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Nudging smokers away from lighting up: A meta-analysis of framing effect in current smokers

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A R T I C L E I N F O

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A B S T R A C T

Should smoking cessation messages be framed in terms of gains or losses? While the risk-framing hypothesis suggests a persuasive advantage for gain-framed messages, empirical evidence so far has been mixed. In defense of the risk-framing hypothesis, researchers have suggested that the diversity of results in this literature stream can be attributed to differences in issue involvement. The present study examined these predictions by employing a meta-analysis (14 studies) comprising of a Correlated and Hierarchical Effects model with Robust Variance Estimation. There was a small persuasive advantage in favour of gain-framed messages ($g = 0.104$, $SE = 0.049$), but this contrast was not statistically significant ($p = 0.070$, $CI_{95} = -0.011, 0.218$). This finding is robust to the values of correlation between sampling errors of the effect sizes, influential outliers, and publication bias. Moreover, issue involvement proxied through nicotine dependence did not moderate the relative persuasiveness of gain and loss-framed messages in encouraging smoking cessation. The conclusion remains unchanged regardless of how nicotine dependence is measured and before and after controlling for study and participant characteristics. These results strongly cast doubt on the applicability of the risk-framing hypothesis that continues to guide research and public-health campaigns.

1. Introduction

Everyday people instinctively form judgments and solve problems. However, given that humans have limited cognition, time and information, judgments are prone to biases. Judgments are particularly susceptible to a type of cognitive bias known as framing effect, a phenomenon where different but logically equivalent descriptions about a problem lead to systematically different decisions (Druckman, 2004). Initially, Tversky and Kahneman (1981) demonstrated framing effect as an incoherence in judgement and decision making, one which violates a central tenet of the normative model of rational choice. Overtime, a plethora of experimental evidence found a notable application of framing effect, as a persuasive communication tool that enables the recipients' choice to be 'nudged' in predictable ways.

In the realm of health communication, deliberately framed messages attempt to motivate healthy behaviours such as, disease detection and disease prevention behaviours. Thus, a central debate in health communication literature has been on the relative persuasiveness of gain and loss-framed messages in promoting healthy behaviours. In this regard, researchers have put forward the risk-framing hypothesis (Van't Riet et al., 2014, 2016), according to which, the relative persuasiveness of gain and loss-framed messages depends on the risk associated with the advocated behaviour (Rothman & Salovey, 1997). Accordingly, gain-framed messages are deemed relatively more persuasive for disease prevention behaviours and loss-framed messages are deemed relatively more persuasive for disease detection behaviours (Rothman & Salovey, 1997). The risk-framing hypothesis is now proactively discussed in literature and widely communicated to practitioners, aspiring academics, and the public (Van't Riet et al., 2016; Updegraff & Rothman, 2013).

Despite the widespread popularity of the risk-framing hypothesis, empirical evidence in its support has always been weak at best (Van't Riet et al., 2014, 2016). Studies have suggested that the theoretical premise of the risk-framing hypothesis essentially rests on a flawed application of framing effect, one that deviates from Tversky and Kahneman's (1981) conceptualization (Van't Riet et al., 2014, 2016). Despite criticisms, the hypothesis is still used to guide research and remains as one of the most dominant paradigms in the field of health communication. This is particularly worrisome as this implies that "public-health campaigns may not be based on sound science" (Van't Riet et al., 2016, p. 449). In defense of the risk-framing hypothesis, researchers have suggested that the hypothesis can be salvaged by taking

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into account the extent to which recipients are personally involved in the health issue in question (issue involvement) (Van't Riet et al., 2014; Rothman et al., 1993; Wansink & Pope, 2015). Accordingly, and irrespective of the risk associated with the advocated behaviour, gain-framed messages should be more persuasive when there is low involvement and loss-framed messages should be more persuasive when there is high involvement (Maheswaran & Meyers-Levy, 1990). However, empirical findings have not consistently conformed to this line of reasoning either (Kim, 2012; Fucito et al., 2010; Moorman & van den Putte, 2008). Besides the aforementioned studies, few have accounted for issue involvement (Van't Riet et al., 2014) suggesting that it may be pre-mature to discard the risk-framing hypothesis in its entirety.

To fill this gap in literature, this study examines the risk-framing hypothesis through a meta-analysis and in relation to smoking cessation, a disease prevention behaviour. Specifically, the objectives of this study are:

(1) To examine the relative persuasiveness of gain and loss-framed messages in encouraging smoking cessation.
(2) To examine issue involvement proxied through nicotine dependence as a potential moderator of the relative persuasiveness of gain and loss-framed messages in encouraging smoking cessation.[1]

According to Rothman et al. (1993), a reasonable proxy can be used to account for the extent to which recipients are personally involved in the health behaviour in question. For example, in their study, Rothman et al. (1993) found that health message framing differentially influenced the intentions of women (who are more concerned about skin cancer; high involvement) and men (who are less concerned about skin cancer; low involvement) in encouraging skin cancer detection behaviour. In a similar way, the present study reasons that, the degree to which individuals are involved in smoking strongly predicts their health outcomes (West, 2017) and in those with smoking-related illnesses, smoking cessation-related messages are likely to be perceived as personally relevant (Borrelli et al., 2010). In other words, smokers with high level of nicotine dependence face higher health risks and are more likely to perceive smoking to be damaging to their health (Moorman & van den Putte, 2008).

An examination of the applicability of the risk-framing hypothesis to the domain of smoking cessation is warranted for a few reasons. Firstly, few meta-analyses have examined whether the risk-framing hypothesis applies to smoking cessation (Gallagher & Updegraff, 2012; O'Keefe & Jensen, 2007). In these meta-analyses, the number of included studies have been far too little to reach definitive conclusions. However, empirical literature has grown since the publication of these meta-analyses which provides an opportunity to provide an updated meta-analysis which better reflects the current and latest body of evidence. Secondly, nicotine dependence (issue involvement) as a potential moderator has not been examined through a meta-analysis, even though relevant participant level data is readily available (i.e., average daily cigarette consumption). Finally, there are methodological limitations of past meta-analyses (Gallagher & Updegraff, 2012; O'Keefe & Jensen, 2007). Specifically, these studies have attempted to avoid dependence between effect sizes by averaging effect sizes in instances where multiple outcomes measures of the same construct have been reported. Averaging effect sizes often yields overestimated standard errors (Moeyaert et al., 2017) which can affect the validity of results (Matt & Cook, 2009). Many researchers have therefore, advocated against simply averaging effect sizes (Raudenbush et al., 1988), especially when more reliable techniques that model the dependence structure (Van den Noortgate et al., 2013) along with Robust Variance Estimation (RVE; Hedges et al., 2010) are available.

The present study makes several major contributions to literature. This study provides the most comprehensive meta-analysis of framing effect in current smokers since it synthesizes greater number of studies compared to past meta-analyses. Furthermore, this study explicitly accounts for issue involvement via the moderating role of nicotine dependence. Past studies have mostly tested the generic effects of framing effect in the domain of disease prevention without differentiating between the degree of issue involvement (Van't Riet et al., 2014). In pursuit of providing rigorous evidence, this study explicitly models for the dependence structure and utilizes RVE. The use of RVE is advantageous over other techniques (such as averaging effect sizes) since it allows all dependant effect sizes to be included in the analysis, thereby further preserving valuable within-study variations (this is not possible if effect sizes are averaged) (Cheung, 2019). This is an important consideration for the present meta-analysis since within-study variations potentially stemming from multiple outcome categories (measures) can be modelled through a multivariate model. Furthermore, the use of RVE is advantageous since it protects inferences (the calculated p-values and confidence intervals) against potential misspecification of the multilevel model (Harrer et al., 2021). Again, this is an important consideration since in practice, sources of dependence between effect sizes are more complex than what can be explicitly modelled (Harrer et al., 2021). To provide robust evidence of the moderating role of nicotine dependence, this study includes several artifacts from study characteristics and participant characteristics as control variables. Given these considerations, this study will provide researchers, practitioners, and policy makers with sound evidence of the applicability of the risk-framing hypothesis to smoking cessation and more broadly, disease prevention behaviours.

