected, the analyses would involve both the news-only and the no-message baseline control conditions.

R1: How do High-prevalence conditions overall affect reality descriptive norm perceptions compared to the control condition(s)?

R2: How do Low-prevalence conditions overall affect reality descriptive norm perceptions compared to the control condition(s)?

R3: How do comments in general (i.e., all treatment conditions combined) affect reality descriptive norm perceptions compared to the control condition(s)?

Size of Majority. The widely-known classic Asch conformity studies have shed important light on this line of inquiry (Asch, 1951, 1955, 1956). Asch conducted a series of experiments to understand the power of conformity in social groups, and one of the crucial questions he asked was the "size of majority" that produced the social pressure in groups. In one set of studies, he varied the number of confederates from 1 to 15, and found that while the participant could still keep his independence in judgments on the length of a line when there was only one confederate, the pressure immediately got substantial when the confederate number increased to two such that the participant succumbed to the group pressure and provided the wrong (but dominant) answer about 14% of time. When the number increased to 3, the error rate jumped to 32%. Interestingly, however, Asch found that increases beyond three persons did not substantially increase conformity, and concluded that there might be a ceiling of normative effects produced by the group sizes. Considering that size of majority can be understood as number of repeated exposures to the same opinion, these results suggested that there might be a threshold value or tipping point that defines "critical mass" which is the minimum amount of exposure needed for people to start forming a perception about the dominant normative direction. In the Asch study, the threshold issue was investigated as a linear function of exposure number, specifically the number of exposures to the dominant opinion (i.e., group size of the majority opinion), and the threshold value was found to be three; after this "magic number," the influence of conformity plateaued.

Later studies tried to identify general functional forms to optimally describe how social influence unfolds as group size of the majority influence increases. Latané and Wolf (1981) proposed the Social Impact Theory (SIT), which disagreed that there should be a turning point in majority size, and posited that the larger the majority size, the larger the conformity effect, with each additional group member (holding the majority opinion) having a smaller impact. Motivated by a core principle in psychology, diminishing marginal sensitivity to stimuli (see Kahneman, 2003; Stevens, 1957), the authors modeled the social influence process mathematically with a power function that defined the amount of social impact as being equal to the power of the number of influence sources (i.e., majority size), which was manifested as a negatively accelerating curve. Tanford and Penrod (1984), on the other hand, challenged the SIT model and argued that it is impossible that additional group members will always bring in additional impacts, and there should be a limit or threshold where majority could not exert further influence. They thus developed the Social Influence Model (SIM), an S-shaped non-linear growth function to describe the relation between group size and social influence. Mullen (1983, 1987) took into consideration not only the influence from the majority, but also the minority, the group which the unwitting participant belongs to. Mullen proposed to use Other-Total Ratio (OTR; See also Stasser & Davis, 1981) to describe how the increase in the majority size (in the meantime the decrease in the minority size), may exert social influence by raising the minority individual's self-attention about the heightened unpopularity of his or her own position. In more recent years, MacCoun (2012) developed a series of burden-of-social-proof models (BOP), where he proposed two crucial parameters, *norm location*, the position of the exposure threshold and *norm clarity*, the extent to which the operative threshold is indeed a shared convention, to account for the relationship between majority size and conformity across paradigms and disciplines. With simulation results, MacCoun pointed out that both location and clarity can vary considerably across domains, and particularly, if clarity is low, it is less likely that a "tipping point" or threshold inflection will be observed.

The brief overview of the previous efforts trying to capture the relationship between majority size and conformity provides food for thought in our endeavor of understanding the underlying process of normative perception formation (for more detailed reviews, see Bond, 2005; Levine & Scott, 2015; MacCoun, 2012). First of all, except for Mullen (1983, 1987), most of the previous studies focused on situations where one-person minorities responded to social influence from unanimous majorities of varying group sizes, without accounting for the potential influence from the minority. In today's unprecedentedly proliferated media platforms, mixed information, diverse opinions and ideas make an unequivocal information environment almost impossible. Thus, it is crucial to consider mutual influence from both majority and minority groups, as well as the reciprocal interactive dynamics between them. Secondly, almost all the prior studies in this area assumed that the target participant initially took the minority stance in the group. The situation where the participant's original opinion or behavior status was either unknown (by the researchers) or uncertain (within themselves) particularly when the topic or the object was less familiar to them, which presumably is a more common scenario in real-life settings, has not been systematically investigated. Thirdly, most of these studies were conducted in face-to-face lab settings where overt pressure to conform was intense (except for the Crutchfield paradigm, see Crutchfield, 1955). Such influence is probably more leaning towards public compliance rather than private acceptance, normative rather than informational, short-term rather than long-term

(Cialdini & Trost, 1998; Deutsch & Gerard, 1955). This idea was also corroborated by Bond (2005) which included 125 Asch-type conformity studies for meta-analysis and found that whether the experimental setup entailed face-to-face interaction (vs. indirect interaction), or participants were required to give a public (vs. private) response, influenced the magnitude of social influence to a great extent. Therefore, examining the issue in more covert settings such as online comment boards that entail no physical appearance of the majority groups, no public responses, and the identities of both the influencers and the influenced are anonymous may help reveal interesting and distinct processes. Finally, almost all of the prior efforts have been devoted to developing a generalized model for prediction and explanation of the majority group influence, and why discrete "tipping points" can or cannot be observed. Bond (2005) made major strides by challenging the dominant assumption that there is a single unitary function that can describe the relationship. It argued that a number of social influence processes can lead to conformity, and that the function should be topic-specific and context-sensitive.

Method wise, the inquiry of exploring the relationship between exposure and social influence was conducted either though face-to-face lab experiments (e.g., Latané & Wolf, 1981; Mullen, 1983; Tanford & Penrod, 1984), observations of the life cycle (i.e., emergence, cascade, and internalization) of actual norm formation among countries (e.g., Finnemore & Sikkink, 1998), or through computer simulations that aimed at modeling real human interactions with artificial agent societies (Andrighetto, Campennì, Cecconi, & Conte, 2010; Hollander & Wu, 2011; MacCoun, 2012; Savarimuthu & Cranefield, 2011). Game theorists also conducted experiments to examine norm formation threshold questions; however, they focused less on individuals' belief changes. Instead, they considered norms as conditioned preferences that are determined by utility, efficiency, equilibrium and potential sanctions (e.g., Bicchieri, 2005; Voss, 2001). To our best knowledge, there have been no studies in the field of communication that have systematically and empirically addressed the exposure threshold issue, particularly in an online setting where social influence may manifest in different ways and functions.

In view of the above considerations, the current study proposes to examine how the social influence process unfolds in the online comment board, particularly how additional exposure to comments that contain normative information may induce descriptive norm perception changes in participants who may not hold strong minority or majority group stances to begin with, as exposure dosages of normative information from the two groups wane and wax systematically. Within the setting of the online comment board on a news website, we are particularly interested in understanding whether we can observe similar shapes or functions of exposure as described in prior studies or identify a unique pattern with our choice of specific topic context and communication modality. In addition, we would like to understand whether there is an exposure threshold that once it is reached, the dominant behavior choice is obvious enough that people start to recognize the descriptive norms within the online comment boards, and strong enough that it starts to influence people's descriptive norm perceptions about the real world. Thus, following the conceptualization of normative exposure from previous studies (i.e., numbers of exposures), we propose the following research question:

R4: What is the relationship between numbers of user-norm comments and reality descriptive norm perceptions?

Other Dimensions of Exposure Dosage. Since public opinions in the real world are almost never unanimous and individuals are often exposed to a mix of descriptive norm information that contains contradictions, we also consider that the percentages of messages with dominant opinions and the total number of messages might matter in the process of descriptive norm perception formation as well. The questions of what the sufficient degree of dominance or prominence of normative information is necessary to beat the opposite side, and whether increase in dominance is still associated with the increment of prevalence estimation after the turning point (if there is a threshold) that initiates the norm cascade (as defined in Finnemore & Sikkink, 1998), could only be effectively quantified and examined with the percentage parameter.

In addition, the size of the overall information pool (i.e., total number of normative messages) might also have implications for how salient the dominant normative information could be in individuals' mental frame of reference such that it is readily available and could serve as a mental shortcut at the time of decision making (Higgins, 1996; Schwarz et al., 1991; Tversky & Kahneman, 1982). On the one hand, a larger sized information pool provides more exposure opportunity to make sure the majority opinions or dominant normative messages reach its audience and potentially lends more credibility to the dominant side with a larger group of people endorsing it; on the other, larger numbers of total messages could, in the meantime, also increase the exposure to the opposite normative information (assuming the percentage is kept constant) thus diluting the salience of the dominant descriptive norm, and decreasing the prevalence estimation. Therefore, in addition to examining the number of exposure to comments with the dominant norm direction, we also take into consideration of its interaction with the number of total exposures to messages, to delineate a more complete picture of the normative perception formation process.

R5: What is the relationship between percentages of user-norm (vs. non-user norm)[6] comments and the reality descriptive norm perceptions?

R6: Are there any interaction effects between percentages of user-norm comments and total numbers of comments?[7]

The Role of Unanimity. Another intriguing pattern detected by previous conformity studies was that unanimity plays an important role in affecting the dynamics of social influence in groups such that the existence of even one dissenter (no matter whether he was in support of the participant or not) to the majority opinion in the group would remarkably disturb the power dynamics in the group, free up the participant from group pressure, and decrease yielding to the wrong answers significantly (Asch, 1955). The presence of the crucial dissenter that substantially counteracted the conformity effects observed in the Asch study makes us ponder on the potentially different impacts of unanimous norm (i.e., all messages are consistent in one normative direction) and

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[6] In the current study, we followed our practices in Chapter 4 and only included two types of comments across all treatment conditions, i.e., user-norm and non-user-norm. The percentages of non-user-norm comments are therefore linear transformations of the percentages of user-norm comments in each condition. Thus, any effects of percentage of user-norm comments should be considered as in comparison to the effects of the corresponding percentage of non-user-norm comments in that condition.

[7] Considering that number of user-norm comments is highly dependent and significantly associated with the total number of comments ($r = 0.49$, $p < .001$), we only proposed to examine the potential interaction effects between percentages of user-norm comments and total numbers of comments.

dominant norm (i.e., majority of the messages are in one normative direction, while the minority provides normative information in the opposite direction) on normative perception formation. Comparing the two situations would allow us to better understand the extent to which the mere existence of the opposite norm information would make a huge difference and disturbance in people's perceptions and decision. When taking the norm direction into account, we can examine whether the "dissenter" comments affect the reality descriptive norm perceptions to the same extent for both High-prevalence and Low-prevalence conditions. Considering the online comment board setting of the current study, it is also possible that we may not observe the similar patterns found in more traditional lab settings, as participants may raise doubts about the credibility of unanimous online comments as being produced for promotional purposes.

H6: Unanimous High-prevalence conditions on average produce significantly higher reality descriptive norm perceptions, compared to that of the dominant High-prevalence conditions.

H7: Unanimous Low-prevalence conditions on average produce significantly lower reality descriptive norm perceptions, compared to that of the dominant Low-prevalence conditions.

Considering that the overall combined test of the two datasets in Chapter 4 suggested that our experimental manipulation produced consistent influence on descriptive norm perceptions across two behaviors, we still use the same experimental setup to stimulate normative perceptions. We chose vaping or using e-cigarettes, which demonstrated successful experimental manipulation and stable result patterns in both pilot study and its replication study, as the target behavior in the current study.

Method

Study Design and Procedures

The overall study design, particularly the experimental procedures each participant went through, was fundamentally similar to that in Chapters 3 and 4, but with much more elaborated treatment conditions. To most systematically examine the exposure threshold issue in the process of descriptive norm perception formation, we took into consideration sources of potential influence, total numbers of comments and percentages of user-norm comments in each condition. We followed our practices in Chapter 4 and only included two types of comments, user-norm and non-user norm comments in the design. Therefore, percentages of non-user-norm comments are linear transformations of the percentages of user-norm comments in each condition (i.e., 20% user-norm comments conditions equal to 80% non-user-norm comments conditions). Considering that we observed significant effects in the 20-comments conditions in both the pilot and replication studies, we set the maximum total number of comments to be 20, and we varied the total number of comments from 1 to 20 across conditions, with an increment of 1. In a similar vein, we also set the number of user-norm comments to vary from 0 to 20 (with the upper limit to be the total number of comments in each condition), with an increment of 1. We then listed all possible combinations varying the two variables. In this way, we could also calculate the percentages of user-norm comments in each condition. Table 5.1 visually demonstrated all the 230 combinations with total number of comments on the x-axis and number of user-norm comments on the y-axis, and each cell showing the percentage of user-norm comments.

The 230 combinations could be divided into 5 categories: 1) Unanimous Low-prevalence conditions: all of the comments contain non-user-norm (i.e., the number of user-norm comments equals to 0; cells highlighted in purple, n = 20); 2) Dominant Low-prevalence conditions: the conditions where user-norm percentages are lower than 50% but higher than 0% (cells highlighted in blue, n = 90); 3) Balanced norm conditions: the conditions where user-norm and non-user-norm comments have an equal number, or the user-norm percentage equals to 50% (cells highlighted in yellow, n = 10); 4) Dominant High-prevalence conditions: the conditions where user-norm percentages are higher than 50% but lower than 100% (cells highlighted in orange, n = 90); 5) Unanimous pro-norm conditions: all of the comments contain user-norm (i.e., the number of non-user-norm comments equals to 0; cells highlighted in red, n = 20). In addition to the treatment conditions, we also included a news-only control condition, and a no-message baseline control condition to obtain the anchoring descriptive norm perceptions. Therefore, in total we have 232 conditions (230 treatment conditions and 2 control conditions) in the current study.

Table 5.1 *All Possible Exposure Conditions Varying Total Number of Comments and Number of User-Norm Comments*

Total # \ User-norm #	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.0%	100.0%																			
2	0.0%	50.0%	100.0%																		
3	0.0%	33.3%	66.7%	100.0%																	
4	0.0%	25.0%	50.0%	75.0%	100.0%																
5	0.0%	20.0%	40.0%	60.0%	80.0%	100.0%															
6	0.0%	16.7%	33.3%	50.0%	66.7%	83.3%	100.0%														
7	0.0%	14.3%	28.6%	42.9%	57.1%	71.4%	85.7%	100.0%													
8	0.0%	12.5%	25.0%	37.5%	50.0%	62.5%	75.0%	87.5%	100.0%												
9	0.0%	11.1%	22.2%	33.3%	44.4%	55.6%	66.7%	77.8%	88.9%	100.0%											
10	0.0%	10.0%	20.0%	30.0%	40.0%	50.0%	60.0%	70.0%	80.0%	90.0%	100.0%										
11	0.0%	9.1%	18.2%	27.3%	36.4%	45.5%	54.5%	63.6%	72.7%	81.8%	90.9%	100.0%									
12	0.0%	8.3%	16.7%	25.0%	33.3%	41.7%	50.0%	58.3%	66.7%	75.0%	83.3%	91.7%	100.0%								
13	0.0%	7.7%	15.4%	23.1%	30.8%	38.5%	46.2%	53.8%	61.5%	69.2%	76.9%	84.6%	92.3%	100.0%							
14	0.0%	7.1%	14.3%	21.4%	28.6%	35.7%	42.9%	50.0%	57.1%	64.3%	71.4%	78.6%	85.7%	92.9%	100.0%						
15	0.0%	6.7%	13.3%	20.0%	26.7%	33.3%	40.0%	46.7%	53.3%	60.0%	66.7%	73.3%	80.0%	86.7%	93.3%	100.0%					
16	0.0%	6.3%	12.5%	18.8%	25.0%	31.3%	37.5%	43.8%	50.0%	56.3%	62.5%	68.8%	75.0%	81.3%	87.5%	93.8%	100.0%				
17	0.0%	5.9%	11.8%	17.6%	23.5%	29.4%	35.3%	41.2%	47.1%	52.9%	58.8%	64.7%	70.6%	76.5%	82.4%	88.2%	94.1%	100.0%			
18	0.0%	5.6%	11.1%	16.7%	22.2%	27.8%	33.3%	38.9%	44.4%	50.0%	55.6%	61.1%	66.7%	72.2%	77.8%	83.3%	88.9%	94.4%	100.0%		
19	0.0%	5.3%	10.5%	15.8%	21.1%	26.3%	31.6%	36.8%	42.1%	47.4%	52.6%	57.9%	63.2%	68.4%	73.7%	78.9%	84.2%	89.5%	94.7%	100.0%	
20	0.0%	5.0%	10.0%	15.0%	20.0%	25.0%	30.0%	35.0%	40.0%	45.0%	50.0%	55.0%	60.0%	65.0%	70.0%	75.0%	80.0%	85.0%	90.0%	95.0%	100.0%

Unanimous Low-prevalence Conditions | **Dominant Low-prevalence Conditions** | **Balanced Conditions** | **Dominant High-prevalence Conditions** | **Unanimous High-prevalence Conditions**

Note: All percentages were calculated by dividing the number of user-norm comments by the total numbers of comments.

While it would be ideal to examine all the conditions listed in Table 5.1, it is very inefficient and prohibitively expensive if we want to ensure that each of the cells would have enough power to detect any significant effect, making the traditional "test and control cell" method almost impossible. In view of this situation, instead of conducting traditional analyses where treatment conditions are compared to control conditions or planned contrasts are performed among treatment conditions, we treated all cells (i.e., all eligible combinations of total numbers and user-norm numbers as listed in Table 5.1) as point estimates that are used to estimate best-fit models. In this way, the sample size required for each cell is sharply less, as we do not claim to have a stable estimate for each cell. By doing this, our goal would be to examine the fit of equations representing possible hypotheses about the functional forms of the coefficients and the shapes of the associations rather than comparing among cells, which requires great statistical power. This would allow us to compare across a wide range of different possible shapes and hypotheses related to exposure threshold. The two control conditions, however, will still need to have stable estimates and sufficient power to allow direct comparisons. Therefore, we still randomly assigned eligible participants to one of the experimental conditions, but with n = 5 as the quota for each of the 230 treatment cells, and n = 70 for each of the two control conditions, which was just above the minimum required sample size (i.e., n = 67) that can produce a reliable point estimate to allow later comparisons as determined by the power analysis.

As in the previous studies, the current study also used online Qualtrics-based surveys, distributed through MTurk. A similar set of experiment procedures was employed as well. Participants in the treatment and the news-only control conditions first read a short news article about e-cigarettes (with no normative information and balanced in tone towards the behavior), and those in the no-message baseline control condition were directly brought to the outcome measure assessment pages without being exposed to any reading materials. After reading the news article, participants in the news-only control group were assessed for their descriptive norm perceptions towards e-cigarette use and other outcome measures. For participants assigned to treatment conditions, they then read comments that varied in total number and number of user-norm, depending on the conditions (among 230 conditions) they were assigned to, before their descriptive norm perceptions were assessed. The comment allocation was made to maximally address the case-category confounding issue in the way such that each participant saw a different set of comments randomly drawn from our comments pool based on his/her condition assignment. That is to say, even for participants in the same cell, although the total number and number of comments that contain user-norm they saw were fixed, the specific comment combination generated for each of them was different. For conditions where the total number of comments ≤ 10, only one page of comments was displayed. For conditions where total number of comments > 10 but ≤ 20, two pages of comments were displayed, and participants were instructed to click on "continue" to read the second page after they finished reading the first 10 comments. Demographics and other measures were assessed at the end. See Appendix G for details on question wordings, question sequence, programming instructions, and skip patterns used in the current study.