The rest of the paper is structured as follows: Section 2 reviews the relevant literature and develops the hypotheses. Section 3 describes the methods employed in the present meta-analysis. Section 4 presents the main results. Section 5 discusses the findings along with the implications.

2. Literature review

In this section, the framing postulate of prospect theory is briefly reviewed (Section 2.1). Next, the risk-framing hypothesis is developed as it emerges from the domain of smoking cessation (Section 2.2). The next section develops the hypothesis in support of the moderating role of nicotine dependence (Section 2.3). The final section reviews studies that justify the inclusion of appropriate control variables (Section 2.4).

2.1. The framing postulate of prospect theory

Tversky and Kahneman (1992) formulated cumulative prospect theory (initially known as prospect theory; Tversky & Kahneman, 1979) in order to examine judgement and decision making under both risk and uncertainty. Prospect theory has since emerged as a leading theory in economics since it addresses the challenges posed by expected utility function's linear weighting of probabilities. Prospect theory accomplishes this by assigning value to gains and losses rather than to final assets and by replacing probabilities with weights (Kahneman & Tversky, 1979, p. 263). Thus, the value function of prospect theory is concave for gains and convex for losses (Kahneman & Tversky, 1979).

Prospect theory highlights three central features which affects individual's judgments and decisions (Kahneman & Tversky, 1979). The first feature is that of a reference dependence whereby individuals evaluate their losses or gains relative to a reference point. The second feature is loss aversion. Loss aversion implies that the dependence on a reference point has a greater effect on losses than it does on gains, hence the value function is concave for gains and convex for losses. The third distinct feature of prospect theory highlights that individuals experience diminishing marginal sensitivity. As a result, the marginal effect of

[1] Nicotine dependence as a proxy for issue involvement has been utilized in past studies (Fucito et al., 2010; Moorman & van den Putte, 2008).

losses or gains decreases when the associated loss or gain decreases, and vice versa (Beggs & Graddy, 2009).

The fact that individuals derive utility differentially for losses and gains relative to a reference point has major practical implications. The most prominent of which is framing effect. The effect occurs when equivalent descriptions of a decision problem, framed as either a loss or a gain, leads to systematically different decisions (i.e., violation of invariance axiom of expected utility theory; Tversky & Kahneman, 1981). Framing effect was initially demonstrated through a hypothetical vignette-based task, famously known as the Asian disease problem (Tversky & Kahneman, 1981). In this task, participants were required two choose between two alternatives designed to protect against a disease expected to kill 600 people. Adopting the first alternative would save 200 lives and adopting the second alternative would result in a 1/3 probability that 600 people will be saved and a 2/3 probability that no one will be saved. The alternatives were also framed in terms of losses. If the first alternative is adopted, 400 people will die and if the second alternative is adopted, there is a 1/3 probability that nobody will die and a 2/3 probability that 600 people will die. Tversky and Kahneman (1981) found that most participants who received the gain-framed alternatives, chose the risk-averse option and most participants who received the loss-framed alternatives, chose the risky option. Building on Tversky and Kahneman's (1981) seminal paper on framing effect, follow-up studies found that choices can be framed such that the desired outcome becomes salient, and individuals are more biased towards choosing it (Lempert & Phelps, 2016). In this way, framing effect is exploited as an intervention that promotes desirable behaviours, such as healthy behaviours.

2.2. The risk-framing hypothesis

The application of framing effect as a persuasive health communication tool dates back to a study by Meyerowitz and Chaiken (1987) who applied prospect theory's framing postulate to breast self-examination (BSE) messages. Relative to gain-framed messages, they found a greater persuasive advantage for loss-framed messages in encouraging BSE attitudes, intentions and behaviours. Rothman and Salovey (1997) provided a taxonomy of the relative persuasiveness of gain and loss-framed health messages. They reasoned that messages that encourage disease detection behaviours entail the possibility of illness detection and akin to prospect theory, individuals are risk-seeking when they perceive the behaviour to involve some uncertainty. In this way, loss-framed messages have a persuasive advantage when it comes to disease detection behaviours. Several studies have found empirical support for this assertion (Rothman et al., 1999; Williams et al., 2001; Cox & Cox, 2001). Rothman and Salovey (1997) further argued that messages that encourage disease prevention behaviours, entail relatively certain illness prevention and similar to prospect theory, individuals are risk-aversive when they perceive the behaviour to involve a relatively certain outcome. In this way, gain-framed messages have a persuasive advantage when it comes to disease prevention behaviours, with a host of studies finding support for this assertion (Arora & Arora, 2004; McCall & Ginis, 2004; Meyers-Levy & Maheswaran, 2004).

Studies that assess the relative persuasiveness of gain and loss-framed messages in promoting smoking cessation fall within the domain of disease prevention. Typically, the focus of the health message is on the health outcome associated with smoking cessation (e.g., quitting smoking reduces your risk of developing cancer and other diseases; Toll et al., 2008) or the drawbacks of smoking continuation (e.g., continuing to smoke increases your risk of developing cancer and other diseases; Toll et al., 2008). Some studies have focused on a message appeal other than health, such as time and money (Nobel, 2022). Regardless of the message appeal, the gains associated with smoking cessation are relatively more certain than the losses associated with smoking continuation (Steward et al., 2003). For example, a meta-analysis of randomised controlled trials and observational longitudinal studies found that smoking cessation improves prognostic outcomes even after lung cancer diagnosis (Parsons et al., 2010). To corroborate the risk-framing hypothesis however, the question is not whether the gains associated with smoking cessation are factually certain, but whether smokers are aware of this certainty. In this regard, several cross-sectional studies indicate that smokers are moderately aware of the benefits of smoking cessation (Zhang et al., 2019; Weld-Blundell et al., 2022). On the flip side, losses associated with smoking are perceived to be relatively less certain. Studies have found that smokers tend to rationalise their smoking behaviours in order to reduce dissonance (Fotuhi et al., 2013; Sidhu et al., 2022). In doing so, smokers can develop 'self-exempting' beliefs about smoking (Chapman et al., 1993) and undermine the negative health consequences of smoking (Borland et al., 2009; Weinstein et al., 2005). Thus, given that smoking cessation is seen as a disease prevention behaviour with a relatively certain outcome and consistent with the risk-framing hypothesis, this study hypothesizes the following:

H1: Gain-framed messages have a persuasive advantage over loss-framed messages in promoting smoking cessation.

2.3. The moderating role of nicotine dependence

Several studies have indicated that framing effect depends on the degree to which individuals are involved in the health issue in question (Rothman et al., 1993; Maheswaran & Meyers-Levy, 1990) and that such findings theoretically align with the dual-process theory of persuasion (Rothman et al., 2006). According to the dual-process theory of persuasion, individuals process information through two routes, namely the central route and the peripheral route (Kahneman, 2011). The central route involves systematic, logical, and deliberative information processing while the peripheral route relies on intuitive, fast, and superficial cues to process information (Kahneman, 2011). When there is high motivation to process a given message frame, individuals are more likely to engage in the central route to process the given information (Gawronski & Creighton, 2013). In this way, negative affect serves as an indication to individuals that they may not be achieving the intended task, leading them to expand greater cognitive effort (McCormick & McElroy, 2009). Studies suggest that under the central route, loss-framed messages are more persuasive than gain-framed messages (Nan et al., 2018; Rothman et al., 2006; Maheswaran & Meyers-Levy, 1990). Similarly, when there is low motivation to process a given message frame, individuals are more likely to engage in the peripheral route to process the given information (Gawronski & Creighton, 2013). In this way, positive affect serves as an indication that an individual is doing well, leading them to inhibit additional cognitive effort (McCormick & McElroy, 2009). Under the peripheral route, gain-framed messages are more persuasive than loss-framed messages (Nan et al., 2018; Rothman et al., 2006; Maheswaran & Meyers-Levy, 1990). In other words, these differential effects may exist because deliberate and careful consideration (central route) to the presented information make losses salient. On the other hand, intuitive and fast (peripheral route) information processing is enough to induce positive affect thereby making gains salient.

While the above-mentioned studies indicate that when there is high involvement in the health issue in question, loss-framed messages are more persuasive and vice versa, the evidence is not clear cut. For example, Rothman et al. (1993) found that gain-framed messages were more persuasive for the more involved cohort (i.e., women) in encouraging skin cancer prevention behaviour. Similarly, Fucito et al. (2010) found that for high-dependant smokers, gain-framed messages were more persuasive in encouraging smoking cessation and no framing effect was observed for low-dependant smokers. Conversely, Moorman and van den Putte (2008) found that gain-framed messages were more persuasive for low-dependant smokers and loss-framed messages were more persuasive for high-dependant smokers in encouraging smoking cessation. Suffice to say, the degree to which individuals are involved in smoking affects the persuasiveness of the message frame. Given this, the present study hypothesizes the following:

H2: Nicotine dependence moderates the relative persuasiveness of gain and loss-framed messages in promoting smoking cessation

2.4. Control variables

The present study includes two artifacts of study characteristics (frame mode and outcome measure) and two artifacts of participant characteristics (gender and age) as control variables. However, as suggested by Hünermund and Louw (2020), substantive meaning is not attached to the control variables and their primary purpose is to account for confounding influence factors between the treatment (message framing) and the outcome (smoking cessation).

2.4.1. The role of study characteristics

Researchers have found that the mode through which messages are communicated as well as certain pragmatics of the treatment language can result in framing effect modifications (Korn et al., 2018; Welkenhuysen et al., 2001; Powell et al., 2019; Huang & Rau, 2018; Keysar et al., 2012; Elbert & Ots, 2018). For example, such effects can arise due to variations in emotional resonance associated with the treatment language (i.e., foreign versus native language; Keysar et al., 2012), and due to differential information processing mechanisms associated with the mode of treatment (i.e., visual versus text; Powell et al., 2019). Risk aversion in turn, is dependant upon both, domain, and the associated outcome antecedent (Weber et al., 2002; Dohmen et al., 2011). For example, Baluku et al. (2021) found a significant and negative association between risk aversion and entrepreneurial intention but not for risk aversion and entrepreneurial attitude.

2.4.2. The role of participant characteristics

Variations in internal dispositions across demographics can further result in framing effect modifications. For example, women tend to experience stronger emotions than men (Sprecher & Sedikides, 1993; Croson & Gneezy, 2009). Emotional experiences in turn, affects the utility of risky choice (Croson & Gneezy, 2009), as well as risk taking propensity (Druckman & McDermott, 2008). As a stylized fact, women tend to be relatively more risk averse than men and have stronger preference for certainty than the mere probable (Rothman et al., 1993; Harrant & Vaillant, 2008; Hersch, 1996). Prospect theory encapsulates risk aversion under a gain frame (see also certainty effect; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). Studies have therefore found the effectiveness of message framing interventions in promoting smoking cessation to vary by gender (Toll et al., 2008). Researchers have also found older adults to be relatively more risk averse than younger adults (Rolison et al., 2014; Albert & Duffy, 2012; Deakin et al., 2004; Weller et al., 2011). Primarily, older adults tend to weigh certainty more heavily and focus more on positive emotions (Mather et al., 2012).

3. Methodology

This section describes the literature search strategy (Section 3.1), the inclusion criteria against which studies were screened (Section 3.2), the data that was extracted and coded from the included studies (Section 3.3) and the meta-analytic procedures (Section 3.3).

3.1. Literature search

For every step involved within the meta-analysis, the established meta-analytical protocols by Wilson and Lipsey (2001) were followed. Studies included in the present meta-analysis were retrieved from two channels. First, Scopus was utilized since it is widely considered as the most comprehensive data base in terms of journal coverage (Falagas et al., 2008). The following search string was utilized to retrieve relevant studies: TITLE-ABS ((frame OR framing OR "gain framed" OR "loss framed" OR "framing effects") AND (cigarette OR tobacco OR nicotine OR smok*) AND (cessation OR abstinence OR intervention OR quit*)). The search string was calibrated such that potential combinations of the relevant search terms concerning framing effect and smoking cessation were maximized. The search on Scopus yielded 445 potential studies to be included in the analysis. Additionally, 14 potential studies were retrieved by considering all relevant records from previous related meta-analyses (O'Keefe & Jensen, 2007; Gallagher & Updegraff, 2012).

3.2. Inclusion criteria

Potential studies were screened against six inclusion criteria: (1) The intervention must be a message framed in terms of gains and losses (2) the outcome must be smoking cessation measured through intention, attitude, or behaviour (3) the sample must consist of current smokers (4) studies must be experimental in nature (5) there should be enough statistics reported to enable effect size extraction, and (6) studies must be published.

Studies were screened against the inclusion criteria in two steps. The stepwise screening process allowed for any effect of burn out and unreliability to be minimized (Polanin et al., 2019). The first step involved screening for studies that were experimental and consisted of a relevant intervention (message framing) and outcome of interest (smoking cessation as measured through intention, attitude, or behaviour). Additional records from O'Keefe and Jensen (2007) as well as Gallagher and Updegraff (2012) were also screened to ensure that only published studies were included in the analysis. Unpublished research works were excluded given their potentially questionable methodological quality (i.e., lower risk of bias; Egger et al., 2003; Nielsen et al., 2018). According to Montori et al. (2000), excluding unpublished studies from a meta-analysis does not bias the results, provided publication bias checks are met. In the second step, studies that consisted of current smokers were considered.

After screening against the inclusion criteria and the removal of duplicates, the screening process yielded a total of 14 studies that were eligible to be included in the present meta-analysis.

3.3. Data extraction and coding

3.3.1. Outcome variable

The outcome of interest was smoking cessation as measured through intention, attitude, and behaviour. Following the approach utilized by O'Keefe and Jensen (2007), these artifacts were combined to yield a single measure of smoking cessation. According to O'Keefe (2021), when examining the relative persuasiveness of a given message frame, attitudinal, intention and behavioural outcomes are interchangeable and subsequent conclusions about the relative persuasiveness will be the same regardless which of these outcomes is examined. Intention, attitude, and behaviour were coded such that higher values represented greater persuasion towards smoking cessation, as was the norm in the included studies. In three instances across two studies this was not the case (Nobel, 2022; Goodall & Appiah, 2008). The extracted effect sizes were reverse coded in these studies.

3.3.2. Moderating factor

The moderating factor of interest was nicotine dependence. Data concerning nicotine dependence was extracted based on the average number of cigarettes participants smoke per day. Nicotine dependence was coded as a categorical variable, specifically as low-dependant smokers (between 1 and 15 cigarettes per day) versus medium and high-dependant smokers (greater than 15 cigarettes per day) (Schane et al., 2010). Past studies have examined nicotine dependence by utilizing a similar measure (i.e., "on average, how many cigarettes do you smoke each day?") (Heatherton et al., 1989; Mollen et al., 2017).

3.3.3. Control variables

Based on the literature discussed, data concerning two artifacts of study characteristics (frame mode and outcome measure) and two artifacts of participant characteristics (gender and age) were extracted and included as control variables. Frame mode was coded as a categorical variable, specifically as text-based treatment versus mixed treatment (a combination of video, image, and/or text). Outcome measure was coded as a categorical variable, specifically as behavioural measure (actual behaviour) versus non-behavioural measure (intention and attitude). The categorical coding of gender was based on the included studies' composition (i.e., >50% males or females). Finally, age was measured on a continuous scale (average reported age of participants).

3.3. Meta-analytic procedures

3.3.1. Effect size calculation

The present study utilized the standardized mean difference (SMD) as an estimate for the treatment effect. In meta-analysis, SMD is the preferred summary statistic when the included studies with similar outcomes are measured in a variety of ways (Wilson & Lipsey, 2001). This is relevant to the present study. Specifically, Hedges' *g* was utilized as a measure for the extracted effect size. Hedges' *g* is the bias corrected version of Cohen's *d* and belongs to the SMD family. Cohen's *d* slightly overestimates the intervention's effect in small samples, whereas, Hedges' *g* corrects for this upwards bias and can be utilized in both, large and small samples (Hedges, 1981; Hedges & Olkin, 1985). Subsequently, Hedges' *g* yields a more conservative estimate of the magnitude of group differences in small samples and converges to Cohen's *d* in large samples (Wilson and Lipsey, 2001; Hedges & Olkin, 1985).