Participants

A total of 1303 U.S. adults were recruited through MTurk. We requested high-quality MTurk workers (who had above 97% approval ratings and who had been approved more than 100 times), and allowed only those who passed the screening test of the "foil" question to enter the experiment. More than half of the participants were female (53.26%), and the mean age of the sample was 37.78 (*SD* = 12.49), ranging from 18 to 87. Most of the sample had finished high school (89.10%) and 51.80% had finished college. Majority of the participants were Non-Hispanic White (76.52%), 7.75% Non-Hispanic African American, 6.22% Non-Hispanic Asian/Pacific Islander, 6.37% Hispanic/Latino, and 3.15% more than one race. Most of the participants had heard of vaping or using e-cigarettes before the study date (97.08%). Among those who had heard about the topic, a sizeable portion had ever used an e-cigarette, including one or two puffs (42.85%). About half of the sample (49.58%) had smoked 100 cigarettes or more in their lifetime.

Stimulus Materials. The same news article and comments pool from Study 1 in Chapter 4 was used in the current study, but to facilitate the examination of the unanimous conditions (when number of total comments equals to 20), we added in two additional themes, with one being positive (i.e., *stress relief*), and the other negative towards e-cigarette use (i.e., *addiction*). See Appendix C for the news article and the comments stimuli; the notes underneath the comments pool table described in detail which comments were newly added and which comments were modified for cleaner manipulation after the pilot study. As in the previous studies, we also developed a comment allocation algorithm to ensure that the comments each participant saw were balanced in valence (i.e., half positive and half negative towards e-cigarette use), if the total number of comments was an even number. For conditions where total number of comments was an odd number, we programmed the randomization algorithm in a way such that the possibility of negatively-valenced comments being the mode (i.e., has one extra comment compared to the number of positively-valence comments), and the possibility of positively-valenced comments being the mode remained equal. In this way, the comments across conditions where total exposures were odd numbers on average remained balanced in valence. The algorithm also made sure that the order of the comments was randomized before presentation to the participants.

Measures

Constructed descriptive norm perceptions. For participants in the treatment conditions, the same set of the two questions as in the pilot study and Study 1 was used to assess whether they would correctly perceive the numerical majority in behavior choices through comments. The two items (after reverse coding the second) were highly correlated (r = .78, p < .001). We thus averaged the two items (after standardization) to create the constructed descriptive norm perceptions variable.

Reality descriptive norm perceptions. Following our practice in the previous studies, the reality descriptive norm perceptions about e-cigarette use in the real world were assessed with two sets of questions. The first set of questions asked participants to gauge the prevalence of e-cigarette use among seven different reference groups (Cronbach's α = .82 based on the standardized items). The second set of questions asked participants to indicate how much they agreed or disagreed with six statements about e-cigarette use prevalence (Cronbach's α = .84 based on the standardized items). The average scores of the two question sets were significantly correlated (r = 0.69, p < .001). We thus combined the 13 standardized items and observed the highest reliability (Cronbach's α = .89). Therefore, the 13 standardized items were then averaged to create an overall reality descriptive norm perceptions variable to serve as the focal outcome variable in our analysis.

Valence manipulation check variables. To make sure that the valence or tone towards e-cigarette use is perceived as neutral and balanced in both news article and comments as we intended, we asked the participants in the news-only condition, and the participants in the treatment conditions, to indicate respectively whether the news article and the comments are in favor of or against e-cigarette use on a 5-point scale ranging from "*strongly disagree*" to "*strongly agree.*" Substantial correlations were observed for both news valence and comment valence perception measures ($r = 0.56$, $p < .001$ for the two news valence measures; $r = 0.74$, $p < .001$ for the two comments valence measures). We then created two valence variables, news valence and comments valence separately by averaging the two items measuring each.

See Appendix E for details on question wordings, question sequence, programming instructions, and skip patterns used in the current study.

Results

Testing for Random Assignment

To ensure that there were no differences among the experimental groups with respect to age, gender, education, race/ethnicity, topic familiarity, e-cigarette use status, and established smoking status, we conducted tests for success of random assignment.

Considering that the limited sample size for each of the treatment conditions may yield unstable estimations of the demographics distribution, we combined the cells based on major norm directions to make sure the sample size for each comparison category is more comparable. To be specific, we created a five-category variable that included baseline control condition, news-only control condition, Low-prevalence treatment conditions (percentages of user-norm comments range from 0% to 40%), Balanced treatment conditions (percentages of user-norm comments range from 41% to 60%), High-prevalence treatment conditions (percentages of user-norm comments range from 61% to 100%). It is worth noting that we broadened the range of the balanced treatment conditions because the cells that had exactly 50% of user-norm comments included only a small group of participants ($n = 51$), we therefore expanded the range so that the current Balanced conditions included $n = 209$ participants, which would produce more stable estimates of the demographics distributions. Chi-square tests suggested that there were no significant differences regarding the demographics variables among the five groups, with p-values ranging from 0.22 – 0.82.

Manipulation Check

A news manipulation check was conducted among participants in the news-only condition, and comments manipulation check was conducted among participants across all the treatment conditions. Our manipulation check confirmed that, participants in the news-only condition rated the news article as relatively balanced ($M = 3.03$, $SD = 0.78$), and was not significantly different from the midpoint (i.e., 3) of the scale ($t(71) = 0.38$, $p = 0.71$). Participants across all treatment conditions on average rated comments valence as relatively more negative towards e-cigarette use compared to the midpoint of the scale ($M = 2.80$, $SD = 0.97$, $t(1156) = -6.92$, $p < 0.001$). This result was consistent with what we observed in the previous Chapters, such that the “spill-over” effects of norm manipulation, and the stronger effects detected within the Low-prevalence conditions, jointly determined that the comments valence perceptions were influenced downwards. We also presented formal hypotheses tests regarding this pattern in the current study, particularly with H4 and R2, in the section below. Considering this “spill-over” effect and that a mean of 2.80 is still close to the balance point on the scale, we do not consider the observed difference as convincing evidence that challenges the effectiveness of the comments valence manipulation.

Hypothesis Testing

We first examined whether the crucial results we observed in the previous studies still held in the current study where the exposure dosage was varied across different levels. We observed that perceived behavior choice distributions within the online comment boards across all levels of exposure were affected by our experimental conditions as expected, such that participants in the High-prevalence conditions (i.e., percentages of user-norm comments range from 61% to 100%) on average were significantly more likely to agree that the comments they read were posted mostly by vapers or commenters who know others who vape, compared to those in the Low-prevalence conditions (i.e., percentages of user-norm comments range from 0% to 40%), F (1, 1155) = 660.71, $p < .001$; Cohen's d = 1.70. H1 was supported. We also confirmed that High-prevalence conditions (M = 0.09, SE = 0.03) on average had significantly higher reality descriptive norm perceptions (F (1, 1296) = 20.52, $p < .001$) compared to that of the Low-prevalence conditions (M = -0.13, SE = 0.03). H2 was supported. Mean constructed and reality descriptive norm perceptions across conditions are summarized in Table 5.2.

Table 5.2

Mean Perceived Constructed and Reality Norms of E-cigarette Use across Conditions

Conditions	Sample Size	Constructed Norms	Reality Norms
	n	*M* (*SE*)	*M* (*SE*)
1. High-prevalence	467	0.62 (0.03)	0.09 (0.03)
2. Balanced	209	0.08 (0.06)	0.02 (0.04)
3. Low-prevalence	483	−0.63 (0.04)	−0.13 (0.03)
4. News-only Control	72	--	0.23 (0.10)
5. Baseline Control	72	--	0.01 (0.08)

Note: Means and standard errors were calculated based on standardized items. Balanced conditions here refer to the conditions where percentages of user-norm range from 41% - 60%. Therefore, dominant High-prevalence conditions here refer to the ones where percentages of user-norm range from 61% - 99%, and dominant Low-prevalence conditions were the ones where the percentages range from 1% - 40%.

Experimental manipulation on norms also affected valence perceptions, such that participants in the High-prevalence conditions perceived the valence of news and comments towards e-cigarette use as significantly more positive compared to that of the Low-prevalence conditions (news: F (1, 1227) = 13.11, p < .001; Cohen's d = 0.24; comments: F (1, 1154) = 443.10, p < .001; Cohen's d = 1.37). H3 and H4 were supported. Mean news and comments valence perceptions towards e-cigarette use are summarized in Table 5.3.

Table 5.3

Mean Valence Perceptions towards E-cigarette Use across Conditions

Conditions	Sample Size	News Valence	Comments Valence
	n	*M* (*SD*)	*M* (*SD*)
1. High-prevalence	467	2.98 (0.81)	3.39 (0.84)
2. Balanced	209	2.84 (0.87)	2.75 (0.84)
3. Low-prevalence	483	2.79 (0.82)	2.26 (0.81)
4. News-only Control	72	3.03 (0.78)	--
5. Baseline Control	72	--	--

Note: The mean scores and standard deviations of the three variables were calculated based on the raw scores. News valence and comments valence were measured on 5-point scales ranging from "strongly disagree" to "strongly agree," with higher scores indicating more positive valence perceptions.

In Chapter 4 Study 1, we observed that while news consumption did slightly increase the reality descriptive norm perceptions from the no-message baseline control condition, the difference was not statistically significant. Based on this observation, H5 predicted that, reality descriptive norm perceptions would not be significantly different between the news-only and no-message baseline control conditions in the current study. Our results suggested that, consistent with what we observed earlier, after reading the news article, participants' reality descriptive norm perceptions were increased (M = 0.23, SE = 0.10) from that in the baseline control condition (M = 0.01, SE = 0.08). We also found that such increase was significant (F (1, 1296) = 4.06, p = .04. Therefore, the prediction of H5 such that there is no significant difference between the news-only and the baseline control conditions was not supported. The increasing pattern in the news-only condition did dovetail with what we observed in Chapter 4.

R1 – R3 asked how treatment conditions affected reality descriptive norm perceptions compared to the control conditions. The results suggested that the reality descriptive norm perceptions in the High-prevalence conditions were not significantly different compared to the baseline control condition (F (1, 1298) = 0.81, p = .37), and were slightly lower compared to the news-only control condition, although such difference was marginal (F (1, 1298) = 3.08, p = .08). When compared to the baseline condition, the Low-prevalence conditions produced slightly lower but not significantly different reality descriptive norm perceptions (F (1, 1298) = 2.81, p = .09); however, when compared to the news-only condition, reading the comments in the Low-prevalence conditions had significantly decreased the reality descriptive norm perceptions anchored by the news consumption (F (1, 1298) = 18.82, p < .001). When combing all the treatment conditions as a whole, we observed that the average reality descriptive norm perceptions across all treatment conditions (M = -0.02, SE = 0.02) were not different from that of the baseline control condition (F (1, 1298) = 0.06, p = .81), but were significantly lower compared to that in the news-only control condition (F (1, 1298) = 8.99, p < .01). This set of results echoed the previous results in that, when the directions are incongruent between news-induced and comments-induced norms, the descriptive norm perceptions formed through reading the news article, will be significantly modified towards the direction of the comments-induced norms after reading the comments. Figure 5.1 summarized the significant comparison results we discussed above. To sum up, the results discussed above almost replicated all the crucial findings we observed earlier in the previous Chapters. Considering that the current study systematically varied the exposure levels, the evidence of consistent patterns speaks to the robustness of our results and conclusions identified in the previous Chapters.

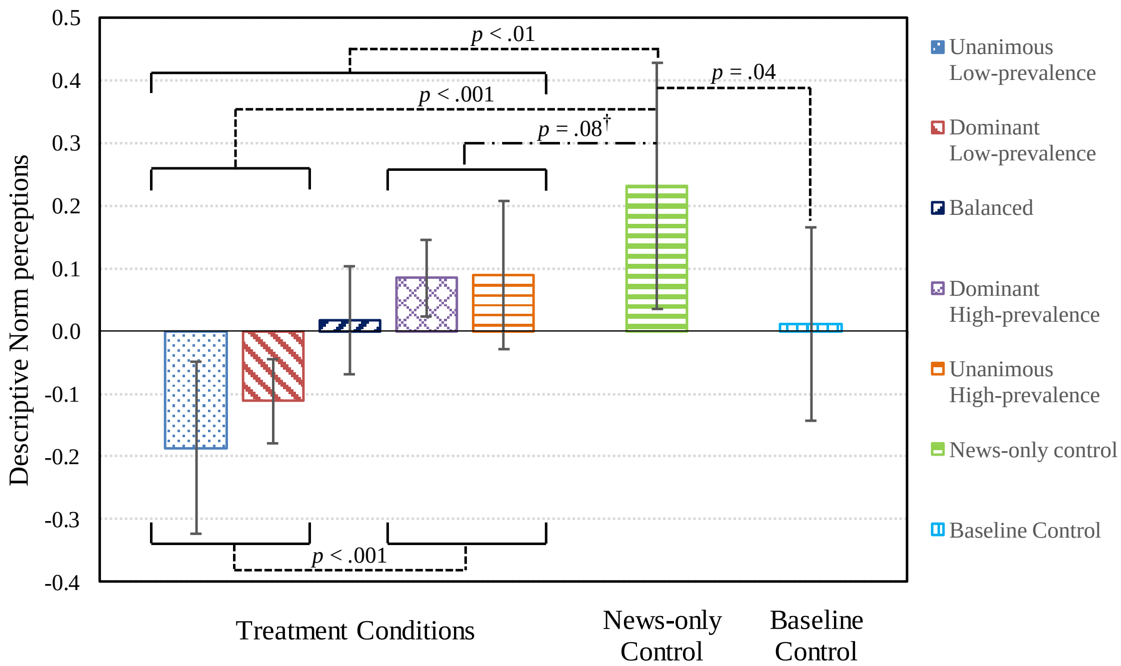


Figure 5.1. Mean perceived e-cigarette use reality norms and significant contrasts

Note: Error bars represent the 95% CIs. The reality descriptive norm perception measure is an average of the 13 standardized norm items. Significant differences were marked with corresponding p-values. Balanced conditions here refer to the conditions where percentages of user-norm range from 41% - 60%. Therefore, dominant High-prevalence conditions here refer to the ones where percentages of user-norm range from 61% - 99%, and dominant Low-prevalence conditions were the ones where the percentages range from 1% - 40%.

We next focused on examining the research questions and hypotheses aiming at exploring the exposure – norm relationships. R4 conceptualized repeated exposure as the number of user-norm comments and asked which functional forms can most optimally describe the relationship between the pure number of user-norm comments and the reality descriptive norm perceptions. To answer this question, we first calculated mean reality descriptive norm perceptions at each level of user-norm numbers. To increase the stability of each point estimation of the mean reality descriptive norm perceptions but in the meantime to preserve as many data points as possible for curve fitting, we created a new categorical variable that collapsed the previous 21 exposure levels (i.e., ranging from 0 to 20 number of user-norm comments) into 11 levels by combining two original levels next to each other as one level. Table 5.4 listed the 11 levels of the new number of exposure variable, and the corresponding sample size and mean perceived reality norms in each level.

Table 5.4

Mean Perceived Reality Norms across Number of User-Norm Exposure Levels

Number of User-Norm	Exposure Levels	n	Reality Norms	Adjusted Reality Norms (+0.20)
0	1	99	−0.19 (.70)	0.01 (.70)
1 - 2	2	198	−0.07 (.69)	0.13 (.69)
3 - 4	3	177	−0.05 (.66)	0.15 (.66)
5 - 6	4	155	−0.06 (.63)	0.14 (.63)
7 - 8	5	140	0.00 (.64)	0.20 (.64)
9 - 10	6	111	0.05 (.58)	0.25 (.58)
11- 12	7	96	0.09 (.60)	0.29 (.60)
13 - 14	8	75	0.13 (.63)	0.33 (.63)
15 - 16	9	58	0.10 (.63)	0.30 (.63)

Number of User-Norm	Exposure Levels	n	Reality Norms	Adjusted Reality Norms (+0.20)
17 - 18	10	35	0.00 (.54)	0.20 (.54)
19 - 20	11	15	0.18 (.64)	0.38 (.64)

*N*ote: n = number of participants in each exposure level. Reality norm perceptions were calculated based on 13 standardized norm measures, and were averaged across participants within each exposure level. To facilitate requirements of some functional models, 0.20 standard deviation was added to each of the raw reality norm perceptions values to ensure that all values used in the dependent variable were positive. The last two columns displayed means and standard deviations of the raw and adjusted reality norm perceptions variables.

With the mean descriptive norm perceptions at each level of user-norm numbers, we next explored across a wide range of different possible shapes and functions to examine which one could best describe the relationship between the two variables. To be specific, we empirically tested the relationship with Linear, Logarithmic, Inverse, Quadratic, Cubic, Power, Compound, S-Curve, Logistic, Growth, and Exponential functions. To facilitate the requirements of fitting some of the models, given that positive independent variable values are necessary for the Logarithmic and Power models, and positive dependent variable values are necessary to allow log-transformation in the Compound, Power, S, Growth, Exponential, and Logistic models, we shifted the standardized reality norm perceptions variable upward with 0.20 standard deviation to make every mean reality value to be above zero, considering that the original estimation ranged from -0.19 to 0.18 (Table 5.4); for the independent variable, we used the new categorical variable (with values ranging from 1 – 11) as the independent variable, which effectively avoided including zero in the values. Table 5.4 also displays the adjusted values for the dependent variables. With the exposure level as the independent variable and the adjusted reality norm perceptions as the dependent variable, we fitted the aforementioned models. The results are summarized in Table 5.5.

As shown in Table 5.5, all models were significant ($p < 0.01$). We then identified the five highest adjusted R^2, and the corresponding models were the best fitted models. The results revealed that the S-Curve, Logarithmic, Power, Quadratic, Cubic, and Linear functions produced the most optimally fitted models (with Cubic and Linear models having the same value). The predicted curves produced by these models were plotted against the scatterplot of the observed raw reality descriptive norm perception values at each exposure level in Figure 5.2. As can be seen from Figure 5.2, the observed values demonstrated an increasing trend as the exposure levels got higher, and all the six predicted curves seemed to describe the data quite nicely. We next conducted formal tests to compare across these models, and examined whether some model(s) fitted the data significantly better.

Table 5.5

Results of Curve Fitting on Number of Exposure – Perceived Reality Norms Relationship with Linear and Non-Linear Models

Models	Functional Forms	Unadjusted R^2	Adjusted R^2	F-test [a]	b_0	b_1	b_2	b_3
Linear	$Y = b_0 + (b_1*X)$	.745	.716	$F(1,9) = 26.270$	.051	.028		
Logarithmic	$Y = b_0 + (b_1*\ln(X))$	.800	.778	$F(1,9) = 35.957$	.014	.128		
Inverse	$Y = b_0 + (b_1/X)$	.692	.657	$F(1,9) = 20.186$	.307	−.328		
Quadratic	$Y = b_0 + (b_1*X) + (b_2*X^2)$	.794	.742	$F(2,8) = 15.389$	−.015	.058	−.003	
Cubic	$Y = b_0 + (b_1*X) + (b_2*X^2) + (b_3*X^3)$	.801	.716	$F(3,7) = 9.407$	−.056	.092	−.009	.000
Compound	$\ln(Y) = \ln(b_0) + (\ln(b_1)*X)$	.547	.497	$F(1,9) = 10.873$	.050	1.229		
Power	$\ln(Y) = \ln(b_0) + (b_1*\ln(X))$	.785	.761	$F(1,9) = 32.855$	.030	1.101		
S-Curve	$\ln(Y) = b_0 + (b_1/X)$	.930	.922	$F(1,9) = 118.922$	−.849	−3.306		
Growth	$\ln(Y) = b_0 + (b_1*X)$	.547	.497	$F(1,9) = 10.873$	−2.995	.206		
Exponential	$\ln(Y) = \ln(b_0) + (b_1*X)$	.547	.497	$F(1,9) = 10.873$	.050	.206		
Logistic	$\ln(1/Y-1/u) = \ln(b_0) + (\ln(b_1)*X)$ [b]	.547	.497	$F(1,9) = 10.873$	19.993	.813		

Note: Y = adjusted reality descriptive norm perceptions, X = exposure levels (number of user-norm comments). b_0, b_1, b_2, b_3 are unstandardized regression coefficients. [a]. All F-tests are significant at $p = .01$ level. [b]. u is the upper boundary value that needs to be specified for the Logistic model. The value must be a positive number that is greater than the largest dependent variable value. We used the default $u = 0.50$ in SPSS 24.0.

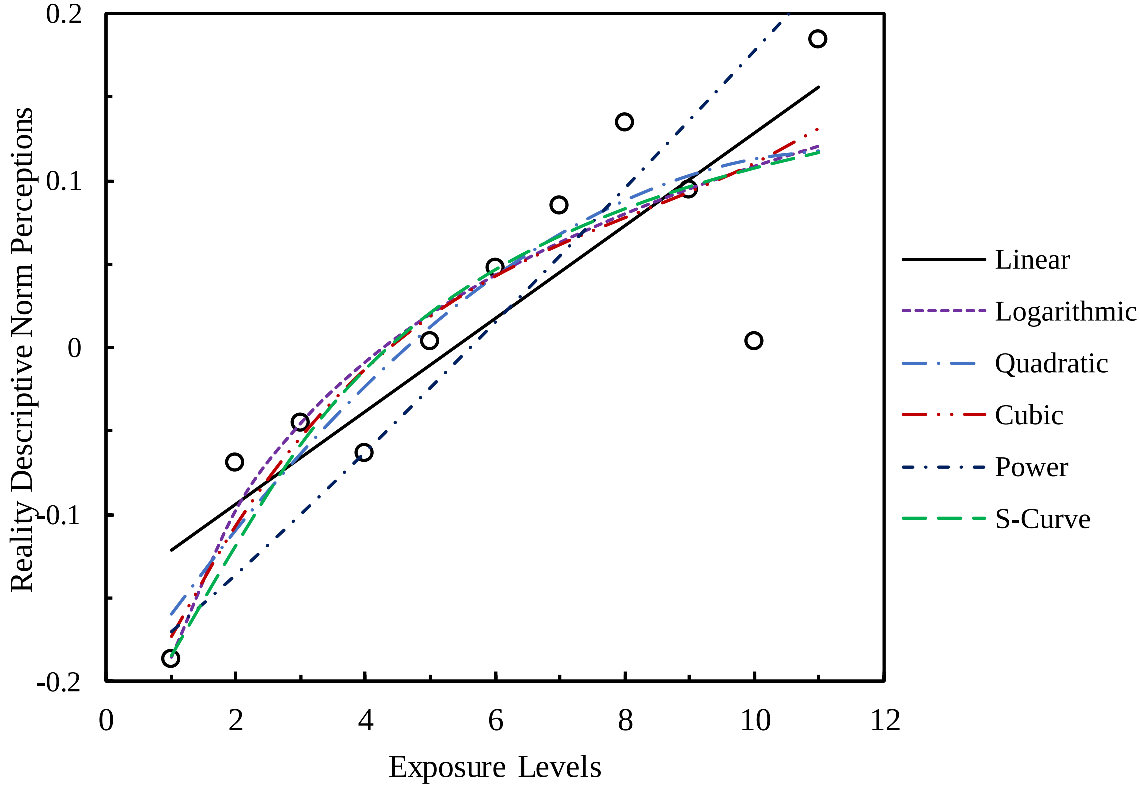


Figure 5.2. Predicted curves of number of user-norm – reality norm relation

Note: The scatterplot describes the relationship between the raw reality norm perceptions variable (instead of the adjusted values) and the exposure levels. The predicted curves of the six best fitted models (Cubic and Linear models produced the same adjusted R^2) are plotted on top of the scatterplot.

Considering that most of the models were not special cases of the others (except for Linear, Quadratic and Cubic models), maximum-likelihood ratio tests comparing the goodness-of-fit among nested models were not appropriate here. We thus performed two different tests to compare across the three non-nested models. First of all, we conducted paired t-tests on the differences in residuals of the models, with the criterion such that the model(s) having significantly lower residuals being the better model(s); if the models are not significantly different in residuals, then the simplest model is preferred (Garson, 2012). We summarized the differences in residuals and results of the 15 paired t-tests in Table 5.6, which suggested that none of the residual differences was significant (with p-values ranging from 0.20 – 0.90). This indicated that the simplest model among the six, i.e., the Linear model, was the comparatively most appropriate function in describing the relationship.

To further confirm this finding, we used another criterion, Akaike's Information Criterion (AIC), which is a measure of model quality that identifies the relative likelihood of each model being correct; the smaller the AIC value, the more likely the model is correct (Akaike, 1998; Motulsky & Christopoulos, 2004). It is calculated using the equation $AIC = N \times \ln\left(\frac{SS}{N}\right) + 2K$, where N is the number of data points, K is the number of parameters fitted plus one, and SS is the residual sum of squares from regression. In practice, AICc is more recommended than AIC, as the former takes sample size into account by having a greater penalty for model complexity (i.e., extra parameters) with small data sets (Claeskens & Hjort, 2008; Hurvich & Tsai, 1989). As sample size gets larger, AICc converges to AIC. AICc can be calculated by plugging AIC in the equation $AIC_c = AIC + \frac{2K(K+1)}{N-K-1}$. When the AICc scores for two models are drastically different, we conclude that there is overwhelming evidence that the model with the smaller AICc is likely to be correct. When the scores are close, the probability of choosing the correct model (i.e., the one with smaller AICc) can be computed using the equation $probability = \frac{e^{-0.5\Delta}}{1+e^{-0.5\Delta}}$ which ranges from 0 to 1, with *probability* =1 serving as strong evidence that the two models are different, and the one with smaller AICc is the correct model to choose (see Motulsky & Christopoulos, 2004, pp. 143-145 for more details). We thus computed AICc for each of the six models, the differences of AICc scores between all pairs of models, and the probability scores for each pair of comparisons. The results are also summarized in Table 5.6.

Table 5.6

Model Fit Comparisons with Paired T-Tests and Akaike's Information Criterion

	Paired t-test			Akaike's Information Criterion	
	Δ Residual	*t*	*p*	Δ AICc	Probability
Linear - Logarithmic	0.0081	0.98	0.35	2.55	0.22
Linear - Quadratic	0.0048	0.73	0.48	−2.69	0.79
Linear - Cubic	0.0062	0.91	0.39	−10.02	0.99
Linear - Power	−0.0070	−0.74	0.48	−45.67	1.00
Linear - S-curve	0.0059	0.68	0.51	−33.38	1.00
Logarithmic - Quadratic	−0.0033	−0.90	0.39	−5.24	0.93
Logarithmic - Cubic	−0.0019	−1.00	0.34	−12.57	1.00
Logarithmic - Power	−0.0151	−1.36	0.20	−48.22	1.00
Logarithmic - S-curve	−0.0022	−0.96	0.36	−35.93	1.00

	Paired t-test			Akaike's Information Criterion	
	Δ Residual	*t*	*p*	Δ AICc	Probability
Quadratic - Cubic	0.0013	0.51	0.63	−7.33	0.98
Quadratic - Power	−0.0118	−1.25	0.24	−42.98	1.00
Quadratic - S-curve	0.0011	0.35	0.74	−30.69	1.00
Cubic - Power	−0.0132	−1.30	0.22	−35.65	1.00
Cubic - S-curve	−0.0003	−0.12	0.90	−23.36	1.00
Power - S-curve	0.0129	1.24	0.24	12.29	0.00

Note: AICc scores for the Linear, Logarithmic, Quadratic, Cubic, Power, and S-curve models are -55.89, -58.44, -53.21, -45.87, -10.22, and -22.51 respectively. Both Δs were computed by subtracting the values of the latter model from that of the former model in each row. *df* = 10 for all paired t-tests. Two-tailed p-values are presented. Probability scores in AICc tests are different from p-values, with higher probability scores indicating greater likelihood that the model with smaller AICc in the comparison being the correct one.

As shown in Table 5.6, almost all comparisons involving the Linear model suggested that it is likely to be a more correct model, with great confidence. The comparison result between the Linear and the Logarithmic models also corroborated the conclusion such that even though the AICc score of Logarithmic model was comparatively lower, but the probability that it was the correct model was only 0.22.

Additional maximum likelihood ratio tests comparing the nested models (Liner, Quadratic and Cubic models) also suggested that adding the quadratic term ($\chi^2(1) = 0.36$, $p = 0.55$) and the cubic term ($\chi^2(2) = 1.31$, $p = 0.52$) did not significantly improve the model fit. That is to say, the two alternative functional forms did not add to the variance explained by the Linear model. We also tested for linearity and deviation from linearity between the number of user-norm comments and reality descriptive norm perceptions with all the data points in the overall dataset (i.e., not the aggregated reality descriptive norm perceptions at each exposure level). The test for linearity showed significance ($F(1, 1138) = 16.27$, $p < 0.001$), indicating that there was a linear relationship between the two variables. The test for deviation from linearity, however, was not significant ($F(19, 1138) = 0.86$, $p = 0.64$), which meant that there was no non-linear relationship in addition to the linear component. Therefore, to sum up, all the tests above provided strong evidence that the Linear model is the best functional form that describes the relationship between number of user-norm comments exposure and reality descriptive norm perceptions (R4)[8]. Since the two variables were found to have a positive dose-response relationship, there were no thresholds or inflection points in the relationship.

The next research question (R5) conceptualized the amount of repeated exposure with percentage of user-norm comments and asked which functional forms can best describe the relationship between the percentages of user-norm comments participants were exposed to and their reality descriptive norm perceptions. We followed our practice

[8] The non-symmetric distribution of cases in each exposure category though, may hint at possible complexity of conceptualizing exposure from the perspective of number of user-norm versus non-user-norm comments. We speculate that the model for non-user norms may be different since the cases in each category are quite different and that might influence the shape of the curve. Our initial exploratory analysis revealed a potential quadratic exposure – norm pattern if using the number of non-user-norm comments as the independent variable, which could serve as an interesting and promising next step for future exploration.

in addressing R1 and R2, by first calculating the mean reality descriptive norm perceptions at each level of user-norm percentages, and then comparing across a variety of possible models to select the best model(s) in describing the relationship between the two variables. Similar to what we did before, we created a new categorical variable with the aim to increase the stability of each point estimation of the mean reality descriptive norm perceptions. To be specific, we created a new categorical variable that collapsed percentages to be within 10% intervals, and then calculated mean reality descriptive norm perceptions for each interval. Table 5.7 listed the 11 levels of the new percentage of exposure variable, and the corresponding sample size and mean reality norm perceptions in each interval.

Table 5.7

Mean Perceived Reality Norms across Percentage of User-Norm Exposure Levels

User-Norm Percentage (%)	Exposure Levels	n	Reality Norms	Adjusted Reality Norms (+0.30)
0	1	99	−0.19 (0.70)	0.11 (0.70)
(0, 10]	2	61	−0.22 (0.58)	0.08 (0.58)
(10, 20]	3	111	−0.12 (0.65)	0.18 (0.65)
(20, 30]	4	101	−0.10 (0.65)	0.20 (0.65)
(30, 40]	5	111	−0.06 (0.75)	0.24 (0.75)
(40, 50]	6	121	−0.03 (0.64)	0.27 (0.64)

User-Norm Percentage (%)	Exposure Levels	n	Reality Norms	Adjusted Reality Norms (+0.30)
(50, 60]	7	88	0.08 (0.63)	0.38 (0.63)
(60, 70]	8	101	0.00 (0.52)	0.30 (0.52)
(70, 80]	9	115	0.11 (0.65)	0.41 (0.65)
(80, 90]	10	101	0.15 (0.66)	0.45 (0.66)
(90, 100]	11	150	0.09 (0.56)	0.39 (0.56)

Note: *n* = number of participants in each exposure level. Reality norm perceptions were calculated based on 13 standardized norm measures, and were averaged across participants within each exposure level. To facilitate requirements of some functional models, 0.30 standard deviation was added to each of the raw reality norm perceptions values to ensure that all values used in the dependent variable were positive. The last two columns displayed means and standard deviations of the raw and adjusted reality norm perceptions variables.

We next examined across the possible functional forms to see which model fitted our data most optimally. Again, to facilitate curving fitting requirements of some models, we shifted the standardized reality norm perceptions variable upward with 0.30 standard deviation to make every mean reality value to be above zero; the adjusted values are also displayed in Table 5.7. We used the new categorical variable (with values ranging from 1 – 11) as the independent variable, which did not include zero point in the values. The model fitting results are summarized in Table 5.8.

As shown in Table 5.8, all models were significant ($p < 0.01$). Five models with the highest adjusted R^2 were the Cubic, Linear, Quadratic, Power, and Logarithmic functions. The predicted curves produced by these models were plotted against the scatterplot of the observed raw reality descriptive norm perception values at each exposure level in Figure 5.3. Compared to Figure 5.2, the observed values seemed to demonstrate an even more linear and monotonically increasing trend with each 10% increase in percentage of exposure.

Table 5.8

Results of Curve Fitting on Percentage of Exposure – Perceived Reality Norms Relationship with Linear and Non-Linear Models

Models	Functional Forms	Unadjusted R^2	Adjusted R^2	F-test [a]	b_0	b_1	b_2	b_3
Linear	$Y = b_0 + (b_1 * X)$	.892	.880	$F(1,9) = 74.212$	.064	.035		
Logarithmic	$Y = b_0 + (b_1 * \ln(X))$	.831	.812	$F(1,9) = 44.188$	.035	.150		
Inverse	$Y = b_0 + (b_1/X)$	.577	.530	$F(1,9) = 12.280$	.369	−.345		
Quadratic	$Y = b_0 + (b_1 * X) + (b_2 * X^2)$	.903	.879	$F(2,8) = 37.429$	.027	.052	−.001	
Cubic	$Y = b_0 + (b_1 * X) + (b_2 * X^2) + (b_3 * X^3)$	.918	.883	$F(3,7) = 26.169$	.092	−.002	.009	−.001
Compound	$\ln(Y) = \ln(b_0) + (\ln(b_1) * X)$	.829	.810	$F(1,9) = 43.576$	.098	1.164		
Power	$\ln(Y) = \ln(b_0) + (b_1 * \ln(X))$	.851	.835	$F(1,9) = 51.561$	.082	.684		
S-Curve	$\ln(Y) = b_0 + (b_1/X)$	.642	.603	$F(1,9) = 16.170$	−.964	−1.639		
Growth	$\ln(Y) = b_0 + (b_1 * X)$	.829	.810	$F(1,9) = 43.576$	−2.324	.152		
Exponential	$\ln(Y) = \ln(b_0) + (b_1 * X)$	.829	.810	$F(1,9) = 43.576$	.098	.152		
Logistic	$\ln(1/Y-1/u) = \ln(b_0) + (\ln(b_1) * X)$ [b]	.829	.810	$F(1,9) = 43.576$	10.214	.859		

Note: Y = adjusted reality descriptive norm perceptions, X = exposure levels (percentage of user-norm comments). b_0, b_1, b_2, b_3 are unstandardized regression coefficients. [a]. All F-tests are significant at $p = .01$ level. [b]. u is the upper boundary value that needs to be specified for the Logistic model. The value must be a positive number that is greater than the largest dependent variable value. We used the default $u = 0.50$ in SPSS 24.0.

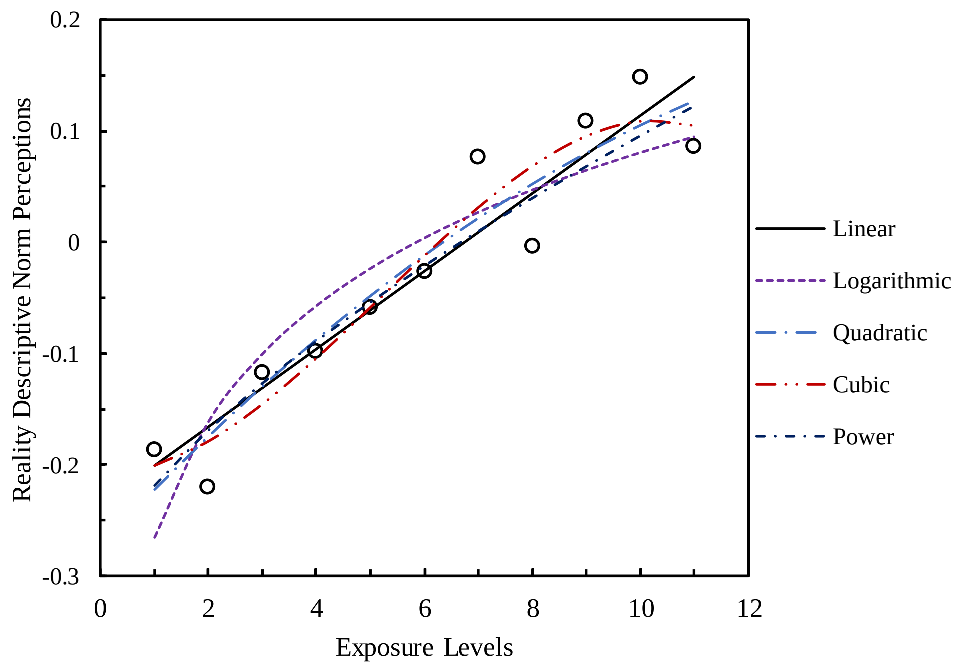


Figure 5.3. Predicted curves of percentage of user-norm – reality norm relation

Note: The scatterplot described the relationship between the raw reality norm perceptions variable (instead of the adjusted values) and the exposure levels. The predicted curves of the five best fitted models were plotted on top of the scatterplot.

We then conducted the paired t-tests and used AICc information to compare across the five models to select the best fitted functional form in describing the relationship. The results of the two comparisons are presented in Table 5.9. As shown in Table 5.9, the paired t-tests comparing the differences in model residuals suggested that none of the residual differences was significant when the comparisons involved the Linear model. There were two marginally significant difference both involving the Logarithmic model, indicating that it had larger model residuals compared to the Cubic and Quadratic models. Thus the Logarithmic had relatively poorer model fit compared to the other four models. When we examined the models against the AICc criterion, we observed that almost all comparisons showed high probabilities that the model with smaller AICc being the more correct model. When comparing the two models with the highest R^2, i.e., the Cubic and the Linear models, we could conclude with high confidence (probability = 0.99) that Linear model (AICc =-62.44) was more likely to be the correct model compared to the Cubic model (AICc = -53.03).

Table 5.9

Model Fit Comparisons with Paired T-Tests and Akaike's Information Criterion

	Paired T-Tests			Corrected Akaike's Information Criterion	
	Δ Residual	t	*p*	Δ AICc	Probability
Linear - Logarithmic	−0.0137	−1.43	0.18	−4.91	0.92
Linear - Quadratic	−0.0021	−0.55	0.60	−4.53	0.91
Linear - Cubic	0.0034	0.58	0.57	−9.41	0.99
Linear - Power	−0.0019	−0.52	0.61	−36.78	1.00
Logarithmic - Quadratic	0.0116	1.86	0.09	0.38	0.45
Logarithmic - Cubic	0.0171	2.22	0.05	−4.50	0.90
Logarithmic - Power	0.0117	1.80	0.10	−31.87	1.00
Quadratic - Cubic	0.0055	1.43	0.19	−4.88	0.92
Quadratic - Power	0.0002	0.06	0.96	−32.25	1.00
Cubic - Power	−0.0054	−1.00	0.34	−27.37	1.00

*N*ote: AICc scores for the Cubic, Linear, Quadratic, Power, and Logarithmic models are -53.03, -62.44, -57.91, -25.66, and -57.53 respectively. Both Δs were computed by subtracting the values of the latter model from that of the former model in each row. df = 10 for all paired t-tests. Two-tailed p-values are presented. Probability scores in AICc tests are different from p-values, with higher probability scores indicating greater likelihood that the model with smaller AICc in the comparison being the correct one.