In estimating the relative persuasiveness of the respective message frames, the unit of analysis was the message pair (i.e., gain and loss-framed message treatments). In doing so, a single effect size was estimated for each message pair. These effect sizes were then combined to yield an overall effect size. In instances where the SMD favoured the gain-framed message, the effect size was represented by a positive sign (+). When the SMD favoured the loss-framed message, the effect size was represented by a negative (-) sign. This approach to the unit of analysis was similar to that of O'Keefe and Jensen (2007) and Gallagher and Updegraff (2012). Effect size-based calculations were performed in R (version 4.2.1; R Core Team, 2022) using the 'esc' package (version 0.5.1; Lüdecke, 2019) which is an implementation of a web-based effect size calculator (Wilson, 2015). A summary of the cases analysed is given in Appendix A1.

3.3.2. Empirical model

A meta-analysis fundamentally assumes that effect sizes are independent. In reality, the independence assumption is rarely met due to prevalent sources of dependencies. Dependency can arise from the included studies from which effect sizes are extracted (e.g., multiple outcomes are assessed from the same sample), or dependency can be introduced by the meta-analyst (e.g., a substantive focus on analysing studies that are more alike) (Cheung, 2014). Ignoring dependant effect sizes leads to inflated type I error rates (López-López et al., 2018) since standard error of estimates are likely to be underestimated resulting in narrower confidence intervals (Becker, 2000). There are two ways to account for dependency.

The first approach essentially attempts to avoid dependence (Van den Noortgate et al., 2013). This approach includes averaging effect sizes to yield one synthetic average effect size per study and has been applied by past related meta-analyses (Gallagher & Updegraff, 2012; O'Keefe & Jensen, 2007). This method will yield an accurate average effect size estimate only if effect sizes within a study are homogenous (Marín-Martínez & Sánchez-Meca, 1999). Moreover, the precision of the standard error of a within-study averaged effect is dependant upon the correlations between the included effect sizes (López-López et al., 2018). However, studies rarely report such correlation structures and estimates cannot be obtained unless the meta-analyst has access to participant level data (López-López et al., 2018). The second approach to dealing with dependant effect sizes involves selecting one effect size per study. However, by restricting the meta-analysis to one effect size per study, valuable information is lost, and statistical precision and power are compromised (López-López et al., 2018). Moreover, both strategies do not permit an examination of moderating factors to account for within-study heterogeneity (Cheung, 2019).

The more complex approach is to model the dependence (Van den Noortgate et al., 2013). The present meta-analysis utilizes this approach through a Correlated and Hierarchical Effects (CHE) model with Robust Variance Estimation (RVE) (Pustejovsky & Tipton, 2022). The hierarchical structure of the model comprises of three levels that accounts for dependency arising from multiple effect sizes (outcomes) from the same studies (samples). The model clusters effect sizes within studies (level 2) and pools the aggregated cluster effects to derive the true effect size (level 3). Thus, variance is split into two parts, namely true effect size differences within studies and effect size differences between studies (Harrer et al., 2021).

The hierarchical (three-level) model takes the following functional form:

Level 1 model

$$\hat{y}_{ij} = \theta_{ij} + \epsilon_{ij} \tag{1}$$

Where θ_{ij} is an estimate of the true effect size, the estimator $\hat{y}_{ij}$ is the *i*th effect size in *j*th study and $\mathrm{Var}(\epsilon_{ij}) = v_{ij}$ is the known sampling variance in the *i*th effect size in *j*th study.

Level 2 model

$$\theta_{ij} = k_j + \delta_{(2)ij} \tag{2}$$

Where k_j is the average effect size in the jth study and Var $(\delta_{(2)ij}) = \tau^2_{(2)}$ captures the heterogeneity in effect sizes within the same study when more than one observation is noted.

Level 3 model

$$k_j = \mu + \delta_{(3)j} \tag{3}$$

Where μ is the overall average population effect and $\mathrm{Var}(\delta_{(3)j}) = \tau^2_{(3)}$ captures the heterogeneity between studies after controlling for multiple observations at level 2.

The formulae are combined as follows:

$$\hat{y}_{ij} = \mu + \delta_{(2)ij} + \delta_{(3)j} + \epsilon_{ij} \tag{4}$$

Since multiple effect sizes were extracted from the same sample, their sampling errors (ϵ_{ij}) will have some degree of correlation. Thus, within studies, the effect sizes are dependant. To account for this dependence, the model was extended to a CHE model. Since the included studies reported little to no information about the degree of correlation, $\rho = 0.5$ was chosen as the default within-study correlation of estimates. Subsequent sensitivity analysis is also carried out to note changes in the summary effect size when the degree of correlation between estimates is varied for $\rho = [0, 0.9]$. Conservatively assuming that the dependence structure is only partially known, the model was further extended to include RVE with CHE model as the working model for dependence (Pustejovsky & Tipton, 2022). The primary advantage of RVE is that it does not require knowledge about the true dependence structure of the multiple effect sizes (Tipton, 2013) and only requires a working model (CHE) to approximate the dependence structure, even if not entirely correct (Pustejovsky & Tipton, 2022). Thus, even if the CHE model does not capture the intricate dependence structure in its entirety, RVE can guard inferences (the calculated *p*-values and confidence intervals) against potential misspecification of the multilevel model (Harrer et al., 2021). To ensure that RVE provides valid estimates despite a small number of studies included in the meta-analysis, a bias-reduced linearization adjustment to the standard error was applied (Tipton & Pustejovsky, 2015).

The model parameters were estimated via Restricted Maximum Likelihood (REML) by utilizing the 'metafor' package (version 3.4–0; Viechtbauer, 2010) and 'clubSandwich' package (version 0.5.8; Pustejovsky, 2020) in R (version 4.2.1; R Core Team, 2022).

3.3.3. Sensitivity analyses and robustness checks

Given that a moderate correlation ($\rho = 0.5$) between sampling errors of the effect sizes was assumed to derive the summary effect size, a sensitivity analysis was undertaken to note if varied degrees of correlation between sampling errors substantially changes the summary effect size. Thus, different values of correlations were assumed, and subsequent summary effect sizes were noted.

Next, one synthetic average effect size per study was derived and fixed-effects models as well as random-effects models were derived. This is a common approach employed by a large number of meta-analyses. Thus, by comparing the results of the meta-analysis derived from a widely utilized approach (averaging effect size) with a more robust approach (CHE model with RVE), a more accurate estimate of the summary effect size can be provided. Average effect sizes and their respective variances were estimated following the procedures suggested by Borenstein et al. (2021) by utilizing the Mad package (version 0.8–3; Del *Re* & Hoyt, 2010) in R (version 4.2.1; R Core Team, 2022).

Robustness of the fitted model is demonstrated by excluding influential outliers and refitting the CHE model with RVE. According to Viechtbauer and Cheung (2010), outliers are influential if exclusion of a study from the analysis leads to considerable changes to the fitted model. Each effect size estimate was assessed by computing Cook's distances and values exceeding the 50th percentile of a chi-square distribution with 1 degree of freedom ($\chi^2_{1;0.5} = 0.45$) were considered influential (Cook & Weisberg, 1982).

Publication bias was examined in several ways. First, year of publication as a potential moderator of the persuasiveness of gain and loss-framed messages was examined. Publication bias refers to selective publication based on the study results (Sutton, 2009). Therefore, there would be no reason to expect the reported persuasiveness of gain and loss-framed messages to vary across year of publication, unless over time, selective publications skew the results in favour of a particular message frame. Secondly, a funnel plot was generated, and its asymmetry was noted. Specifically, effect size estimates from large studies with high precision (lower standard error) would approach the true effect size estimate while studies with lower precision (high standard error) would entail effect size estimates that are evenly distributed on either side of the true effect size thereby creating a funnel-shaped plot (Simmonds, 2015). Publication bias is indicated if low-precision studies with non-significant results are absent (not published) thereby yielding an asymmetric funnel plot (Simmonds, 2015). A more objective approach known as precision-effect test and precision-effect estimate with standard errors (PET-PEESE) (Stanley, 2017) was additionally undertaken to uncover publication bias.

3.3.5. Moderation analysis

To examine the hypothesized source of heterogeneity in effect sizes (moderation analysis), two approaches were utilized. First, a univariate model was developed for each predictor. This approach provides benchmark values for comparison with the multivariate model (Cadario & Chandon, 2020). Next, a multivariate model was developed that simultaneously included all the predictors which were, the hypothesized moderating variable (nicotine dependence) as well as the control variables (frame mode, outcome measures, gender and age). This approach provides evidence of true moderating effects (Assink & Wibbelink, 2016).

4. Results

The results are presented in three steps. In Section 4.1, the summary effect size is presented. Section 4.2 provides the results from the sensitivity analyses and robustness checks. Section 4.3 provides the results from the moderation analysis.

4.1. Summary effect size

4.1.1. Working model

Out of the 36 extracted effect sizes, 22 favoured gain-framed messages and 14 favoured loss-framed messages. Considering the hierarchical (three-level) model only, the model yielded a summary effect size in favour of gain-framed messages ($g = 0.122$, $SE = 0.065$), however, the persuasive advantage of gain-framed messages was not statistically significant ($p = 0.066$, $CI_{95=}$-0.009, 0.253). Furthermore, the underlying heterogeneity was significant ($Q = 108.440$, $p < 0.001$) and the estimated variance components were $\tau^2_{Level\ 3} = 0.032$ (between-study heterogeneity; $I^2_{Level\ 3} = 53.73\%$) and $\tau^2_{Level\ 2} = 0.016$ (within-study heterogeneity; $I^2_{Level\ 2} = 26.25\%$). Compared to a two-level model with level 3 heterogeneity constrained to zero, the three-level model provided a significantly better fit ($\chi^2_1 = 5.03, p < 0.05$). Appendix B1 and B2 additionally establish that it was essential to account for within-study variance (i.e., H_0: $\sigma^2_{(2)} = 0$) as well as between-study variance (i.e., H_0: $\sigma^2_{(3)} = 0$). Considering the CHE model, the model yielded a summary effect size significantly in favour of gain-framed messages ($g = 0.104$, $SE = 0.049$, $p < 0.05$, $CI_{95=}$0.008, 0.199). The underlying heterogeneity was significant ($Q = 142.532$, $p < 0.001$) and the estimated variance components were $\tau^2_{Level\ 3} = 0.002$ (between-study heterogeneity) and $\tau^2_{Level\ 2} = 0.032$ (within-study heterogeneity).

4.1.2. Robust variance estimation

CHE model with RVE yielded a summary effect size in favour of gain-framed messages ($g = 0.104$, $SE = 0.049$) which was not statistically significant ($p = 0.070$, $CI_{95=}$-0.011, 0.218). The results, therefore, did not support hypothesis 1. A graphical representation of the results from the meta-analysis are presented in a forest plot shown in Fig. 1.

4.2. Sensitivity analyses and robustness checks

4.2.1. Correlated and hierarchical effects model with robust variance estimation

The summary effect size remains in favour of gain-framed messages, albeit statistically insignificant, when the degree of correlation between effect size estimates is varied for $\rho = [0, 0.9]$ in increments of 0.1 (Table 1). Thus, the findings are robust to the values of correlation between sampling errors of the effect sizes.

4.2.2. Averaging effect sizes

The summary effect sizes derived from averaging effect sizes range from $g = 0.085$ to $g = 0.123$ which is almost similar to the summary effect size derived from the CHE model with RVE ($g = 0.104$). Furthermore, the analysis strategy based on averaging effect sizes suggests a significant persuasive advantage in favour of gain-framed messages. However, simulation studies have shown that inferences drawn from this approach is often problematic when dealing with multiple outcomes in a meta-analysis (Moeyaert et al., 2017). In this way, the results derived from the CHE model with RVE is unbiased (Moeyaert et al., 2017) and more reliable (Pustejovsky & Tipton, 2022). Table 2 summarizes summary effect sizes from averaging effect sizes.

4.2.3. Influential outliers

Although none of the calculated Cook's distances exceeded the suggested threshold ($\chi^2_{1;0.5} = 0.45$), two Cook's distances were relatively large (> 0.09) as shown in Fig. 2. To demonstrate that even the two most influential cases with relatively large Cook's distances of 0.094 (Marchado et al., 2019) and 0.109 (Arendt et al., 2018) themselves do

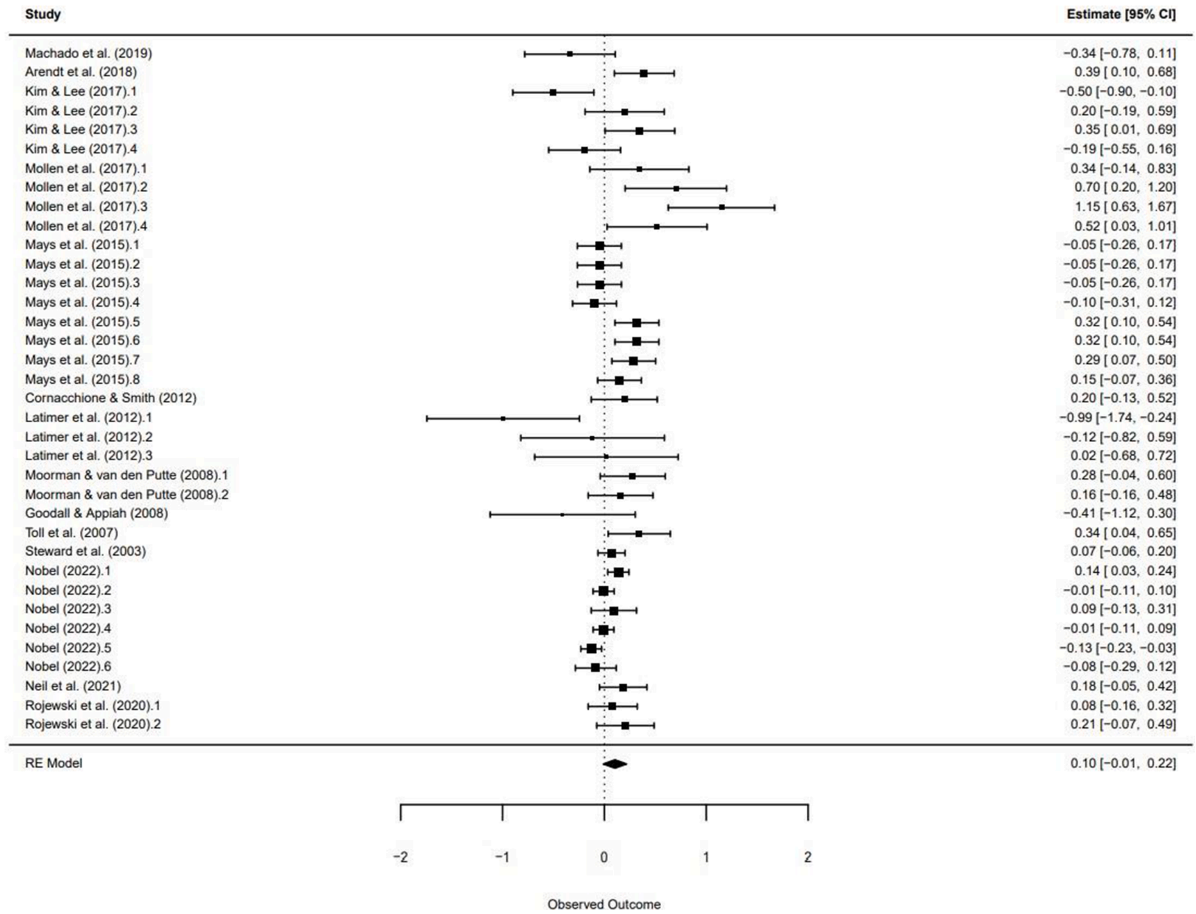

Fig. 1. Forest plot.