Maximum likelihood tests comparing the Linear and the Quadratic models ($\chi^2(1) = 0.36$, $p = 0.55$), and the Linear and the Cubic Models ($\chi^2(2) = 1.31$, $p = 0.52$) also found the same pattern such that adding the polynomial terms did not significantly improve the model fit. Finally, the test for linearity showed significance ($F(1, 1030) = 29.57$, $p < 0.001$) for linearity and insignificance for deviation from linearity ($F(9, 1148) = 1.58$, $p = 0.92$), adding further evidence to the conclusion that the Linear model can best describe the relationship between the percentage of user-norm comments exposure and the reality descriptive norm perceptions (R5).

R6 focused on the potential interaction effects between the percentage of user-norm comments and total number of comments. We first examined the interaction effects using the continuous version of the two variables, and found no evidence for interaction effects ($\beta = 0.14$, $p = .10$). Considering that in the pilot study, we only observed effects in conditions with double dose of exposure but did not detect any significance when the total number of exposure was 10 comments, it is also possible that the dose-response relationship we observed between percentage of user-norm comments and descriptive norm perceptions was only driven by conditions where total exposure was higher (e.g., exposed to more than 10 comments), which may explain why the interaction effect could not be observed when using the continuous total exposure variable.

We thus visually inspected the relationship between percentage of user-norm comments and the reality descriptive norm perceptions at each total number of exposure (n = 20). The descriptive figures were plotted and presented in Figure 5.4. Considering that when examining the relationship at each total exposure level, fewer data points would be available to estimate mean reality norm perceptions for each level of percentage of user-norm exposure, therefore, to allow a more reliable estimation, bootstrapping procedures with 1000 replications were performed to obtain each mean reality norm perceptions estimate on Figure 5.4 and the 95% confidence intervals surrounding them. As can be seen from Figure 5.4, while the relationship between the percentage and reality norm perceptions variables was not quite clear initially when the total number was low, we observed a relatively consistent, positively increasing trend in each facet of the figure when the total number is higher, particularly after the total number reached a point around n = 10.

One may raise the possibility that the reason why patterns were different between lower and higher levels of total exposure was due to the fact that, way fewer data points were available for estimation when the total exposure levels were low. Therefore, to further confirm our speculation, we categorized total number of comments into four bigger categories (1 – 5, 6 – 10, 11 – 15, 16 – 20 total comments) to get a more reliable pattern for each category by utilizing more data points for estimation. The results are presented in Figure 5.5.

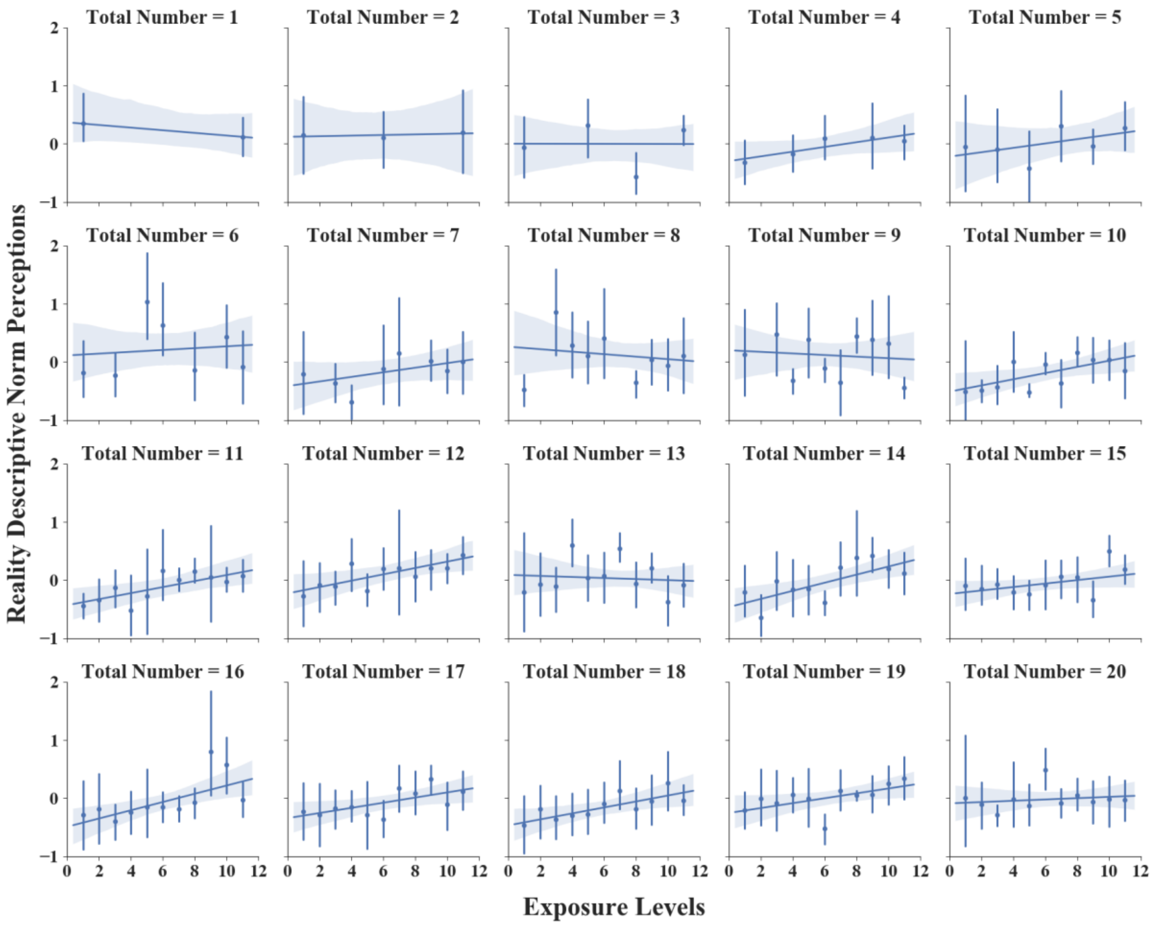


Figure 5.4. Percentage of user-norm comments – reality norm relation varying total exposure levels (n = 20)

Note: The 20 facets in the figure represent total number of comments ranging from 1 to 20. In each facet of this figure, x-axis represents the percentage of user-norm comments (11-level categorical variable). Y-axis represents the reality descriptive norm perception measure, which is an average of the 13 standardized norm items. The data points in each facet of the figure were bootstrapped mean reality descriptive norm perceptions among participants who were exposed to the same level of percentage of user-norm comments. The data points were also surrounded by bootstrapped 95% confidence intervals. The grey confidence bands around the regression lines were generated by the 95% confidence intervals that the true values for the predicted values fall within that range for each individual percentage level.

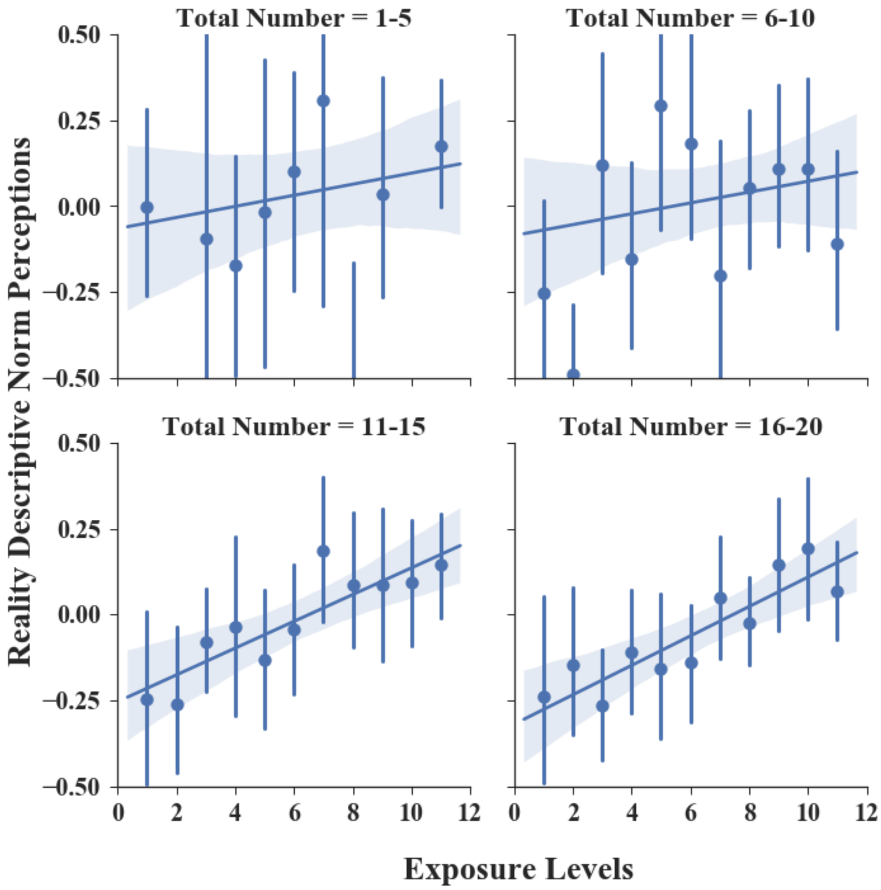


Figure 5.5. Percentage of user-norm comments – reality norm relation varying total exposure levels (n = 4)

Note: In each facet of this figure, x-axis represents the percentage of user-norm comments (11-level categorical variable). Y-axis represents the reality descriptive norm perception measure, which is an average of the 13 standardized norm items. The data points in each facet of the figure were bootstrapped mean reality descriptive norm perceptions among participants who were exposed to the same level of percentage of user-norm comments. The data points were also surrounded by bootstrapped 95% confidence intervals. The grey confidence bands around the regression lines were generated by the 95% confidence intervals that the true values for the predicted values fall within that range for each individual percentage level.

From Figure 5.5 we can see that with more data points, there was still not overwhelming evidence to suggest a monotonically increasing pattern when total exposure was low (1 – 10 comments). However, the pattern was even more apparent when total exposure was high (11 – 20 comments). To confirm our speculation, we thus created a binary total exposure variable with total number of comments of 1 – 10 and 11 – 20 as two categories, and examined its interaction with percentage of user-norm comments again. The results confirmed a significant interaction between the two variables ($\beta = 0.14$, $p = .03$). We also conducted regression analyses within each of the four categories of total exposure, and observed that while the regression slopes were positive at low total exposure levels, they were not significantly different from zero (total number = 1 – 5: $\beta = 0.10$, $p = .34$; total number = 6 – 10: $\beta = 0.05$, $p = .42$). On the other hand, when the total exposure was at high levels, both regression slopes were positive and significant, and had similar magnitude of effects (total number = 11 – 15: $\beta = 0.20$, $p < .001$; total number = 16 – 20: $\beta = 0.20$, $p < .001$; a post-hoc test comparing the two regression slopes suggested no significant difference, $p = 0.83$).

Both the visual explorations and the statistical analyses suggested that there is a significant interaction between percentage of user-norm exposure and total exposure (R6), such that the percentage – norm association is manifested in two discrete steps: the reality descriptive norm perceptions do not substantially increase as the percentage of user-norm comments gets higher when the total exposure to comments is low; as total number of comments exceeds n = 10, which can be regarded as a threshold cut-off point of total exposure, there is a dose-response positive linear association between percentage of user-norm comments exposure and reality descriptive norm perceptions. That is to say, the main effect of percentage of user-norm comments (vs. non-user-norm comments) on reality norm perceptions observed in R4 was driven by conditions with high levels of total exposure.

To examine whether unanimous conditions on average produced significantly stronger effects compared to the dominant conditions, we conducted two planned contrasts within High-prevalence and Low-prevalence conditions respectively. The results suggested that the unanimous High-prevalence conditions (M = 0.09, SE = 0.06) had very similar reality descriptive norm perceptions to the dominant High-prevalence conditions (M = 0.09, SE = 0.03), and the difference was not significant (F (1, 1296) = 0.00, p = .95). The similar pattern was observed when we examined the Low-prevalence conditions, such that although the unanimous Low-prevalence conditions (M = -0.19, SE = 0.07) did produce lower reality descriptive norm perceptions, they were not significantly different (F (1, 1296) = 1.05, p = .31) from that of the dominant Low-prevalence conditions (M = -0.11, SE = 0.03). Therefore, H6 and H7 were not supported.

Discussion

This study systematically examined the relationship between repeated exposure and reality descriptive norm perceptions in the context of online comment boards, which is a unique context that reflects the increasingly participatory feature of the current media environment. We aimed to understand, among different functional forms, which one(s) can best describe the shape of the relationship, how different conceptualizations of repeated exposure may affect the pattern, and whether there is any threshold or turning point that is crucial for the normative perception formation process. We also examined whether unanimous repeated exposure can influence normative perceptions most strongly as observed by previous conformity studies. In addition to the focal questions, we also examined and established that the crucial patterns we observed in previous Chapters when the amount of exposure was fixed, still held in the current design where the exposure dosage was varied systematically.

After probing a number of possible linear and non-linear functions, we observed that both dimensions of repeated exposure, numbers and percentages of user-norm comments were positively associated with reality descriptive norm perceptions in a linear dose-response way. An important exposure threshold was found in the interactive relation between total exposure and percentage of exposure to the user-norm (vs. non-user norm) information, such that only after people were exposed to a sufficient pool of normative information that contains messages of both norm directions ($n = 10$, in our case), the increase of the percentage of information with a particular norm direction (user-norm comments, in our case) would start to be sensed and exert influence in people's reality descriptive norm perception formation. In terms of the role unanimity plays in the current study setting, we observed that unanimous conditions were not statistically different than their corresponding dominant conditions, which also corroborated the linear relationship between exposure and reality norm perceptions we had derived from curve fitting and comparisons. In addition, we also observed that across all exposure levels, High-prevalence conditions on average yielded higher descriptive norm perceptions compared to that in the Low-prevalence conditions, which provided convincing evidence, on top of the findings from the previous studies we conducted, that constructed behavior choice distribution worked effectively with people's instinctual quasi-statistical sense in affecting their normative perceptions about the reality. Finally, we also found that reading the news article can significantly raise the anchoring descriptive norm perceptions about e-cigarette use in the real world from the baseline, and reading comments in general lowered the descriptive norm perceptions anchored by the news reading. The findings provide important implications for theory and practice.

Dose-Response Quasi-Statistical Sense. One of the major findings in the current study is the consistent positive linear association we observed between the amount of exposure (both defined as the absolute number and the relative prevalence) and reality descriptive norm perceptions. Public opinion literature informed us that human beings have a quasi-statistical sense that automatically collects opinion climate information from their surroundings to help decide their best moves in certain situations (Noelle-Neumann, 1993; Scheufele & Moy, 2000). Nevertheless, little is known about the underlying process of how such quasi-statistical sense operates when encountering an array of situational cues, potentially of different directions and having different behavioral implications. Findings from the current study advanced our understanding by illuminating that the quasi-statistical sense can be so acutely sensitive and sophisticated that it responds to normative cues in a dose-response manner. While previous literature studying conformity in group settings almost all assumed the minority stance of the target participant, and used a prevailing majority holding an opposite stance to stimulate social influence, our study provides novel evidence that even if no default initial stance is assumed, no overwhelming dominance of the target norm direction is in force (e.g., situations where percentages of user-norm exposure are under 50%), and no coerciveness imposed, people still piece together and iteratively modify the overall picture of behavior choice distribution as every bit of new evidence flows into their pool of social proof, in a fairly automatic and associative fashion. This finding identified exciting possibilities not only for theoretical development, but also for practice by offering a promising way to effectively accelerate and precipitate this normative inferential process that may ultimately lead to desirable behavior change.

Beyond a Reasonable Doubt. Another interesting result revealed by the current study is that when conceptualizing repeated exposure as percentage of user-norm comments (vs. non-user-norm comments), the overall relationship between exposure and reality norm perceptions was manifested as a step-function, such that only after participants read more than 10 comments, the positive linear association between the two variables kicked in; however, before this total exposure level, no discernable pattern was detected. This conditional effect highlighted the important role of total amount of exposure which serves as a threshold criterion in determining how convincing the perceived behavior choice distribution within a more immediate, local environment, is in representing the reality norms. As Levine and Scott (2015) pointed out, we as humans, may be predisposed to "follow the crowd" because of a fundamental desire to be accepted as well as to be accurate. Normative and informational influences almost always intertwine and underlie the notion of social proof (Deutsch & Gerard, 1955). Therefore, sufficient repetitive total exposure has bearings on the perceived validity of the majority's position. That is to say, holding relative prevalence of the target norm direction constant, exposure to a larger pool of evidence lends stronger credibility and greater endorsement to those who hold the dominant target norm direction, such that they are more likely to be deemed as being truly representative of the collective truth. Thus, once the dominant norm direction gains perceived legitimacy through a larger pool of evidence, it gets beyond a reasonable doubt; even when little or no persuasive argumentation is presented, it may be effective in producing influence because its correctness has been established with evidence from a large crowd. All being said, it is also worth noticing that even though we did not observe any effect with the low total exposure (i.e.,10-comment) conditions in the pilot study (Chapter 3), we did detect significant influences in those conditions in the replication study (Chapter 4 Study 1), when the dominance ratio was set to be higher (i.e., 8:2 instead of 7:2:1). Therefore, it is also important to take into consideration the joint influences from the total exposure and the degree of norm prominence to better estimate the likelihood and magnitude of social influence.

Comments as Social Annotations. Consistent with what we speculated earlier, the results from the current study also provided evidence for the potential "incongruence bias" phenomenon. We found that across all exposure levels and treatment conditions, reading comments significantly lowered the reality descriptive norm perceptions from that of the news-only condition, which initially increased descriptive norm perceptions from the baseline. Interestingly, High-prevalence conditions had slightly lower reality norm perceptions compared to that of the news-only condition too. This may suggest that even when non-user-norm comments were minorities in those conditions, their presence could still serve as strong evidence that offsets the prevalence perception formed through the news consumption. Online comments are social annotations that may tint the news article with a different color, modify interpretations, and reshape readers' reactions. Each additional dose of exposure of such social annotations is effective in affecting people's understanding about the reality. Wilder (1977) argued that we can count on sturdy increases in the target's conformity by simply adding numbers to the majority group, only under conditions when majority members are seen as distinct social entities who have arrived independently at their common position. This resonates with Asch's (1951) statement that "consensus is valid only to the extent to which each individual asserts his own relation to facts and retains his individuality." The unique format of the online comments facilitates perceptions of such individuality for each of the social annotations, which makes every endorsement or opposition expressed by the distinct commenters adding to normative perception changes so effectively.

Limitations and Future Directions. Finally, we would like to acknowledge some potential limitations of the current study, and point out some promising future research directions. First of all, to facilitate better display of the comments and sustain participants' attention, when they were in conditions where total number of comments > 10 but ≤ 20, we designed a two-page display of the comments. Therefore, these participants were instructed to click on "continue" to read the second page after they finished reading the first 10 comments. In contrast, those who read less than 10 comments only read from one page. Thus, an alternative explanation for the threshold value in total number of comments we observed (n = 10), may be caused by participants' interaction with the screen and reengagement with the comment board. Future studies can test this concern by having a one-page 20-comments design, and examine whether the results from the current design can be replicated. Secondly, while in the real world, revisions of normative perception usually take place when people encounter an array of norm-relevant instances over an extended period of time (Bicchieri & McNally, 2016), our study found that we can effectively accelerate such a process with a constructed social sphere and behavior choice distribution. A potential problem of this relatively fast modification though, is that it also can be short-lived. Therefore, longitudinal studies in real-world settings may be an important future direction to help understand how sustainable such constructed normative perception changes can be. Thirdly, related to the last point, we created an almost ideal comment board specifically devoted to our study purposes. This comment board is static, civil, and with no traces of any identity information of the commenters. However, actual online comment boards are usually very different from this constructed public space. People can interact with each other; incivility and hostility are so prevailing in online comments now that some news websites had to disable the comment functions; some comment boards have now requested real identity information to improve the degraded online discussion due to anonymity. Through these distinct features, we see exciting opportunities for future endeavors applying a more naturalistic experimental design, to tap into questions such as whether real-time interactions and discussions with other online users may accelerate or impede the process of achieving group consensus, how incivility may affect the quality and effectiveness of each exposure dosage, and how social identity may come into play – potentially less exposure repetition is needed to stimulate changes if the commenters who supply normative information are deemed as having high competence. Finally, the amount of exposure that is necessary to bring in norm perception changes as well as the ways to achieve this goal may vary by contexts, topics, and behaviors, etc. There is no single generalized model the explains every pair of exposure – norm relationships. Therefore, the findings of the current study may also be a special case, which is worth replication and re-examination under different situations, with different communication modalities, and when behaviors of different attributes are under investigation.