Table 1
Summary effect size as a function of varying correlations between sampling errors.

ρ	g	SE	p-value	95% confidence interval	
				Lower bound	Upper bound
0	0.122	0.064	0.082.	−0.018	0.263
0.1	0.122	0.060	0.069	−0.011	0.255
0.2	0.120	0.057	0.060	−0.006	0.245
0.3	0.116	0.053	0.056	−0.003	0.235
0.4	0.110	0.050	0.059	−0.005	0.225
0.5	0.104	0.049	0.070	−0.011	0.218
0.6	0.100	0.048	0.079	−0.015	0.215
0.7	0.100	0.048	0.078	−0.015	0.215
0.8	0.100	0.048	0.077	−0.014	0.215
0.9	0.100	0.048	0.078	−0.015	0.215

not lead to considerable changes to the fitted model, these effect sizes were excluded, and the model was refitted to note changes to the summary effect size.

Excluding the first case ($g_{\text{excluded } 1} = -0.34$; Merchado et al., 2019) did not lead to a considerable change in the fitted model ($g_{\text{refitted } 1} = 0.118$, $SE = 0.050$, $p = 0.051$, $CI_{95} = -0.001, 0.238$) and the underlying heterogeneity remained significant ($Q = 139.279$, $p < 0.001$). Excluding the second case ($g_{\text{excluded } 2} = 0.39$; Arendt et al., 2018) lead to similar conclusions. Specifically, there was no considerable change in the fitted model ($g_{\text{refitted } 2} = 0.088$, $SE = 0.047$, $p = 0.110$, $CI_{95} = -0.027, 0.202$) and the underlying heterogeneity remained significant ($Q = 137.74$, $p < 0.001$). Thus, the summary effect size is robust to potentially influential cases.

4.2.4. Publication bias

The test of moderator (publication year) was not significant (F [1, 3.68] = 0.549, $p = 0.503$) suggesting that the persuasiveness of gain and loss-framed messages does not vary as a function of publication year. Additionally, Fig. 3 did not visually indicate an asymmetrical funnel plot. More objectively, both PET ($\beta_0 = 0.143$, $p = 0.414$; $\beta_1 = -0.224$, $p = 0.860$, $CI_{95} = -3.412, 2.962$) and PEESE ($\beta_0 = 0.166$, $p = 0.062$; $\beta_1 = -1.990$, $p = 0.538$) models did not indicate any significant evidence of publication bias. Collectively, these findings provide strong evidence of the absence of publication bias.

4.3. Moderating factors

Univariate analysis revealed that low-dependant smokers are more persuaded by gain-framed messages ($g = 0.167$) than medium and high-dependant smokers ($g = 0.034$), however, this contrast was not statistically significant (F [1, 2.9] = 2.247, $p = 0.234$). Additionally, the relative persuasiveness of gain and loss-framed messages did not significantly differ by frame mode (video, picture, or text combination [$g = 0.086$] versus text [$g = 0.1364$]; $p = 0.658$), gender (males [$g = 0.036$] versus females [$g = 0.131$]; $p = 0.644$), age ($\beta_1 = -0.002$, $p = 0.706$) and outcome measure (behavioural measure [$g = 0.039$] versus non-behavioural measure [$g = 0.0937$]; $p = 0.419$). The lack of moderating effect of nicotine dependence was also evidenced in the multivariate model. Specifically, after controlling for the effects of frame mode, gender, age and outcome measures, the moderating effect of nicotine dependence remained statistically insignificant (F [1, 0.85] = 10.634, $p = 0.268$). The results provide a clear-cut conclusion that

Table 2
Summary effect size estimates based on one synthetic average effect size per study.

	Fixed-effects model		Random-effects model		
	WLS	ULS	REML	ML	DL
g	0.101**	0.085	0.119**	0.114**	0.123*
SE	0.033	0.052	0.044	0.040	0.051
CI_{95}	0.036, 0.165	−0.018, 0.187	0.033, 0.206	0.036, 0.192	0.023, 0.223
Q-statistic			24.273*	24.273*	24.273*
I^2 (%)			30.96	19.44	46.44
s	14	14	14	14	14
k	14	14	14	14	14

Note. WLS = Weighted least squares; ULS = Unweighted least squares; REML = Restricted maximum likelihood estimator; ML = Maximum likelihood estimator; DL = DerSimonian-Laird estimator; s = number of studies; k = number of effect size estimates
** $p < 0.01$
* $p < 0.05$.

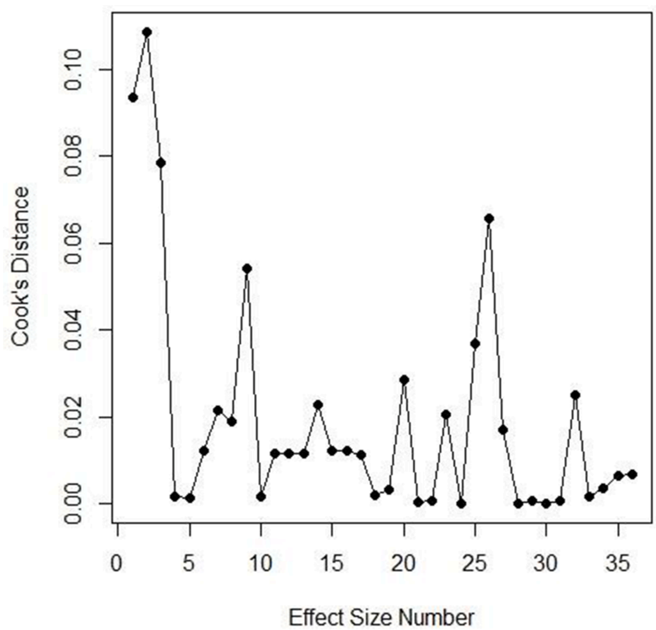

Fig. 2. Cook's distance.
Note. Cook's distance effect size number 1 = 0.094 (Merchado et al., 2019); Cook's distance effect size number 2 = 0.109 (Arendt et al., 2018).

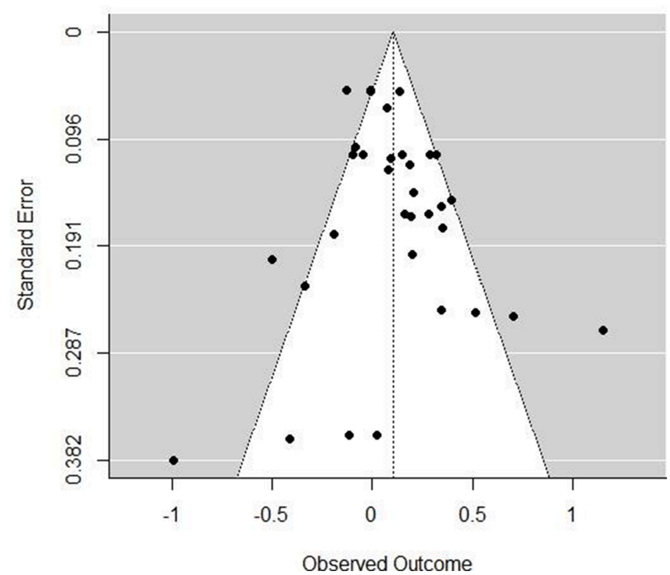

Fig. 3. Funnel plot.
Note. Funnel plot was derived from the working model (CHE model)

Table 3
Univariate models.

	β_1	SE	p-value	95% confidence interval		s	k
				Lower bound	Upper bound		
Nicotine dependence	−0.133	0.089	0.234	−0.421	0.155	11	30
Frame mode	−0.051	0.111	0.658	−0.304	0.203	14	36
Gender	−0.095	0.169	0.644	−1.109	0.918	14	36
Age	−0.002	0.004	0.706	−0.013	0.009	14	36
Outcome measure	0.055	0.058	0.419	−0.136	0.246	14	36

Note. β_1 = coefficient for moderators; s = number of studies; k = number of effect sizes; Reference category for nicotine dependence = light smokers; Reference category for frame mode = text; Reference category for gender = female; Reference category for outcome measure = non-behavioural (intention and attitude).

nicotine dependence does not moderate the relative persuasiveness of gain and loss-framed messages. Thus, hypothesis 2 was not supported.[2] Results from the univariate and multivariate analysis are summarised in Table 3 and Table 4, respectively.

5. Discussion

In this section, the results of testing the risk-framing hypothesis (Section 5.1) and the moderating role of nicotine dependence (Section 5.2) are discussed. The findings are then reconciled, and implications are discussed (Section 5.3).

5.1. Hypothesis 1

Historically, the risk-framing hypothesis has had enormous influence on the message-framing literature and the hypothesis continues to guide research and practice (Van't Riet et al., 2016). The risk-framing hypothesis suggests that the relative persuasiveness of gain and loss-framed messages depends on the risk associated with the advocated behaviour (Rothman & Salovey, 1997). In this way, gain-framed messages should be more persuasive for health prevention behaviours since the advocated behaviour entails relatively certain illness prevention (Rothman & Salovey, 1997). The present study tested this hypothesis in relation to smoking cessation, a disease prevention behaviour. The results of the meta-analysis did not support the risk-framing hypothesis

[2] The results remain unchanged when nicotine dependence is measured on a continuous scale, i.e., no significant moderating effect of nicotine dependence (univariate model: $\beta_1 = -0.007$, $p = 0.541$, $CI_{95} = -0.042, 0.028$; multivariate model: $\beta_1 = -0.026$, $p = 0.280$, $CI_{95} = -0.093, 0.042$).

Table 4
Multivariate model.

	β	SE	p-value	95% confidence interval	
				Lower bound	Upper bound
Intercept	0.142	0.059	0.096	−0.046	0.329
Nicotine dependence	−0.376	0.037	0.002	−0.495	−0.258
Frame mode	0.103	0.066	0.192	−0.079	0.285
Gender	−0.248	0.051	0.018	−0.413	−0.083
Age	0.004	0.002	0.103	−0.002	0.010
Outcome measure	0.159	0.060	0.108	−0.081	0.399

Note. Reference category for nicotine dependence = light smokers; Reference category for frame mode = text; Reference category for gender = female; Reference category for outcome measure = non-behavioural (intention and attitude); Number of studies = 11; Number of effect size estimates = 30.

and this conclusion is robust to the values of correlation between sampling errors of the effect sizes, influential outliers, and publication bias. Moreover, the results align with a previous meta-analysis in relation to smoking cessation (O'Keefe & Jensen, 2007) as well as several studies in relation to the broader domain of disease prevention (Van't Riet et al., 2014; O'Keefe & Nan, 2012; Jiang et al., 2022; Borah, 2022).

The results of the present study are in stark contrast to another previous meta-analysis (Gallagher & Updegraff, 2012) as well as several other studies (Toll et al., 2007; Arendt et al., 2018; Mays et al., 2015) that found a significant persuasive advantage for gain-framed messages in encouraging smoking cessation. How can these differences in findings be interpreted? The meta-analysis undertaken by Gallagher and Updegraff (2012) included only three studies, whereas the present study provides an updated meta-analysis comprising of fourteen studies. As such, the results of the present meta-analysis provide a more precise estimate of the true effect size. As summarized in Appendix A1, a growing number of studies are reporting results with overlapping confidence intervals and meta-analysing a small subset of these studies would result in a biased summary effect size.

Secondly, Rothman and Salovey's (1997) taxonomy of the relative persuasiveness of gain and loss-framed messages deviates from the tenets of the framing postulate of prospect theory in important ways. It is because of this deviation that the risk-framing hypothesis simply does not provide coherent and consistent results across studies relating to smoking cessation. According to Van't Riet et al. (2016), prospect theory conceptualizes risk as uncertainty whereas, the risk-framing hypothesis conceptualizes risk as perceived danger or perceived vulnerability. Moreover, in Tversky and Kahneman's (1981) original Asian disease problem, the two alternatives given to participants entails certain and uncertain outcomes. When it comes to smoking cessation, it cannot be said with absolute certainty that smoking cessation will lead to improved health outcomes. In fact, a plethora of studies have found that the risk of developing lung cancer following smoking cessation is contingent upon a complex number of factors (Tse et al., 2018; Reddy et al., 2017). In other words, the certainty associated with smoking cessation is not as clear cut and absolute as depicted in the Asian disease problem (i.e., "If Program A is adopted, 200 people will be saved"; Tversky & Kahneman, 1981).

Given the overwhelming evidence that refutes the risk-framing hypothesis, why does it continue to guide research and practice on smoking cessation? According to Van't Riet et al. (2016), this is because the risk-framing hypothesis offers clear cut recommendations. Moreover, "the research community is sometimes more inclined to interpret specific results as partially in line with the risk-framing hypothesis than as mostly inconsistent with it" (Van't Riet et al., 2016, p. 454). To guard against this inclination, the present study found support for the risk-framing hypothesis when the meta-analysis approach entailed averaging effect sizes, but not when RVE is used. For a hypothesis to be validated, it must pass rigorous testing and, in this way, the use of RVE as the choice of analysis strategy offers a more rigorous and valid conclusion (see for example, Moeyaert et al., 2017; Pustejovsky & Tipton, 2022)

5.2. Hypothesis 2

In defense of the risk-framing hypothesis, researchers have suggested that the hypothesis can be salvaged by taking into account the degree to which participants are personally involved in the health issue in question (Van't Riet et al., 2016). In this way, when individuals have lower motivation to process a given message frame, they are more likely to process the given information superficially leading to a persuasive advantage for gain-framed messages, and vice versa (Gawronski & Creighton, 2013). The present study further tested whether issue involvement proxied through nicotine dependence moderates the relative persuasiveness of gain and loss-framed messages in encouraging smoking cessation. Regardless of how nicotine dependence was coded (as a categorical or a continuous variable) the results of the meta-analysis did not support this line of reasoning either. The conclusion remains unchanged before and after controlling for study and participant characteristics such as, frame mode, gender, age, and outcome category.

The results contradict findings from past studies that found nicotine dependence to moderate the relative persuasiveness of message framing in promoting smoking cessation (Moorman & van den Putte, 2008; Fucito et al., 2010). However, the result from the present study aligns with Moorman and van den Putte's (2008) study in the sense that the prediction of dual-process theory was not validated. Specifically, Moorman and van den Putte (2008) found a persuasive advantage for loss-framed messages amongst high-dependant smokers whereas, dual-process theory predicts a persuasive advantage for gain-framed messages in encouraging smoking cessation. What may explain this inconsistency? One plausible explanation may be that the sample in Fucito et al.'s (2010) study comprised of treatment-seeking smokers. Research has shown that health concerns result in greater motivation toward smoking cessation (Martins et al., 2021; Hyland et al., 2004). Thus, active treatment seeking smokers are more likely to be involved in smoking-related health issues. The present meta-analysis however, controlled for the effect of several variables, including participants' age and gender. Thus, the present meta-analysis offers a more robust inference and evidence regarding the lack of moderating effect of nicotine dependence in the sense that the inference is not distorted by other extraneous variables (see for example, Hox et al., 2017). For example, motivation toward smoking cessation tends to vary by age and gender (Fahey et al., 2023; Clark et al., 1997; Rodríguez-Bolaños et al., 2021).

5.3. Conclusion and implications

The present meta-analysis strongly casts doubt on the applicability of the risk-framing hypothesis to smoking cessation, a disease prevention behaviour. Moreover, the results strongly cast doubt on the role of issue involvement in explaining the diversity of results in this literature. Collectively, the rigorous evidence presented within this study coupled with contradictory evidence from past studies, provides very little basis to support the following advice on how smoking cessation messages should be framed: "the European Commission should reconsider the use of warning labels that stress long-term health problems that result from continued smoking. The current study suggests that, rather, at least amongst younger, highly educated smokers, it seems more effective to communicate short-term benefits associated with quitting smoking" (Mollen et al., 2017, p.26).