Concluding Remarks

While the previous chapters explicated why repeated media exposure matters in the formation of descriptive norm perceptions, the current study deals with the question of how each dose of exposure is associated with normative perception formation. To our best knowledge, the current study is the first study that systematically examined how comprehensively varying the important elements of exposure may affect normative perception changes through a constructed social sphere. We delineated a comprehensive picture of exposure – norm relationship by taking into consideration information from opposite norm directions. The findings from the current study are meaningful and enlightening particularly in the current media environment where it is almost impossible to hear overwhelmingly consonant or even unanimous opinions. Through the manipulation of normative information expressed in covert online settings, we observed normative perception changes as internalized private acceptance, which provided important implications of how profoundly social annotations to mainstream media content may have changed the equation of dominant public opinion generation and dissemination.

CHAPTER 6.

CONCLUSIONS AND FINAL REFLECTIONS

A Reiteration of Rationale

We as health communication researchers, have always been trying to find ways to make desirable behavior changes less effortful, more automatic, and long-lasting. According to Strack and Deutsch (2004), human behaviors are controlled by two systems that follow different operating principles, the reflective and the impulsive systems. While the former motivates behavior through a deliberative decision process that is based on knowledge about facts and values related to the behavior, the latter generates behavior through associative links which are often irrelevant to the substance of the behavior itself (e.g., pros and cons entailed in conducting the behavior). To instigate behavior change with the reflective system, intensive cognitive efforts and sufficient ruminations are required. However, when the impulsive system is at work, behavior decisions are often made quite automatically, and behavior changes happen more quickly, demanding little cognitive analysis.

The way in which descriptive norm perceptions take effects has exactly exhibited the character of automaticity, and is thus considered a promising mechanism that can elicit effective behavior changes through the impulsive system with less conscious efforts. Human beings are instinctually sensitive to social consensus information, and most of the time they collect such information without conscious awareness (Asch, 1955; Bond & Smith, 1996; Chudek & Henrich, 2011; Festinger, 1954; Kahneman & Miller, 1986; Leary & Baumeister, 2000). But the effects of such automatically gathered social proof information, serving as heuristic cues or mental shortcuts for decision making, are often quite powerful. There is ample evidence showing that descriptive norm information alone is sufficient in bringing about cognition and behavior changes even in the event of no persuasive arguments being provided, and people are often not cognizant about the fact that others' behaviors are indeed a causal antecedent leading to their own behavior decisions (Aarts & Dijksterhuis, 2003; Asch, 1951, 1955, 1956; Cialdini et al., 2006; MacCoun, 2012; Nolan, Schultz, Cialdini, Goldstein, & Griskevicius, 2008). Such characteristics of the way descriptive norm perceptions exercise influence are extremely useful in that they enable one to engage in behavior changes in a natural, mindless, and automatic fashion, without back-and-forth deliberative reasoning or effortful self-persuasion.

However, most of the available research on descriptive norm perceptions is largely confined to studies in which descriptive norm perceptions are treated as the predictor variable and are delivered in the form of summary prevalence information. Very few studies have examined the underlying mechanism of how descriptive norm perceptions are formed in the first place. Most importantly, directly providing summary prevalence information such as that from census data or research reports, does not approximate the most typical way in which individuals form their own subjective perceptions of behavior prevalence based on their every-day experience of observing scattered behavior evidence surrounding them, and may not reflect the real underlying mechanism that motivates them to change. Having a more thorough understanding of how descriptive norm perceptions are formed and the conditions under which they operate most effectively are the prerequisites of optimally leveraging the power of descriptive norms to promote desirable behavior change.

Therefore, this dissertation sets out to unpack the underlying mechanisms of descriptive norm perception formation. In particular, as communication scholars, we are curious about the role of media content in shaping people's perceptions about social reality. We therefore examine how individuals formulate their prevalence estimation based on the preponderance of a behavior mentioned or depicted in mass media contents, as well as in user-generated media contents. We seek to understand: 1. Can people correctly sense the repeated implicit descriptive norm cues contained in the media contents with repeated exposure? 2. Are descriptive norm perceptions formed in this way influential and useful? 3. What are some of the crucial patterns being revealed in the perception formation process that we need to know, to more effectively harness the power of descriptive norms?

What Have We Learned?

When we step back and reflect across studies, we are delighted to find that this dissertation has offered evidence and food for thought for each of the above questions, and has greatly contributed to advancing our understanding by explicating an important underlying mechanism of descriptive norm perception formation as a result of repeated media exposure.

Can people sense the implicit normative cues through repeated exposure? First of all, we confirmed that people are acutely sensitive to the implicit descriptive norm information conveyed through repeated exposure to media contents. No matter whether this signal comes from encounters to the topic repeatedly across multiple media sources, or from observations of others' behavior choices repeatedly from user-generated online comments, people do not miss a single dose of exposure with their "quasi-statistical sense," as each exposure dosage contributes to increase in descriptive norm perceptions in a dose-response way.

Are descriptive norm perceptions formed this way influential? Second, we observed that people's descriptive norm perceptions formed this way could impact intentions and behaviors. Particularly considering the anonymous non-coercive online setting constructed in our experiments, people's descriptive norm perception changes could be deemed as their internalized private acceptance rather than superficial public compliance. Our analyses of the mediation pathways with both the survey and experiment data confirmed that the descriptive norm perceptions formed though repeated media exposure are capable of ultimately leading to intention and behavior changes. Specifically, we observed that descriptive norm perceptions produced by repeated exposure across media channels lead to behavior changes concurrently and longitudinally six months later. Our experimental manipulation varying exposure dosage to normative information also found its way to influence intentions to engage in the target behavior through shifts in reality descriptive norm perceptions. Across studies, intention and behavior changes all happen in the intended direction.

What are the core principles we need to know? Last but not least, several crucial patterns emerged in the descriptive norm perception formation process help us understand more deeply about human sociality and inform us how to better utilize the rules to most effectively promote behavior changes.

Perceived independence among sources. A consistent pattern we observed across studies is that, descriptive norm perceptions are more likely to be influenced when each member of the majority behavior choice group is seen as having arrived independently at their position. This rule applies to online user-generated comments where anonymous commenters, who seem to have no opportunity to achieve an agreement beforehand, resonate with each other in terms of behavior choices. It also applies to contents mentioning the target behavior across media sources. Considering their differences in communication modality, target populations, priorities, etc., if individuals sense synergy across media sources in covering the same topic, they are more likely to perceive that the topic must be popular and prominent enough to receive such heightened attention in the communication environment. In sum, individuality of each source providing normative cues is core to effective descriptive norm perception formation.

Perceptions formed through subjective experience weigh more. We observed that people seem to put great weight on the normative perceptions formed through reading comments in which the individual behavior cues are embedded. In other words, it seems that people trust the perceptions obtained through their own subjective experience and efforts even though the online comment boards are constructed and not interactive, and the commenters are anonymous and not representative, knowledgeable, credible, or authoritative. This result is particularly meaningful in the current media environment where user-generated contents often appear on the same page where mainstream news articles are broadcast. The pattern also nicely illustrates how effectively mere repetition works to trigger quasi-statistical sense, and points out the great potential of applying this mechanism in promoting behavior changes.

A large information pool grants legitimacy for inference making. In addition to the dose-response association between repeated media exposure and descriptive norm perceptions, we also asked whether there is any important exposure threshold in their relation. We observed that, the size of the overall information pool (i.e., total number of messages containing normative information) has implications for the descriptive norm perception formation process such that the clear dose-response association is only observed when the overall information pool is relatively large (in our case, above a total exposure of 10 comments), when holding the dominant behavior ratio constant. A larger overall information pool may provide more exposure opportunity to make sure the majority opinion or the dominant norm direction reaches its audience and potentially lends more credibility to the dominant side with a larger group of people endorsing it. This result pattern speaks to the importance of having sufficient overall exposure in the descriptive norm perception process so that the inference people make through repeated exposure may be perceived as more convincing.

Interpersonal processes should not be underestimated. In the survey study, we observed that having interpersonal discussions with others in their social circle effectively shaped people's interpretations of the media content as well as descriptive norm perceptions about the social reality. In the experiment studies, we constructed an online social sphere where people are exposed to other commenters' behavior choices, and found that the perceived behavior prevalence as implicated in the behavior choice distribution on the constructed comment board served as a solid basis for people to infer the behavior prevalence in the real world. Evidence across studies consistently indicates that the crucial role of interpersonal processes in shaping social perceptions, no matter online or offline, should not be underestimated. To maximize effectiveness, mass media behavior change interventions or campaigns applying normative appeals may benefit from focusing on strategizing mass media messages to elicit intended interpersonal discussions, and constructing descriptive norm perceptions within a more immediate, local environment that may ultimately lead to changes in descriptive norm perceptions at the population level.

Concluding Remarks

As a whole, this dissertation work contributes to the field by unravelling the multiple layers of an intricate communication phenomenon – how people form descriptive norm perceptions in their everyday communication environment. We investigated this question with different forms and conceptualizations of media exposure, engaging in different lines of inquiry in the literature and utilizing both observational and experimental methods. Throughout these examinations, we found a reoccurring theme that is core to the descriptive norm perception formation process: repeated media exposure is of utmost importance, and it affects descriptive norm perceptions so effectively and precisely, in a dose-response fashion; even though this concept may have very diverse manifestations in the current ever-evolving media landscape. That becomes the key to our successful harnessing of social norms in promoting behavior changes moving forward.

APPENDICES

Appendix A. Cross-sectional Regression Analyses Results of the Proposed Pathways

Hypotheses	H1: EXP → BEH		H2: EXP → DN		H3: DN → BEH	
DVs / IVs	E-cigarette Use		Norm Perceptions		E-cigarette Use	
	N = 9,551		N = 9,554		N = 9,573	
	OR (SE)	95% CI	B (SE)	95% CI	OR (SE)	95% CI
Media Scanning	1.23 (0.05)***	1.14, 1.33	0.12 (0.01)***	0.09, 0.14		
Interpersonal Conversations						
Norm Perceptions					2.38 (0.12)***	2.16, 2.64
Age	0.98 (0.02)	0.95, 1.02	0.01 (0.00)	0.00, 0.01	0.97 (0.02)	0.94, 1.01
Gender (ref. = Female)	1.34 (0.12)**	1.13, 1.59	−0.01 (0.02)	−0.04, 0.03	1.38 (0.13)**	1.15, 1.65
Race (ref. = White)						
Hispanic	0.93 (0.11)	0.74, 1.17	0.13 (0.03)***	0.08, 0.18	0.82 (0.10)	0.64, 1.04
Black	0.54 (0.08)***	0.41, 0.73	−0.01 (0.03)	−0.07, 0.05	0.55 (0.08)***	0.41, 0.73
Other	0.94 (0.13)	0.71, 1.25	0.08 (0.03)*	0.02, 0.14	0.87 (0.12)	0.65, 1.14
Education	1.04 (0.06)	0.92, 1.17	0.01 (0.01)	−0.02, 0.03	1.07 (0.07)	0.94, 1.21

Hypotheses	H1: EXP → BEH		H2: EXP → DN		H3: DN → BEH	
DVs	E-cigarette Use		Norm Perceptions		E-cigarette Use	
	N = 9,551		N = 9,554		N = 9,573	
IVs	OR (SE)	95% CI	B (SE)	95% CI	OR (SE)	95% CI
School Performance	0.91 (0.05)†	0.82, 1.00	−0.06 (0.01)***	−0.08, −0.03	0.93 (0.05)	0.84, 1.04
Sensation Seeking	1.67 (0.16)***	1.38, 2.02	0.19 (0.02)***	0.15, 0.23	1.41 (0.13)***	1.17, 1.70
Past-30-day Cigarette Use	4.06 (0.42)***	3.31, 4.97	0.11 (0.03)**	0.04, 0.17	4.19 (0.45)***	3.39, 5.18
Parental Education	1.00 (0.04)	0.93, 1.07	−0.04 (0.01)***	−0.05, −0.02	1.04 (0.04)	0.97, 1.12
Live with a Vaper (ref. = no)	2.41 (0.28)***	1.92, 3.04	0.34 (0.04)***	0.26, 0.42	1.92 (0.24)***	1.50, 2.46
Household Rule (ref. = no)	3.34 (0.31)***	2.78, 4.01	0.23 (0.03)***	0.18, 0.29	2.96 (0.28)***	2.46, 3.57

Note: EXP = breadth of routine media exposure; BEH = e-cigarette use behavior; IC = interpersonal conversations; DN = descriptive norm perceptions. All analyses are weighted.

Appendix A (continued):

Hypotheses	H5: EXP → IC		H6: IC → DN	
DVs / IVs	Interpersonal Conversations		Norm Perceptions	
	N = 9,558		N = 9,568	
	B (SE)	95% CI	B (SE)	95% CI
Media Scanning	3.10 (0.10)***	2.91, 3.32		
Interpersonal Conversations			0.42 (0.03)***	0.37, 0.47
Norm Perceptions				
Age	0.97 (0.02)*	0.94, 1.00	0.01 (0.00)	0.00, 0.01
Gender (ref. = Female)	1.00 (0.08)	0.86, 1.17	0.00 (0.02)	−0.04, 0.03
Race (ref. = White)				
Hispanic	0.69 (0.07)**	0.56, 0.85	0.14 (0.03)***	0.09, 0.20
Black	0.56 (0.07)***	0.44, 0.72	0.01 (0.03)	−0.05, 0.07
Other	0.94 (0.11)	0.75, 1.17	0.08 (0.03)*	0.02, 0.14
Education	1.06 (0.06)	0.95, 1.19	0.01 (0.01)	−0.02, 0.03
School Performance	1.05 (0.05)	0.95, 1.16	−0.06 (0.01)***	−0.08, −0.03
Sensation Seeking	1.36 (0.11)***	1.16, 1.59	0.18 (0.02)***	0.14, 0.22

Hypotheses	H5: EXP → IC		H6: IC → DN	
DVs	Interpersonal Conversations		Norm Perceptions	
	N = 9,558		N = 9,568	
IVs	B (SE)	95% CI	B (SE)	95% CI
Past-30-day Cigarette Use	1.40 (0.15)**	1.13, 1.74	0.09 (0.03)**	0.03, 0.15
Parental Education	1.01 (0.03)	0.94, 1.07	−0.04 (0.01)***	−0.05, −0.02
Live with a Vaper (ref. = no)	1.77 (0.21)***	1.40, 2.23	0.31 (0.04)***	0.23, 0.39
Household Rule (ref. = no)	1.76 (0.17)***	1.46, 2.12	0.20 (0.03)***	0.15, 0.26

Note: EXP = breadth of routine media exposure; BEH = e-cigarette use behavior; IC = interpersonal conversations; DN = descriptive norm perceptions. All analyses are weighted.

Appendix B. Longitudinal Regression Analyses Results of the Proposed Pathways

Hypotheses	H1: EXP → BEH		H2: EXP → DN		H3: DN → BEH	
DVs	E-cigarette Use		Norm Perceptions		E-cigarette Use	
	N = 2,755		N = 2,755		N = 2,761	
IVs	OR (SE)	95% CI	B (SE)	95% CI	OR (SE)	95% CI
Media Scanning	1.26 (0.12)*	1.05, 1.52	0.04 (0.02)*	0.00, 0.08		
Interpersonal Conversations						
Norm Perceptions			0.55 (0.03)***	0.50, 0.60	2.00 (0.28)***	1.52, 2.63
E-cigarette Use	5.72 (1.37)***	3.57, 9.17			3.97 (0.98)***	2.45, 6.45
Age	1.06 (0.05)	0.97, 1.17	0.02 (0.01)	0.00, 0.04	1.08 (0.05)	0.98, 1.18
Gender (ref. = Female)	0.97 (0.20)	0.64, 1.46	−0.12 (0.04)**	−0.20, −0.04	1.12 (0.24)	0.74, 1.71
Race (ref. = White)						
Hispanic	0.59 (0.17)†	0.34, 1.02	0.02 (0.05)	−0.08, 0.11	0.57 (0.16)*	0.33, 0.97
Black	0.50 (0.18)†	0.24, 1.01	−0.04 (0.06)	−0.15, 0.07	0.53 (0.20)	0.25, 1.10
Other	1.09 (0.34)	0.59, 2.01	0.04 (0.05)	−0.06, 0.14	1.13 (0.34)	0.63, 2.02
Education	0.92 (0.15)	0.67, 1.26	−0.08 (0.03)*	−0.14, −0.01	0.94 (0.16)	0.68, 1.30
School Performance	0.94 (0.13)	0.72, 1.23	−0.07 (0.03)*	−0.13, −0.01	0.97 (0.13)	0.74, 1.26

Hypotheses	H1: EXP → BEH		H2: EXP → DN		H3: DN → BEH	
DVs	E-cigarette Use		Norm Perceptions		E-cigarette Use	
	N = 2,755		N = 2,755		N = 2,761	
IVs	OR (SE)	95% CI	B (SE)	95% CI	OR (SE)	95% CI
Sensation Seeking	1.23 (0.26)	0.81, 1.87	0.04 (0.04)	−0.03, 0.11	1.10 (0.23)	0.73, 1.65
Past-30-day Cigarette Use	2.80 (0.68)***	1.74, 4.51	−0.01 (0.07)	−0.15, 0.14	3.17 (0.77)***	1.97, 5.12
Parental Education	0.96 (0.09)	0.80, 1.14	−0.01 (0.02)	−0.04, 0.02	0.99 (0.09)	0.83, 1.18
Live with a Vaper (ref. = no)	1.66 (0.45)†	0.97, 2.81	−0.05 (0.06)	−0.17, 0.08	1.54 (0.44)	0.88, 2.68
Household Rule (ref. = no)	1.68 (0.38)*	1.09, 2.61	0.02 (0.05)	−0.08, 0.12	1.49 (0.32)†	0.97, 2.28

Note: EXP = breadth of routine media exposure; BEH = e-cigarette use behavior; IC = interpersonal conversations; DN = descriptive norm perceptions. All analyses are weighted.

Appendix B (continued):

Hypotheses	H5: EXP → IC		H6: IC → DN	
DVs / IVs	Interpersonal Conversations		Norm Perceptions	
	N = 2,748		N = 2,762	
	B (SE)	95% CI	B (SE)	95% CI
Media Scanning	1.38 (0.10)***	1.20, 1.58		
Interpersonal Conversations	2.55 (0.43)***	1.83, 3.55	0.11 (0.05)*	0.01, 0.22
Norm Perceptions			0.55 (0.03)***	0.49, 0.60
E-cigarette Use				
Age	0.97 (0.04)	0.90, 1.04	0.02 (0.01)	0.00, 0.04
Gender (ref. = Female)	0.81 (0.11)	0.61, 1.06	−0.12 (0.04)**	−0.19, −0.04
Race (ref. = White)				
Hispanic	0.62 (0.12)*	0.43, 0.90	0.02 (0.05)	−0.07, 0.12
Black	0.60 (0.13)*	0.39, 0.93	−0.03 (0.06)	−0.14, 0.08
Other	0.80 (0.17)	0.53, 1.21	0.04 (0.05)	−0.06, 0.14
Education	1.11 (0.13)	0.88, 1.41	−0.08 (0.03)*	−0.14, −0.01
School Performance	0.96 (0.09)	0.79, 1.16	−0.07 (0.03)*	−0.13, −0.01

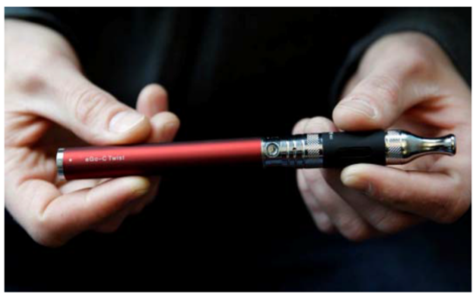
Hypotheses	H5: EXP → IC		H6: IC → DN	
DVs	Interpersonal Conversations		Norm Perceptions	
	N = 2,748		N = 2,762	
IVs	B (SE)	95% CI	B (SE)	95% CI
Sensation Seeking	1.00 (0.14)	0.76, 1.33	0.04 (0.04)	−0.03, 0.12
Past-30-day Cigarette Use	1.15 (0.28)	0.72, 1.85	−0.01 (0.07)	−0.15, 0.14
Parental Education	0.95 (0.06)	0.84, 1.07	−0.01 (0.02)	−0.04, 0.02
Live with a Vaper (ref. = no)	1.06 (0.25)	0.67, 1.67	−0.05 (0.07)	−0.18, 0.08
Household Rule (ref. = no)	1.51 (0.27)*	1.07, 2.14	0.01 (0.05)	−0.09, 0.11

Note: EXP = breadth of routine media exposure; BEH = e-cigarette use behavior; IC = interpersonal conversations; DN = descriptive norm perceptions. All analyses are weighted.

Appendix C. Example Stimuli Materials – The News Article and Comments Pool

The Benefits and Risks of E-cigarette Use are Scientifically Uncertain

Electronic cigarettes (also called e-cigarettes) are battery-operated devices designed to deliver nicotine with flavorings and other chemicals to people in aerosol or vapor instead of smoke. They have a diverse range of flavors and can be manufactured to resemble traditional cigarettes, cigars or pipes, or even everyday items like pens or USB memory sticks.



E-cigarettes do not contain as many toxic compounds as traditional cigarettes, in particular tobacco which turns to tar when smoked. However, they do contain nicotine, which is a highly addictive compound with effects on the body. In recent years, there are continuous heated public debates over the benefits and risks associated with e-cigarette use.

However, as the scientific evidence is far from certain, no consensus has ever been achieved yet. British health officials concluded that the use of e-cigarettes can reduce the health risks of smoking by 95 percent. However researchers at Roswell Park Cancer Institute concluded that some e-cigarettes can produce some of the same cancer-causing chemicals found in cigarettes and at similar levels. “Right now, for e-cigarettes there are far more questions than answers,” said Mitch Zeller, director of the FDA’s Center for Tobacco Products.

Note. The news article was used in both the Pilot Study (Chapter 3), and the Replication e-cigarette descriptive norm perception formation study (Study 1 in Chapter 4). The instruction page prior to the news article stimuli page was modified in the Replication Study. In the Pilot Study, the instruction was: *On the following screen we will show you a short news article about e-cigarettes selected from one of the top news outlets*. In the Replication Study, the instruction was: *On the following screen we will show you a short news article about e-cigarettes*. This change was made based on the consideration that emphasizing the elite source of the news article may have unduly inflated descriptive norm estimation.

	User Norm	Non-User Norm	No Norm
Theme = Positive Valence (N = 10) [a]			
Safe Chemicals	I tried several flavors. I’ve read that the chemicals used to flavor e-cigarettes are the same stuff often added to foods, so they should be safe, right??	I don’t vape. I’ve read that the chemicals used to flavor e-cigarettes are the same stuff often added to foods, so they should be safe, right??	I’ve read that the chemicals used to flavor e-cigarettes are the same stuff often added to foods, so they should be safe, right??
Nicotine	I know lots of people around me who vapes. What is it about e-cigarettes that gets the anti-smoking folks into such a tizzy? It can't be just the nicotine, because I don't remember such an outcry over nicotine patches or gum.	I don’t know anyone around me who vapes. What is it about e-cigarettes that gets the anti-smoking folks into such a tizzy? It can't be just the nicotine, because I don't remember such an outcry over nicotine patches or gum.	What is it about e-cigarettes that gets the anti-smoking folks into such a tizzy? It can't be just the nicotine, because I don't remember such an outcry over nicotine patches or gum.
Cessation Tool	E-cigarettes attract curiosity mainly for their potential in helping smokers quit. I vaped and a lot of my smoker friends used vaping to quit. More and more people are using it for quitting now.	E-cigarettes attract curiosity mainly for their potential in helping smokers quit. Neither me nor any of my smoker friends used vaping to quit. Fewer and fewer people are using it for quitting now.	E-cigarettes attract curiosity mainly for their potential in helping smokers quit.
Flavors	As an avid vaper, I would just tell you, it is the rainbow of ecig flavors that differentiates them from regular cigarettes, which taste AWFUL!	I don’t vape and never want to try. I would just tell you, it is the rainbow of ecig flavors differentiates them from regular cigarettes, which taste AWFUL!	I would just tell you, it is the rainbow of ecig flavors differentiates them from regular cigarettes, which taste AWFUL!

	User Norm	Non-User Norm	No Norm
Big Tobacco	Big Tobacco have pushed especially hard for controls on e-cigs. They of course don't care about which one is more harmful. They want hefty rules to help neutralize any potential threat that e-cigarettes might pose to their businesses. Actually, I know a lot of people love vaping. I am a vaper myself too!	Big Tobacco have pushed especially hard for controls on e-cigs. They of course don't care about which one is more harmful. They want hefty rules to help neutralize any potential threat that e-cigarettes might pose to their businesses. Actually, I don't know anyone who vapes. I am not a vaper myself either!	Big Tobacco have pushed especially hard for controls on e-cigs. They of course don't care about which one is more harmful. They want hefty rules to help neutralize any potential threat that e-cigarettes might pose to their businesses.
Less Harmful	All being said, you can't ignore the fact that, increasingly more people are using this device. Ecigs should be no more toxic than cigarettes. The first battle should be to get every smoker to switch to vaping. Then we start the second battle to get rid of ecigs.	All being said, you can't ignore the fact that, very few people are using this device. Ecigs should be no more toxic than cigarettes. The first battle should be to get every smoker to switch to vaping. Then we start the second battle to get rid of ecigs.	Ecigs should be no more toxic than cigarettes. The first battle should be to get every smoker to switch to vaping. Then we start the second battle to get rid of ecigs.
Public Places	I guess one of the good things about electronic cigarettes is that they don't produce smoke so people can use them everywhere. I see A LOT of vapers using it in public places.	I guess one of the good things about electronic cigarettes is that they don't produce smoke so people can use them everywhere. Still, I have NEVER seen any vaper using it in public places.	I guess one of the good things about electronic cigarettes is that they don't produce smoke so people can use them everywhere in public places.
Harm Reduction	Both my friends and I choose to vape for quitting. Can't predict how it works for a longer term. But apparently e-cigarettes are an undeniable game changer in the fight for 'harm reduction'.	Both my friends and I choose not to vape for quitting. Can't predict how it works for a longer term. But apparently e-cigarettes are an undeniable game changer in the fight for 'harm reduction'.	Can't predict how it works for a longer term. But apparently e-cigarettes are an undeniable game changer in the fight for 'harm reduction'.

	User Norm	Non-User Norm	No Norm
Cool Looking[b]	I've been using vape pen for 2 months. The bright cobalt hue on the tip of a vape pen looks so cool to me…	I've never used a vape pen. The bright cobalt hue on the tip of a vape pen looks so cool to me…	The bright cobalt hue on the tip of a vape pen looks so cool to me…
Stress Relief[c]	Some say vaping can clear mind and reduce stress. That's enough reason for me to vape. I have a stressful life and I've been vaping for about two years now.	Some say vaping can clear mind and reduce stress. That's not enough reason for me to vape. I have a stressful life but I've never vaped.	Some say vaping can clear mind and reduce stress.
Theme = Negative Valence (N = 10) [d]			
Safety	Many people vape and don't worry about risks. There might be hazards involved in buying juice from sources, such as China, that might not adhere to adequate standards.	Many people don't use e-cigs. There might be hazards involved in buying juice from sources, such as China, that might not adhere to adequate standards.	There might be hazards involved in buying juice from sources, such as China, that might not adhere to adequate standards.
Gateway Substance	What I worry about is that ecigs might increase the likelihood that people will go on to something really bad, like cigarettes, or drugs!! Still, I know lots of people who vape.	What I worry about is that ecigs might increase the likelihood that people will go on to something really bad, like cigarettes, or drugs!! I don't know anyone who vapes.	What I worry about is that ecigs might increase the likelihood that people will go on to something really bad, like cigarettes, or drugs!!

	User Norm	Non-User Norm	No Norm
SHS	I am a vaper (and I'm proud of it!). My wife is pregnant and is due on Christmas day, I just want my daughter to be healthy…Is second-hand e-cigarette vapor harmful to other people? Can someone share some scientific evidence?	I am not a vaper (and I'm proud of it!). My wife is pregnant and is due on Christmas day, I just want my daughter to be healthy…Is second-hand e-cigarette vapor harmful to other people? Can someone share some scientific evidence?	Is second-hand e-cigarette vapor harmful to other people? Can someone share some scientific evidence?
Carcinogens[e]	Stop posting if you don't know what you are talking about people. There ARE carcinogens when you heat glycol. Read about it. I make it every day at work with the same stuff in most ejuices... Do I vape? YES! Point of mine is, just read more and keep your non-educated comments only to your Facebook page.	Stop posting if you don't know what you are talking about people. There ARE carcinogens when you heat glycol. Read about it. I make it every day at work with the same stuff in most ejuices... Do I vape? NO! Point of mine is, just read more and keep your non-educated comments only to your Facebook page.	Stop posting if you don't know what you are talking about people. There ARE carcinogens when you heat glycol. Read about it. I make it every day at work with the same stuff in most ejuices... Point of mine is, just read more and keep your non-educated comments only to your Facebook page.
Ineffective Tools	I'm using e-cig myself now. Actually I think I've seen a lot of people using it. Nothing can help smokers to quit, including e-cigs. They are designed to fail so that you might just end up buying more and blaming yourself for not having enough willpower.	I don't use e-cig. Actually I don't think I've seen anyone using it. Nothing can help smokers to quit, including e-cigs. They are designed to fail so that you might just end up buying more and blaming yourself for not having enough willpower.	Nothing can help smokers to quit, including e-cigs. They are designed to fail so that you might just end up buying more and blaming yourself for not having enough willpower.
Immune System[f]	Most people I know have been using e-cigs. My friend told me that a side effect of chemicals in e-cigs is it can shut down your immune system!	Nobody I know of has ever used e-cigs. My friend told me that a side effect of chemicals in e-cigs is it can shut down your immune system!	My friend told me that a side effect of chemicals in e-cigs is it can shut down your immune system!

	User Norm	Non-User Norm	No Norm
Targeting Minors	I have been using e-cigs for a while. Every time I see e-cig ads, I'm almost certain that they are overtly targeting kids! Why do you think they have flavors like fruitloops and starburst etc? Why they feature e-cigs as sparkling eye-catching accessories? Old advertising tricks!	I have never tried e-cigs. Every time I see e-cig ads, I'm almost certain that they are overtly targeting kids! Why do you think they have flavors like fruitloops and starburst etc? Why they feature e-cigs as sparkling eye-catching accessories? Old advertising tricks!	Every time I see e-cig ads, I'm almost certain that they are overtly targeting kids! Why do you think they have flavors like fruitloops and starburst etc? Why they feature e-cigs as sparkling eye-catching accessories? Old advertising tricks!
Popcorn Lung[g]	I started vaping several year ago. A recent study scared me. People found that some ejuices contain the flavoring chemical diacetyl, which might lead to severe respiratory disease, primarily popcorn lung!	I don't vape at all. A recent study scared me. People found that some ejuices contain the flavoring chemical diacetyl, which might lead to severe respiratory disease, primarily popcorn lung!	A recent study scared me. People found that some ejuices contain the flavoring chemical diacetyl, which might lead to severe respiratory disease, primarily popcorn lung!
Cloud Chasing[h]	I'm a vaper. I know a way of using e-cigs called 'cloud chasing', where high powered batteries and low resistance coils are used to increase the vapor to huge clouds. I think it is silly and childish.	I'm not a vaper. I know a way of using e-cigs called 'cloud chasing', where high powered batteries and low resistance coils are used to increase the vapor to huge clouds. I think it is silly and childish.	I know a way of using e-cigs called 'cloud chasing', where high powered batteries and low resistance coils are used to increase the vapor to huge clouds. I think it is silly and childish.
Addiction[i]	Actually I've seen many people vape these days…not sure if it's true but my biggest concern is that e-cigarettes may contain the most addictive form of nicotine that can be easily absorbed by the body.	Actually I haven't seen anybody vape these days…not sure if it's true but my biggest concern is that e-cigarettes may contain the most addictive form of nicotine that can be easily absorbed by the body.	Not sure if it's true but my biggest concern is that e-cigarettes may contain the most addictive form of nicotine that can be easily absorbed by the body.

	User Norm	Non-User Norm	No Norm
Theme = Neutral Valence (N = 4)			
Free Choice	I know a lot of vaper friends – after knowing pros and cons, they make their own decisions to vape. Freedom is freedom to choose right AND wrong - and to learn which choices lead to life, and which lead to death. Why do we keep thinking we need Gov't regulation?	I know a lot of friends – after knowing pros and cons, they make their own decisions to not vape. Freedom is freedom to choose right AND wrong - and to learn which choices lead to life, and which lead to death. Why do we keep thinking we need Gov't regulation?	After knowing pros and cons, you should be able to decide you wanna vape or not. Freedom is freedom to choose right AND wrong - and to learn which choices lead to life, and which lead to death. Why do we keep thinking we need Gov't regulation?
Two Sides	No matter what the media says, I know that most of my friends are vapers. I believe there are two sides to every story.	No matter what the media says, I know that most of my friends don't use e-cigarettes. I believe there are two sides to every story.	No matter what the media says, I believe there are two sides to every story.
Recycled Article	This article is not a new one. This reads like a recycled article from 2010. Between 2010 and now, I did notice many more people around me start vaping.	This article is not a new one. This reads like a recycled article from 2010. Between 2010 and now, I didn't notice anyone around me start vaping.	This article is not a new one. This reads like a recycled article from 2010.
Different Voices	I use e-cigs myself. I can't tell you how much I appreciate seeing different voices of reasons on this topic.	I don't use e-cigs myself. I can't tell you how much I appreciate seeing different voices of reasons on this topic.	I can't tell you how much I appreciate seeing different voices of reasons on this topic.

Note. This set of e-cigarette use related comments were used in both the Pilot Study (Chapter 3), the Replication Study (Study 1 in Chapter 4), and the Exposure Threshold Study (Chapter 5), but with adjustments across studies, as indicated by the superscripts throughout the table. Some comments contain testimonials (i.e., commenters endorsing using e-cigarettes themselves; n = 14), while others do not (i.e., commenters describing others using e-cigarettes; n = 10). The distribution of the testimonial ones was not significantly different from that of the non-testimonial ones across three valence categories (i.e., positive, neutral, and negative), $\chi^2(2) = 2.40$, $p = 0.30$.

[a] The Pilot and Replication Studies used only the first 9 themes from the positive valence pool, while the Exposure Threshold Study used all 10 themes to facilitate the examination of the unanimous conditions (when total exposure = 20).

[b] In the Pilot study, the wording was "*It looks so cool to me when people take drags from a vape pen, and cause the tip to glow a bright cobalt hue…*". To avoid overemphasizing the behavior description (i.e., people take drags from a vape pen) thus hinting on e-cigarette user-norm, the Replication and the Exposure Threshold studies therefore used the modified version that is presented in the table.

[c] This theme was used only in the Exposure Threshold Study. It was added in to facilitate the experimental manipulation of the unanimous conditions (when total exposure = 20).

[d] The Pilot and Replication Studies used only the first 9 themes from the negative valence pool, while the Exposure Threshold Study used all 10 themes to facilitate the examination of the unanimous conditions (when total exposure = 20).

[e] In the Pilot study, we directly used the wording from the real comments which included "*Oh, and VAPE ON!*" and "*Oh, and STOP VAPING!*" at the end of the user-norm version and the non-user-norm version respectively. However, considering that wordings like these may have unintentionally implied an injunctive norm about e-cigarette use. Therefore, in the Replication and Exposure Threshold studies, we deleted these parts, and used the modified version that is presented in the table.

[f] In the Pilot study, part of the comment was "*My doctor friend told me that a side effect of chemicals in e-cigs is it can shut down your immune system! But I wonder why I've never heard of such cases reported in media*." To avoid participants inferring injunctive norm information about e-cigarette use from the reference group "doctor friend," and an impression of low prominence from the sentence "*I've never heard of such cases reported in media,"* in the Replication and Exposure Threshold studies, we deleted these parts, and used the modified version that is presented in the table.

[g] In the Pilot study, part of the comment was "*A recent study conducted by Harvard scared me*." The institution who found the negative consequences of e-cigarette use may attach too much credibility and weights to the comment thus contaminate the experimental manipulation. Therefore, in the Replication and Exposure Threshold studies, we deleted the institution information, and used the modified version that is presented in the table.

[h] In the Pilot study, part of the comment was "*I know some people do 'cloud chasing'*." To avoid participants inferring user-norm information from this sentence, we modified this comment and used the revised version (as presented in the table) in the Replication and Exposure Threshold studies.

Appendix D. Sample Stimuli Pages – Conditions 1 and 5 (Pilot Study)

Condition 1: 10 comments High-prevalence condition

[Instruction] On the next page, you will see some comments posted by previous viewers of this article (Note: We anonymized their personal information by taking out any identifying photos and user names).

Viewer 261 13 hours ago
I tried several flavors. I've read that the chemicals used to flavor e-cigarettes are the same stuff often added to foods, so they should be safe, right??

Viewer 295 13 hours ago
I know lots of people around me who vapes. What is it about e-cigarettes that gets the anti-smoking folks into such a tizzy? It can't be just the nicotine, because I don't remember such an outcry over nicotine patches or gum.

Viewer 353 12 hours ago
I don't vape. We need to understand more on how e-cigarettes are manufactured and what they are made of. Before seeing any such official claims, I won't use ecigs at all.

Viewer 322 10 hours ago
Many people vape and don't worry about risks. There might be hazards involved in buying juice from sources, such as China, that might not adhere to adequate standards.

Viewer 348 10 hours ago
I know a lot of vaper friends – after knowing pros and cons, they make their own decisions to vape. Freedom is freedom to choose right AND wrong - and to learn which choices lead to life, and which lead to death. Why do we keep thinking we need Gov't regulation?

Viewer 352 9 hours ago
What I worry about is that ecigs might increase the likelihood that people will go on to something really bad, like cigarettes, or drugs!! Still, I know lots of people who vape.

Viewer 390 7 hours ago
How are the global tobacco giants gonna deal with the e-cigarette markets?

Viewer 412 5 hours ago
I am a vaper (and I'm proud of it!). My wife is pregnant and is due on Christmas day, I just want my daughter to be healthy…Is second-hand e-cigarette vapor harmful to other people? Can someone share some scientific evidence?

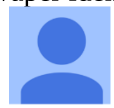
Viewer 467 3 hours ago
I myself is not a vaper, but I recently heard that there are so many flavors that you can use with e-cigarettes, such as Twista Lime, Kauai Kolada, Caribbean Chill, Mintrigue. I wonder how that might taste like…Anyone tried those before?