On the contrary, the results of this study imply that policy makers do not necessarily have to be concerned with whether smoking cessation messages are framed in terms of gains or losses. This conclusion is not new in the domain of disease prevention. In fact, O'Keefe and Nan (2012) arrived at the same conclusion concerning vaccination. There is economic significance to this implication. Specifically, smoking cessation messages do not necessarily have to be tailored. Rather, the message can be framed as a gain or a loss, whichever is easily scalable. Moreover, since the results show that nicotine dependence level has no bearing in determining the effectiveness of a message appeal, as such, substantial costs do not have to be incurred to obtain such private information as a prerequisite (for a breakdown of costs associated with implementation of smoking cessation interventions, see for example, Levy et al., 2022).

Going forward, researchers should not interpret the small positive summary effect size derived from this meta-analysis as a persuasive advantage for gain-framed messages, even though small effects can translate into substantial changes at the population level (Van't Riet et al., 2016). For two reasons, this is a costly interpretation in this case. Firstly, the results show that there is more than a 5% chance (specifically, $p = 0.070$) that there is a 'spurious' persuasive advantage for gain-framed messages. Secondly, there is a cost associated with tailoring smoking cessation messages in favour a particular message frame, as described above, and one which would be worth the pursuit if the results indicated a persuasive advantage with a high level of statistical confidence. Given this, researchers and research groups should attempt to replicate findings in this literature stream. A brief review of literature on message framing and smoking cessation highlights a few research groups that have been actively contributing to this literature stream. By replicating their findings in a different country, geography and context would aid in ensuring the results are truly independent (i.e., effect sizes are not correlated). In fact, a limitation of this meta-analysis is that it did not explicitly model for the dependence structure arising from common features of research groups examining this literature stream. Nonetheless, since the present study utilized RVE, exact knowledge of the dependence structure is not required (Tipton, 2013; Pustejovsky & Tipton, 2022).

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Declaration of Competing Interest

I hereby acknowledge that the author has no conflict of interest.

Data availability

Data will be made available on request.

Appendix A. Summary of cases analysed

Table A1

Table A1
Included studies, effect size and coding.

Study	*g*	95% CI	Coding
Machado et al. (2019)	−0.34	−0.78, 0.11	1/1/0/0/47.89
Arendt et al. (2018)	0.39	0.10, 0.68	0/1/0/0/27.95
Kim & Lee (2017)	−0.50	−0.90, −0.10	1/0/0/0/43.4
Kim & Lee (2017)	0.20	−0.19, 0.59	1/0/0/0/43.4
Kim & Lee (2017)	0.35	0.01, 0.69	1/0/0/0/43.4
Kim & Lee (2017)	−0.19	−0.55, 0.16	1/0/0/0/43.4
Mollen et al. (2017)	0.34	−0.14, 0.83	nd/0/0/0/22.42
Mollen et al. (2017)	0.70	0.20, 1.20	nd/0/0/0/22.42
Mollen et al. (2017)	1.15	0.63, 1.67	nd/0/0/0/22.42
Mollen et al. (2017)	0.52	0.03, 1.01	nd/0/0/0/22.42
Mays et al. (2015)	−0.05	−0.26, 0.17	0/1/0/1/23.8
Mays et al. (2015)	−0.05	−0.26, 0.17	0/1/0/1/23.8
Mays et al. (2015)	−0.05	−0.26, 0.17	0/1/0/1/23.8
Mays et al. (2015)	−0.10	−0.31, 0.12	0/1/0/1/23.8
Mays et al. (2015)	0.32	0.10, 0.53	0/1/0/1/23.8
Mays et al. (2015)	0.32	0.10, 0.53	0/1/0/1/23.8
Mays et al. (2015)	0.29	0.07, 0.50	0/1/0/1/23.8
Mays et al. (2015)	0.15	−0.07, 0.36	0/1/0/1/23.8
Cornacchione and Smith (2012)	0.20	−0.13, 0.52	nd/0/1/0/15.83
Latimer et al. (2012)	−0.99	−1.74, −0.24	1/1/0/1/16.77
Latimer et al. (2012)	−0.12	−0.82, 0.59	1/1/0/1/16.77
Latimer et al. (2012)	0.02	−0.68, 0.72	1/1/0/1/16.77
Moorman and van den Putte (2008)	0.28	−0.04, 0.60	0/0/0/0/21.7
Moorman and van den Putte (2008)	0.16	−0.16, 0.48	0/0/0/0/21.7
Goodall and Appiah (2008)	−0.41	−1.12, 0.30	nd/1/0/0/16
Toll et al. (2007)	0.34	0.04, 0.65	1/1/1/0/42.65
Steward et al. (2003)	0.07	−0.06, 0.20	1/1/0/0/34
Nobel (2022)	0.14	0.03, 0.24	1/0/1/0/32.4
Nobel (2022)	−0.01	−0.11, 0.10	1/0/0/0/32.4
Nobel (2022)	0.09	−0.13, 0.32	1/0/1/0/32.4
Nobel (2022)	−0.01	−0.11, 0.09	1/0/1/0/32.4
Nobel (2022)	−0.13	−0.23, −0.03	1/0/0/0/32.4
Nobel (2022)	−0.08	−0.28, 0.12	1/0/1/0/32.4
Neil et al. (2021)	0.18	−0.05, 0.42	1/1/0/0/62.9
Rojewski et al. (2020)	0.08	−0.16, 0.32	1/0/1/0/42.95
Rojewski et al. (2020)	0.21	−0.08, 0.49	1/0/1/0/44.55

Note. The coding judgments are as follows: nicotine dependence (0 = low-dependant smokers, 1 = medium and high-dependant smokers, nd = no data); frame mode (0 = text, 1 = a combination of video, image, and/or text); outcome measure (0 = non-behavioural measure, 1 = behavioural measure); gender (0 = female, 1 = male); age (continuous scale).

Appendix B. Model fit

B1. Significance of the within-study variance

The proposition that it may be necessary to account for within-study variance in the included meta-analytic model, i.e., H_0: $\sigma^2_{(2)} = 0$ was examined. Thus, a log-likelihood-ratio test was undertaken where the full model (level 2 and 3 model with freely estimated variance) was compared to the fit of the model in which the variance at level 2 model was fixed at zero and the variance at level 3 model was freely estimated. The model without level 2 yielded a significant effect size ($g = 0.126$, $SE = 0.062$, $p < 0.05$). The 95% confidence interval for the effect size were 0.0004 and 0.2509. The Akaike Information Criterion (AIC; 14.536) and the Bayesian Information Criterion (BIC; 19.202) for the full model was lower than that of the reduced model (AIC = 23.968, BIC = 27.079) and the difference was significant ($p < 0.001$). The results indicate that the fit of the full model is significantly better than the reduced model (within-study variance was significant).

B2. Significance of the between-study variance

The significance of the between-study variance was assessed in a similar way, i.e., H_0: $\sigma^2_{(3)} = 0$. The variance at level 2 model was freely estimated and the variance at level 3 model was fixed at zero. The model without level 3 yielded a significant effect size ($g = 0.103$, $SE = 0.030$, $p < 0.05$). The 95% confidence interval for the effect size were 0.025 and 0.182. Both, AIC (14.536) and BIC (19.202) of the full model was lower than that of the reduced model (AIC = 17.562, BIC = 20.673) and the difference was significant ($p < 0.05$). While this does not explicitly model for between-study variance, nonetheless, we can infer that the variability between studies was significant and accept the alternate hypothesis, i.e., H_α: $\sigma^2_{(2)} > 0$. The results indicate that the three-level meta-analytic model had a better fit than the two-level model, where the three-level meta-analytic model captured a significant amount of variability in the included data.

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(References marked with an asterisk indicate studies that are included in the meta-analysis)

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