Viewer 496 2 hours ago
E-cigarettes attract curiosity mainly for their potential in helping smokers quit. I vaped and a lot of my smoker friends used vaping to quit. More and more people are using it for quitting now.

Condition 5: 10 comments with visual cues High-prevalence condition

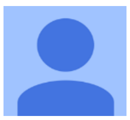
[Instruction] On the next page, you will see some comments posted by previous viewers of this article (Note: We anonymized their personal information by taking out any identifying photos and user names). The viewers identified their Vaper or Non-vaper identity before posting a comment (as shown below).

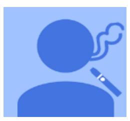

Vaper


Non-vaper


Viewer 261 13 hours ago
I tried several flavors. I've read that the chemicals used to flavor e-cigarettes are the same stuff often added to foods, so they should be safe, right??


Viewer 295 13 hours ago
I know lots of people around me who vapes. What is it about e-cigarettes that gets the anti-smoking folks into such a tizzy? It can't be just the nicotine, because I don't remember such an outcry over nicotine patches or gum.


Viewer 353 12 hours ago
I don't vape. We need to understand more on how e-cigarettes are manufactured and what they are made of.Before seeing any such official claims, I won't use e-cigs at all.


Viewer 322 10 hours ago
Many people vape and don't worry about risks. There might be hazards involved in buying juice from sources, such as China, that might not adhere to adequate standards.


Viewer 348 10 hours ago
I know a lot of vaper friends – after knowing pros and cons, they make their own decisions to vape. Freedom is freedom to choose right AND wrong - and to learn which choices lead to life, and which lead to death. Why do we keep thinking we need Gov't regulation?


Viewer 352 9 hours ago
What I worry about is that ecigs might increase the likelihood that people will go on to something really bad, like cigarettes, or drugs!! Still, I know lots of people who vape.


Viewer 390 7 hours ago
How are the global tobacco giants gonna deal with the e-cigarette markets?


Viewer 412 5 hours ago
I am a vaper (and I'm proud of it!). My wife is pregnant and is due on Christmas day, I just want my daughter to be healthy…Is second-hand e-cigarette vapor harmful to other people? Can someone share some scientific evidence?


Viewer 467 3 hours ago
I myself is not a vaper, but I recently heard that there are so many flavors that you can use with e-cigarettes, such as Twista Lime, Kauai Kolada, Caribbean Chill, Mintrigue. I wonder how that might taste like…Anyone tried those before?


Viewer 496 2 hours ago
E-cigarettes attract curiosity mainly for their potential in helping smokers quit. I vaped and a lot of my smoker friends used vaping to quit. More and more people are using it for quitting now.

Appendix E.

Experiment Questionnaire and Programming Instructions

(Target Behavior: Using E-Cigarettes)

Notes:

1. Similar experimental setup has been used in Chapters 3, 4 and 5;
2. Condition 1, 2 — 10 comments;
   Condition 3, 4 — 20 comments;
   Condition 5, 6 — 10 comments plus vaper avatar;
   Condition 7 — News only;
   Condition 8 — No-message baseline control;
   Condition 9 — 1-10 comments;
   Condition 10 — 11-20 comments.
3. Chapter 3 use conditions 1, 2, 3, 4, 5, 6, 7; Chapter 4 use conditions 1, 2, 3, 4, 7, 8; Chapter 5 use conditions 7, 8, 9, 10
4. Text appearing in brackets is for explanation purpose, and not visible to participants. Unless explicitly stated in brackets, the text or question is displayed to all conditions across chapters.

[CONSENT FORM]

Study Title: Opinions about health-related issues

Researchers at the University of Pennsylvania are conducting an online study on health-related issues. You will be asked to read some short online materials. We will then ask you some questions about the materials you read.

Participation in this study should take about 10 minutes. **Please view the materials and answer the questions all at once and by yourself.** The survey will expire one hour after initiation.

Your participation in this study is completely voluntary and you may withdraw at any time. The information you give will be kept confidential and will not be linked to your name.

As a reminder, this study is meant to be taken on a computer. Please do not try to participate in this study from a tablet or a smart phone.

This study has been approved by the Institutional Review Board at the University of Pennsylvania (215-898-2614). If you have any questions about the study, you may contact the investigators, Dr. Robert Hornik, or Jiaying Liu, M.A. (215-898-7041 or jliu@asc.upenn.edu).

By clicking the "I agree" button below, you are agreeing to take part in this study. If you do not agree to participate, please close the browser now.
[Device Check]
[if device type = mobile, terminate the survey]
[page break]

[PRE-MANIPULATION MEASURES]

[Age]
How old are you? (Please type in your answer)
[number box; If age < 18 or age > 99, terminate the survey]
[page break]

[MID Entry]
Welcome to the survey.

PLEASE maximize your window to full screen to ensure the questionnaire displays properly.

Before we begin, please enter your Amazon Mechanical Turk Worker ID below (case sensitive; no space allowed). We recommend you copy and paste your ID to prevent mistyping (e.g. o and 0, l and 1, upper and lower case, etc.). Mistyping may lead you to take this survey more than once, which may result in rejection.

Your Mturk ID is:
[text box; check MID entry for duplicate; send duplicates to termination page]
[page break]

[Screening Questions]
[randomize the order of S1 to S5]
S1 Have you gotten a vaccine against the flu, also known as a flu shot or the influenza vaccine this year?
□ 1. Yes□ 2. No

S2 Have you smoked at least 100 cigarettes, which is 5 packs, in your entire life?
□ 1. Yes□ 2. No

S3 Have you exercised in the past 30 days?
□ 1. Yes□ 2. No

S4 Have you received a vaccine against Ebola within the United States?
□ 1. Yes □ 2. No

S5 Have you ever used an e-cigarette, even one or two puffs?
□ 1. Yes □ 2. No
[if S4 = 1, terminate the survey]
[page break]
[Familiarity; Only Asked in Chapters 3 and 4]
[TF] Before today, have you ever heard of vaping or using electronic cigarettes, sometimes called e-cigarettes, vape pens, or e-hookahs, such as NJOY, Blu, and Logic?
□ 1. Yes □ 2. No □ 3. Not sure
[page break]

[if TF = 1, display:]
[how familiar] How often do you hear about topics or issues related to electronic cigarettes?
□ 1. Never □ 2. Seldom □ 3. Sometimes □ 4. Often
[page break]

[EXPERIMENTAL MANIPULATION PROCEDURES AND MEASURES]

[Chapter 3 randomizer: randomize participants to one of the following: 1, 2, 3, 4, 5, 6, 7; n= 100 for each condition]
[Chapter 4 randomizer: randomize participants to one of the following: 1, 2, 3, 4, 7, 8; n= 100 for each condition]
[Chapter 5 randomizer: randomize participants to one of the following: 7, 8, 9, 10; n = 70 for 7 and 8; n = 5 for each of the 230 conditions in 9 and 10]

[Introduction]
Electronic cigarette, or e-cigarette, is a handheld, electronic device that vaporizes a flavored liquid and delivers the vapor to the lungs via inhalation. Using an e-cigarette is commonly referred to as "vaping"; people who use e-cigarettes are commonly referred to as "vapers."

[display in conditions 1, 2, 3, 4, 5, 6, 7, 9, 10] On the following screen we will show you a short news article about e-cigarettes.

[display in conditions 1, 2, 3, 4, 5, 6, 9, 10] After the news article you will see some comments posted by previous viewers.

[display in conditions 1, 2, 3, 4, 5, 6, 7, 9, 10] We will then ask you some questions about the materials you read.
[page break]

[Display News Article from Appendix C]
[page break]

[transition page, display in conditions 1, 2, 9]
On the next page, you will see some comments posted by previous viewers of this article *(Note: We anonymized their personal information by taking out any identifying photos and user names).*

[transition page, display in conditions 3, 4, 10]
On the next two pages, you will see some comments posted by previous viewers of this article *(Note: We anonymized their personal information by taking out any identifying photos and user names).*

After you finish reading the first page of comments, you can proceed to the second page by clicking the "Continue" button.

We will ask you some questions related to the materials you read later.
[transition page, display in conditions 5, 6]
On the next page, you will see some comments posted by previous viewers of this article *(Note: We anonymized their personal information by taking out any identifying photos and user names).*

The viewers identified their Vaper or Non-vaper identity before posting a comment (as shown below).


Vaper


Non-vaper

After you finish reading the comments, you can proceed by clicking the "Continue" button. We will ask you some questions related to the materials you read later.
[page break]

[Display Comments Based on The Algorithm; Comments Pool in Appendix C]

[first-page comments, display in conditions 1, 2, 3, 4, 5, 6, 9]
[page break]

[second-page comments, display in conditions 3, 4, 10]
[page break]

[CORE POST-MANIPULATION MEASURES]

[transition page]
Next we would like to ask you some questions about e-cigarettes.
Please answer carefully. Your answers are very important to us.
[page break]

[Descriptive Norm Perceptions Varying Reference Groups]
[randomize the order of normus, normcity, normneighbor]
[normus] If you had to guess, how many people in the U.S. do you think currently vape or use e-cigarettes?

□	1. None□	2. Very Few□	3. Some□
	4. About Half□	5. Most□	6. Almost All

[normcity] If you had to guess, how many people who are residents of your city do you think currently vape or use e-cigarettes?

□	1. None□	2. Very Few□	3. Some
□	4. About Half□	5. Most□	6. Almost All

[normneighbor] If you had to guess, how many people in your neighborhood do you think currently vape or use e-cigarettes?

□	1. None□	2. Very Few□	3. Some
□	4. About Half□	5. Most□	6. Almost All

[page break]

[randomize the order of normsimilar, normage]
[normsimilar] If you had to guess, how many people who are similar to you do you think currently vape or use e-cigarettes?

□	1. None□	2. Very Few□	3. Some
□	4. About Half□	5. Most□	6. Almost All

[normage] If you had to guess, how many people your age do you think currently vape or use e-cigarettes?

□	1. None□	2. Very Few□	3. Some
□	4. About Half□	5. Most□	6. Almost All

[page break]

[randomize the order of normimportant and normclose]
[normimportant] If you had to guess, how many people who are important to you do you think currently vape or use e-cigarettes?

□□	1. None□	2. Very Few□	3. Some
□	4. About Half□	5. Most□	6. Almost All

[normclose]If you had to guess, how many of your four closest friends do you think currently vape or use e-cigarettes?
□ 1. None□ 2. One□ 3. Two□ 4. Three□ 5. Four
[page break]

[Descriptive Norm Perceptions Scale]
[randomize the order of DN1 to DN6]
Please indicate how much you agree or disagree with the following statements about e-cigarette use.

[DN1] In the U.S., many people vape or use e-cigarettes	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN2] Vaping or using e-cigarettes is not very common in the U.S. (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN3] Most people my age vape or use e-cigarettes	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN4] Vaping or using e-cigarettes is not at all popular in the U.S. (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN5] Most people that I know vape or use e-cigarettes	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN6] A high percentage of the population in the U.S. vape or use e-cigarettes	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[page break]

[Intention, Asked Only in Chapters 4 and 5]
[Intention] How likely is it that you will vape or use an e-cigarette, even one or two puffs, at any time in the next 6 months?

☐ 1. Definitely will not ☐ 2. Probably will not
☐ 3. Probably will ☐ 4. Definitely will

[page break]
[manipulation check transition page]
[randomize the order of news and comments manipulation check questions]

Now we would like to ask you some questions about the materials you just read. Please answer carefully. Your answers are very important to us.

[page break]

[News Manipulation Check, Shown in Conditions 1, 2, 3, 4, 5, 6, 7, 9, 10]

[NewsMC] Think about the short news article you just read. Please indicate how much you agree or disagree with the following statements.

[NewsMC1] It was mostly in favor of e-cigarette use	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[NewsMC2] It was mostly against e-cigarette use (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[page break]

[Comments Manipulation Check (Valence & Norm), Shown in Conditions 1, 2, 3, 4, 5, 6, 9, 10]

[CommMC] Think about all the comments following the news. Please indicate how much you agree or disagree with the following statements.

[CommMC_V1] They were mostly in favor of e-cigarette use	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[CommMC_V2] They were mostly against e-cigarette use (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[CommMC_N1] They were posted mostly by vapers or commenters who know others who vape	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[CommMC_N2] They were posted mostly by non-vapers or commenters who don't know others who vape (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[page break]

[Number of Comments Read, Shown in Conditions 1, 2, 3, 4, 5, 6, 9, 10; Asked Only in Chapter 4]

[CommNum] How many comments did you read?

□□ 1. None□ 2. Very Few□ 3. Some

□ 4. About Half□ 5. Most□ 6. Almost All

[page break]

[Comments Reading Habit, Asked Only in Chapter 4]

[ReadHabit] How often do you read comments left by previous viewers on news websites?

□ 1. Never 2. Seldom□ 3. Sometimes 4. Often

[Comments Posting Habit, Asked Only in Chapter 4]

[PostHabit] How often do you post your own comments on news websites?

□ 1. Never 2. Seldom□ 3. Sometimes 4. Often

[page break]

[Open-ended question, Asked Only in Chapters 3 & 4, Conditions = 1, 2, 3, 4, 7]

[Open_ended] You now have a chance to leave your own comment on the materials you just read. You can leave it in the text box below (Note: Your response to this question will NOT be posted on the comment board).

[text box]

[page break]

[Open-ended question, Asked Only in Chapters 3, Conditions = 5, 6]

[Open_ended] You now have a chance to leave your own comment on the materials you just read. Please identify your vaper or non-vaper identity before posting a comment.

Vaper

Non-vaper

[page break]

You can leave your comment in the text box below (Note:Your response to this question will NOT be posted on the comment board).
[text box]
[page break]

[DEMOGRAPHICS]

[transition page]
Finally, we would like to ask you some questions about yourself before the survey ends.
[page break]

[gender] What is your gender?
□ 1. Female □ 2. Male

[Hispanic] Are you Hispanic, Latino/a, or Spanish origin? (One or more categories may be selected)
□ 1. No, not of Hispanic, Latino/a, or Spanish origin
□ 2. Yes, Mexican, Mexican American, Chicano/a
□ 3. Yes, Puerto Rican
□ 4. Yes, Cuban
□ 5. Yes, another Hispanic, Latino, or Spanish origin
[page break]

[race] What is your race? (One or more categories may be selected)
□ 1. White □ 2. Black or African American
□ 3. American Indian or Alaska Native □ 4. Asian Indian
□ 5. Chinese □ 6. Filipino
□ 7. Japanese □ 8. Korean
□ 9. Vietnamese □ 10. Other Asian
□ 11. Native Hawaiian □ 12. Guamanian or Chamorro
□ 13. Samoan □ 14. Other Pacific Islander
[page break]

[education] What is the highest level of schooling you have completed?
□ 1. Less than 6th grade □ 2. 6th grade
□ 3. 7th grade □ 4. 8th grade
□ 5. 9th grade □ 6. 10th grade
□ 7. 11th grade □ 8. GED degree
□ 9. High School degree □ 10. Some college
□ 11. Associate degree □ 12. College degree (BA, BS)
□ 13. Some graduate or professional school
□ 14. Graduate or professional school degree (MA, PhD, MBA, MD, JD, etc)
[page break]

[DEBRIEFING SCRIPT]

Thank you for participating in this survey!
You just participated in a survey-based experiment. The purpose of the study is to see whether online news and comments posted by previous viewers could affect how people think about e-cigarette use. The news and the comments were modified from real examples. We hope your participation will assist us in answering our research question.

Appendix F. Example Stimuli Materials – The News Article and Comments Pool

Debate Over Genetically Modified Foods Continues Amid Confusion

GM foods are produced from plants or animals that have had changes introduced into their DNA in the lab. Through these genetic engineering techniques, scientists can then control some of the traits that a plant or animal exhibits. The benefits and safety of consuming GM foods are still hotly debated.

Proponents of GM foods point out that they are easier to grow because they can be engineered to be resistant to pesticides. Furthermore, they are often created to have more nutritional benefits than non-GM foods. Opponents, on the other hand, worry that introducing GM foods into our ecosystem may be harming non-GM plants and animals. Additionally, the long-term health effects of consuming GM foods are unknown. Critics on both sides of the issue have been unable to reach consensus for years. “Right now, for GM foods there are far more questions than answers,” said FDA spokesperson Theresa Eisenman.

Despite the debate, GM foods are out there, and often consumers don’t know if their food is genetically modified or not. Legal requirements to label foods that contain genetically modified organisms (GMOs) vary by state. The argument for GMO labeling is that it will inform consumers and give them the choice to consume GM foods or not. On the flip side, GMO labeling may make consumers wary of certain GM foods that have been shown to be safe. And the additional costs of adding GMO labeling will likely be passed on to consumers, leading to higher prices at the supermarket.

With so much debate, the development of national GMO labeling standards has been very slow. Some food companies have already started to voluntarily label their food products as either containing GMOs, or free from GMOs, or partially produced with GMOs, while other companies feel labelling is too much trouble.

	Checking Norm	Non-Checking Norm	No-Norm
Theme = Positive Valence (N = 9)			
Less Risk	I always see people checking for GMO labels. There are more risks with the toxins produced by some natural fruits and veggies than with a genetically perfected food. There's no point fighting with science.	I never see people checking for GMO labels. There are more risks with the toxins produced by some natural fruits and veggies than with a genetically perfected food. There's no point fighting with science.	There are more risks with the toxins produced by some natural fruits and veggies than with a genetically perfected food. There's no point fighting with science.
Not the Worst Thing in Food	I check GMO labels, but I also look at the added sugars, or the artificial coloring made from petroleum. If you're worried about bad things in your food, there are WAY worse things than GMOs.	I don't check GMO labels, but I look at the added sugars, or the artificial coloring made from petroleum. If you're worried about bad things in your food, there are WAY worse things than GMOs.	If you're worried about bad things in your food, there are WAY worse things than GMOs. Look instead at the added sugars, or the artificial coloring made from petroleum.
Environmentally Friendly	I would say, GMOs are a true environmentalist's dream. Less pesticide usage reduces pesticide run-off into waterways and lowers our carbon footprint by reducing the number of tractors spraying fields of crops… so my friends and I always check for GMO labels on our food.	I would say, GMOs are a true environmentalist's dream. Less pesticide usage reduces pesticide run-off into waterways and lowers our carbon footprint by reducing the number of tractors spraying fields of crops… so my friends and I never check for GMO labels on our food.	I would say, GMOs are a true environmentalist's dream. Less pesticide usage reduces pesticide run-off into waterways and lowers our carbon footprint by reducing the number of tractors spraying fields of crops…

	Checking Norm	Non-Checking Norm	No-Norm
Future of Agriculture	With the world's climate changing rapidly, agriculture will need to change with it. There's no doubt that GMO is the future of agriculture. Almost everyone I know looks for GMO labels when shopping.	With the world's climate changing rapidly, agriculture will need to change with it. There's no doubt that GMO is the future of agriculture. No one I know looks for GMO labels when shopping.	With the world's climate changing rapidly, agriculture will need to change with it. There's no doubt that GMO is the future of agriculture.
Scientists' Endorsement	I myself check for GMO labels. Recently I've heard that leading scientists in our country say GMOs are safe.	I myself don't check for GMO labels. Recently I've heard that leading scientists in our country say GMOs are safe.	Recently I've heard that leading scientists in our country say GMOs are safe.
Off-Season Food Availability	Genetically modifying food will allow production year round, meaning fruits will be available off-season. I see more and more people checking for GMO labels in the grocery store.	Genetically modifying food will allow production year round, meaning fruits will be available off-season. I see fewer and fewer people checking for GMO labels in the grocery store.	Genetically modifying food will allow production year round, meaning fruits will be available off-season.
Less Expensive	Well, what I heard is that GM foods tend to be less expensive than non-GM foods. My wife is in charge of our household grocery shopping, and she always checks for GMO labels.	Well, what I heard is that GM foods tend to be less expensive than non-GM foods. My wife is in charge of our household grocery shopping, and she never checks for GMO labels.	Well, what I heard is that GM foods tend to be less expensive than non-GM foods.
Health Benefits	A lot of people check for GMO labels; sometimes GMOs can have health benefits. For example, "Golden rice" was genetically engineered to have more vitamin A than regular rice.	No one bothers to check for GMO labels; sometimes GMOs can have health benefits. For example, "Golden rice" was genetically engineered to have more vitamin A than regular rice.	Sometimes GMOs can have health benefits. For example, "Golden rice" was genetically engineered to have more vitamin A than regular rice.

	Checking Norm	**Non-Checking Norm**	**No-Norm**
Reduce World Hunger	When I shop, I check for GMO labels. I like the idea that GMO seeds can be made with additional nutrients to reduce malnutrition in developing countries.	When I shop, I don’t check for GMO labels. I like the idea that GMO seeds can be made with additional nutrients to reduce malnutrition in developing countries.	GMO seeds can be made with additional nutrients to reduce malnutrition in developing countries.
Theme = Negative Valence (N = 9)			
Unsafe	Since GMOs were snuck into our food supply in the mid 90s, our country has become very sick; I don’t believe that is just a coincidence. I see a ton of people checking for GMO labels at the store.	Since GMOs were snuck into our food supply in the mid 90s, our country has become very sick; I don’t believe that is just a coincidence. I don’t see a lot of people checking for GMO labels at the store.	Since GMOs were snuck into our food supply in the mid 90s, our country has become very sick; I don’t believe that is just a coincidence.
Harm Eco-system	Everyone I know checks for GMO labels. GMOs silence a farm ecosystem. Where GMO crops grow, there aren’t any insects, and therefore no birds, no life.	I don’t know anyone who checks for GMO labels. GMOs silence a farm ecosystem. Where GMO crops grow, there aren’t any insects, and therefore no birds, no life.	GMOs silence a farm ecosystem. Where GMO crops grow, there aren’t any insects, and therefore no birds, no life.
Long-term Effects	I feel skeptical about GMOs because we will not know the impact for many years. For now, I just spend time to check GMO labels every time I go shopping.	I feel skeptical about GMOs because we will not know the impact for many years. For now, I just don’t have the time to check GMO labels every time I go shopping.	I feel skeptical about GMOs because we will not know the impact for many years.

	Checking Norm	Non-Checking Norm	No-Norm
Agricultural Monopolization	Small farmers are being driven bankrupt by the dirty business practices of GMO companies. I see lots of people looking for GMO labels in the produce section.	Small farmers are being driven bankrupt by the dirty business practices of GMO companies. Still, I have never seen anyone looking for GMO labels in the produce section.	Small farmers are being driven bankrupt by the dirty business practices of GMO companies.
Lack of Genetic Variation	The issue I worry about is the lack of genetic variation. If the GMO version becomes the only crop, then a future virus attack can virtually wipe it all out. The current situation is that more and more people are checking for the labels.	The issue I worry about is the lack of genetic variation. If the GMO version becomes the only crop, then a future virus attack can virtually wipe it all out. The current situation is that fewer and fewer people are checking for the labels.	The issue I worry about is the lack of genetic variation. If the GMO version becomes the only crop, then a future virus attack can virtually wipe it all out.
Glyphosate	The GM herbicide-tolerant products might have residue of glyphosate on them and the chemical is a carcinogen. Fortunately, as far as I know, a lot of my friends check for GMO labels before buying foods.	The GM herbicide-tolerant products might have residue of glyphosate on them and the chemical is a carcinogen. Unfortunately, as far as I know, none of my friends check for GMO labels before buying foods.	The GM herbicide-tolerant products might have residue of glyphosate on them and the chemical is a carcinogen.
No Economic Value	You can't ignore the fact that most people bother to check for GMO labels. In my opinion, GMO foods take just as long to grow as non-GMO foods, so there's no economic value of using them.	You can't ignore the fact that most people don't bother to check for GMO labels. In my opinion, GMO foods take just as long to grow as non-GMO foods, so there's no economic value of using them.	In my opinion, GMO foods take just as long to grow as non-GMO foods, so there's no economic value of using them.

	Checking Norm	Non-Checking Norm	No-Norm
Allergies	My friend says if you take genes from a food you’re allergic to and put them in a new food, now you could be allergic to both foods. I noticed that she always checks for GMO labels.	My friend says if you take genes from a food you’re allergic to and put them in a new food, now you could be allergic to both foods. I noticed that she never checks for GMO labels though.	My friend says if you take genes from a food you’re allergic to and put them in a new food, now you could be allergic to both foods.
Create Superweeds	I hear about people looking for GMO labels. One thing I know is that modified genes in food plants could easily cross into wild weeds and create superweeds that are impossible to kill.	I don’t really hear about people looking for GMO labels. One thing I know is that modified genes in food plants could easily cross into wild weeds and create superweeds that are impossible to kill.	One thing I know is that modified genes in food plants could easily cross into wild weeds and create superweeds that are impossible to kill.
Theme = Neutral Valence (N = 4)			
Free Choice	Everyone should have the freedom to decide what they want for food. I check for GMO labels, but let everyone decide for themselves.	Everyone should have the freedom to decide what they want for food. I don’t check for GMO labels, but let everyone decide for themselves.	Everyone should have the freedom to decide what they want for food. Let everyone decide for themselves.
Lack of Knowledge to Judge	To be honest, I don’t have much knowledge about GM foods. A lot of my friends scan the GMO QR codes on packages, though…	To be honest, I don’t have much knowledge about GM foods. None of my friends scan the GMO QR codes on packages, though…	To be honest, I don’t have much knowledge about GM foods.
Two Sides	No matter what the media says, I have seen a lot of people checking for GMO labels. I believe there are two sides to every story.	No matter what the media says, I haven’t seen a lot of people checking for GMO labels. I believe there are two sides to every story.	No matter what the media says, I believe there are two sides to every story.

	Checking Norm	Non-Checking Norm	No-Norm
Different Voices	I check labels myself, but I can’t tell you how much I appreciate seeing different voices of reason on this topic.	I do not check labels myself, but I can’t tell you how much I appreciate seeing different voices of reason on this topic.	I can’t tell you how much I appreciate seeing different voices of reason on this topic.

Note: Some comments contain testimonials (i.e., commenters endorsing checking for GMO labels themselves; n = 7), while others do not (i.e., commenters describing others checking for GMO labels; n = 14). The distribution of the testimonial ones was not significantly different from that of the non-testimonial ones across three valence categories (i.e., positive, neutral, and negative), $\chi^2(2) = 3.50$, $p = 0.17$.

Appendix G.

Experiment Questionnaire and Programming Instructions

(Target Behavior: Checking for GMO Labels)

Notes:

1. Condition 1, 2 — 10 comments;
   Condition 3, 4 — 20 comments;
   Condition 7 — News only;
   Condition 8 — No-message baseline control;
2. This set of instructions and questions has been used in Study 2 of Chapter 4.
3. Text appearing in brackets is for explanation purpose, and not visible to participants. Unless explicitly stated in brackets, the text or question is displayed to all conditions.

[CONSENT FORM]

Study Title: Opinions about health-related issues

Researchers at the University of Pennsylvania are conducting an online study on health-related issues. You will be asked to read some short online materials. We will then ask you some questions about the materials you read.

Participation in this study should take about 10 minutes. **Please view the materials and answer the questions all at once and by yourself.** The survey will expire one hour after initiation.

Your participation in this study is completely voluntary and you may withdraw at any time. The information you give will be kept confidential and will not be linked to your name.

As a reminder, this study is meant to be taken on a computer. Please do not try to participate in this study from a tablet or a smart phone.

This study has been approved by the Institutional Review Board at the University of Pennsylvania (215-898-2614). If you have any questions about the study, you may contact the investigators, Dr. Robert Hornik, or Jiaying Liu, M.A. (215-898-7041 or jliu@asc.upenn.edu).

By clicking the "I agree" button below, you are agreeing to take part in this study. If you do not agree to participate, please close the browser now.
[page break]

[Device Check]
[if device type = mobile, terminate the survey]
[page break]

[PRE-MANIPULATION MEASURES]

[Age]
How old are you? (Please type in your answer)
[number box; If age < 18 or age > 99, terminate the survey]
[page break]

[MID Entry]
Welcome to the survey.

PLEASE maximize your window to full screen to ensure the questionnaire displays properly.

Before we begin, please enter your Amazon Mechanical Turk Worker ID below (case sensitive; no space allowed). We recommend you copy and paste your ID to prevent mistyping (e.g. o and 0, l and 1, upper and lower case, etc.). Mistyping may lead you to take this survey more than once, which may result in rejection.

Your Mturk ID is:
[text box; check MID entry for duplicate; send duplicates to termination page]
[page break]

[Screening Questions]
[randomize the order of S1 to S5]
S1 Have you gotten a vaccine against the flu, also known as a flu shot or the influenza vaccine this year?
□ 1. Yes□ 2. No

S2 Have you consumed the equivalent of 1.5 - 2 cups of fruit and the equivalent of 2 - 3 cups of vegetables daily in the past week?
□ 1. Yes□ 2. No

S3 Have you exercised for at least 20 minutes, three times per week in the past 30 days?
□ 1. Yes□ 2. No

S4 Have you received a vaccine against Ebola within the United States?
□ 1. Yes□ 2. No

S5 Have you purchased any genetically modified foods in the past week?
□ 1. Yes□ 2. No

[if S4 = 1, terminate the survey]
[page break]

[Introduction]
<u>Genetically modified foods (GM foods),</u> sometimes called genetically engineered foods, are foods produced from genetically modified organisms (GMO) that have had changes introduced into their DNA using the methods of genetic engineering.

<u>GMO food labels</u> are labels put on the food product packaging that indicate whether the food contains GMOs, is free from GMOs, or is partially produced with GMOs. The labels could be either plain texts, or smartphone-readable QR codes, or toll-free phone numbers, or links to internet websites that would provide customers information related to the presence or absence of GMO ingredients in the foods.
[page break]

[Familiarity]
[TF] Before today, have you ever heard of GM foods?
□ 1. Yes □ 2. No □ 3. Not sure
[page break]

[if TF = 1, display:]
[familiar] How often do you hear about topics or issues related to GM foods?
□ 1. Never □ 2. Seldom □ 3. Sometimes □ 4. Often
[page break]

[if TF = 1 & familiar ≠ 1, display:]
[TFlabel] Before today, have you ever heard of GMO food labels?
□ 1. Yes □ 2. No □ 3. Not sure
[page break]

[if TFlabel = 1, display:]

[familiarlabel] How often do you hear about topics or issues related to GMO food labels?
□ 1. Never □ 2. Seldom □ 3. Sometimes □ 4. Often
[page break]

[if TF = 1, display:]
[Uncertainty] From what you've heard or read, would you say scientists have a clear understanding of the health effects of GM foods?
□ 1. Yes, they have a clear understanding
□ 2. No, they don't have a clear understanding

☐ 3. I'm not sure

[page break]

[if TF = 1, display:]

[Safety] In your opinion, is eating GM foods generally safe or unsafe?

1. Very Unsafe	2. Probably Unsafe	3. Neither Safe nor Unsafe
4. Probably Safe	5. Very Safe	

[page break]

[EXPERIMENTAL MANIPULATION PROCEDURES AND MEASURES]

[display in conditions 1, 2, 3, 4, 7] On the following screen we will show you a short news article about GM foods.

[display in conditions 1, 2, 3, 4] After the news article you will see some comments posted by people who read the article previously.

[display in conditions 1, 2, 3, 4, 7] We will then ask you some questions about the materials you read. You will have a chance to post your comment later.

[page break]

[Display News Article from Appendix F]

[page break]

[transition page, display in conditions 1, 2]

On the next page, you will see some comments posted by previous viewers of this article *(Note: We anonymized their personal information by taking out any identifying photos and user names).*

[transition page, display in conditions 3, 4]

On the next two pages, you will see some comments posted by previous viewers of this article *(Note: We anonymized their personal information by taking out any identifying photos and user names).*

After you finish reading the first page of comments, you can proceed to the second page by clicking the "Continue" button.

We will ask you some questions related to the materials you read later.

[page break]

[Display Comments Based on The Algorithm; Comments Pool in Appendix F]

[first-page comments, display in conditions 1, 2, 3, 4]

[page break]

[second-page comments, display in conditions 3, 4]
[page break]

[CORE POST-MANIPULATION MEASURES]

[transition page]
Next we would like to ask you some questions about GM foods..
Please answer carefully. Your answers are very important to us.
[page break]

[Descriptive Norm Perceptions Varying Reference Groups]
[randomize the order of normus, normcity, normneighbor]
[normus] If you had to guess, how many people in the U.S. have checked for GMO labels to see whether a food product contains any GMO ingredients at least once when shopping for groceries in the past week?
□ 1. None□ 2. Very Few□ 3. Some□
4. About Half□ 5. Most□ 6. Almost All

[normcity]If you had to guess, how many people who are residents of your city have checked for GMO labels to see whether a food product contains any GMO ingredients at least once when shopping for groceries in the past week?
□ 1. None□ 2. Very Few□ 3. Some
□ 4. About Half□ 5. Most□ 6. Almost All

[normneighbor] If you had to guess, how many people in your neighborhood have checked for GMO labels to see whether a food product contains any GMO ingredients at least once when shopping for groceries in the past week?
□ 1. None□ 2. Very Few□ 3. Some
□ 4. About Half□ 5. Most□ 6. Almost All
[page break]

[randomize the order of normsimilar, normage]
[normsimilar] If you had to guess, how many people who are similar to you have checked for GMO labels to see whether a food product contains any GMO ingredients at least once when shopping for groceries in the past week?
□ 1. None□ 2. Very Few□ 3. Some
□ 4. About Half□ 5. Most□ 6. Almost All

[normage] If you had to guess, how many people your age have checked for GMO labels to see whether a food product contains any GMO ingredients at least once when shopping for groceries in the past week?
□ 1. None□ 2. Very Few□ 3. Some
□ 4. About Half□ 5. Most□ 6. Almost All
[page break]

[randomize the order of normimportant and normclose]
[normimportant] If you had to guess, how many people who are important to you have checked for GMO labels to see whether a food product contains any GMO ingredients at least once when shopping for groceries in the past week?
□□ 1. None□ 2. Very Few□ 3. Some
□ 4. About Half□ 5. Most□ 6. Almost All

[normclose] If you had to guess, how many of your four closest friends have checked for GMO labels to see whether a food product contains any GMO ingredients at least once when shopping for groceries in the past week?
□ 1. None□ 2. One□ 3. Two□ 4. Three□ 5. Four
[page break]

[Descriptive Norm Perceptions Scale]
[randomize the order of DN1 to DN6]
Please indicate how much you agree or disagree with the following statements about GMO labels on foods.

[DN1] In the U.S., many people check for GMO labels to see whether a food product contains any GMO ingredients	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN2] Checking for GMO labels to see whether a food product contains any GMO ingredients is not very common in the U.S. (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN3] Most people my age check for GMO labels to see whether a food product contains any GMO ingredients	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[DN4] Checking for GMO labels to see whether a food product contains any GMO ingredients is not at all popular in the U.S. (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN5] Most people that I know check for GMO labels to see whether a food product contains any GMO ingredients	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[DN6] A high percentage of the U.S. population check for GMO labels to see whether a food product contains any GMO ingredients	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[page break]

[Intention]
[intentionlabel] How likely is it that you will check for GMO labels to see whether a food product contains any GMO ingredients during your next visit to a grocery store?

□ 1. Definitely will not □ 2. Probably will not
□ 3. Probably will □ 4. Definitely will

[page break]

[manipulation check transition page]
[randomize the order of news and comments manipulation check questions]
Now we would like to ask you some questions about the materials you just read. Please answer carefully. Your answers are very important to us.
[page break]

[News Manipulation Check, Shown in Conditions 1, 2, 3, 4, 7]

[NewsMC] Think about the short news article you just read. Please indicate how much you agree or disagree with the following statements.

[NewsMC1] It was mostly in favor of checking for GMO labels on foods	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[NewsMC2] It was mostly against checking for GMO labels on foods (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[page break]

[Comments Manipulation Check (Valence & Norm), Shown in Conditions 1, 2, 3, 4]

[CommMC] Think about all the comments following the news. Please indicate how much you agree or disagree with the following statements.

[CommMC_V1] The comments were mostly in favor of checking for GMO labels on foods	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[CommMC_V2] The comments were mostly against checking for GMO labels on foods (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree
[CommMC_N1] The comments were posted mostly by people who check for GMO labels or those who know other people that check them	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[CommMC_N2] The comments were posted mostly by people who don't check for GMO labels or those who know other people that don't check them (R)	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

[page break]

[Number of Comments Read, Shown in Conditions 1, 2, 3, 4]
[CommNum] How many comments did you read?
□ □ 1. None□ 2. Very Few□ 3. Some
□ 4. About Half□ 5. Most□ 6. Almost All
[page break]

[Comments Reading Habit, Shown in Conditions 1, 2, 3, 4]
[ReadHabit] How often do you read comments left by previous viewers on news websites?
□ 1. Never 2. Seldom□ 3. Sometimes 4. Often

[Comments Posting Habit, Shown in Conditions 1, 2, 3, 4]
[PostHabit] How often do you post your own comments on news websites?
□ 1. Never 2. Seldom□ 3. Sometimes 4. Often
[page break]

[Open-ended question, Shown in Conditions 1, 2, 3, 4, 7]
[Open_ended] You now have a chance to leave your own comment on the materials you just read. You can leave it in the text box below (Note: Your response to this question will NOT be posted on the comment board).
[text box]
[page break]

[DEMOGRAPHICS]

[transition page]
Finally, we would like to ask you some questions about yourself before the survey ends.
[page break]

[gender] What is your gender?
□ 1. Female□ 2. Male

[Hispanic] Are you Hispanic, Latino/a, or Spanish origin? (One or more categories may be selected)

- ☐ 1. No, not of Hispanic, Latino/a, or Spanish origin
- ☐ 2. Yes, Mexican, Mexican American, Chicano/a
- ☐ 3. Yes, Puerto Rican
- ☐ 4. Yes, Cuban
- ☐ 5. Yes, another Hispanic, Latino, or Spanish origin

[page break]

[race] What is your race? (One or more categories may be selected)

- ☐ 1. White ☐ 2. Black or African American
- ☐ 3. American Indian or Alaska Native ☐ 4. Asian Indian
- ☐ 5. Chinese ☐ 6. Filipino
- ☐ 7. Japanese ☐ 8. Korean
- ☐ 9. Vietnamese ☐ 10. Other Asian
- ☐ 11. Native Hawaiian ☐ 12. Guamanian or Chamorro
- ☐ 13. Samoan ☐ 14. Other Pacific Islander

[page break]

[education] What is the highest level of schooling you have completed?

- ☐ 1. Less than 6th grade ☐ 2. 6th grade
- ☐ 3. 7th grade ☐ 4. 8th grade
- ☐ 5. 9th grade ☐ 6. 10th grade
- ☐ 7. 11th grade ☐ 8. GED degree
- ☐ 9. High School degree ☐ 10. Some college
- ☐ 11. Associate degree ☐ 12. College degree (BA, BS)
- ☐ 13. Some graduate or professional school
- ☐ 14. Graduate or professional school degree (MA, PhD, MBA, MD, JD, etc)

[page break]

[DEBRIEFING SCRIPT]

Thank you for participating in this survey!
You just participated in a survey-based experiment. The purpose of the study is to see whether online news and comments posted by previous viewers could affect how people think about GM foods. The news article and the comments were modified from real examples. We hope your participation will assist us in answering our research question.

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