A Meta-Analytic Study on Nudge Effectiveness: A Two-Dimensional Perspective of Cognitive Pathway and Transparency

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Abstract

Based on a two-dimensional perspective of "cognitive path" and "transparency", this study conducts a meta-analysis of 108 empirical results from 40 nudge studies published in the specialized behavioral public policy journals Behavioural Public Policy (2017~2022) and Behavioral Science & Policy (2015~2022), systematically evaluating the effectiveness of nudge interventions, comparing the relative advantages of nudges with different cognitive paths and transparency levels, exploring the influencing factors of heterogeneity in nudge effects, and analyzing the interaction effects among cognitive path, transparency, and heterogeneity factors. The findings reveal that: (1) the overall effect size of nudge interventions is relatively small, with significant variation in effect sizes across different studies; (2) the effectiveness of nudges differs across cognitive paths and transparency levels, and there exists an interaction effect between cognitive path and transparency on nudge effectiveness; (3) nudge effects are influenced by research design and behavioral domain, with complex interactive relationships among the cognitive pathways through which nudges operate, the transparency of nudge design, and heterogeneity influencing factors.

Full Text

Preamble

A Meta-Analysis of Nudging Effects: A Dual Perspective on "Cognitive Pathway" and "Transparency"

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Abstract: Based on a dual perspective of "cognitive pathway" and "transparency," this study conducts a meta-analysis of 108 empirical findings from 40 nudge studies published in the leading behavioral public policy journals *Behavioural Public Policy* (2017–2022) and *Behavioral Science & Policy* (2015–2022). We systematically evaluate the effectiveness of nudging interventions, compare the relative advantages of nudges across different cognitive pathways and transparency levels, explore the factors contributing to heterogeneity in nudge effectiveness, and analyze the interactive effects among cognitive pathways, transparency, and heterogeneity factors. Our findings reveal that: (1) the overall effect size of nudging interventions is relatively small, with significant variation across studies; (2) nudge effectiveness differs across cognitive pathways and transparency levels, with an interactive effect between these two dimensions; and (3) nudge effectiveness is influenced by research design and behavioral domains, with complex interactions among the cognitive pathways through which nudges operate, their transparency, and heterogeneity factors.

Keywords: behavioral public policy, nudge, meta-analysis, policy effectiveness, cognitive pathway, transparency

1. Introduction

As the "flagship initiative" of behavioral public policy, the nudge approach has rapidly gained global traction since its inception, with countries such as the United Kingdom, United States, Germany, Australia, and Singapore establishing dedicated research institutions to explore how behavioral science can advance policy objectives. While nudging has proven effective in areas like energy conservation, education, and poverty alleviation, substantial empirical evidence indicates that it is not a panacea for correcting individual "behavioral biases." Public acceptance of nudges shows marked cross-cultural variation; nudging interventions exhibit "short-term effects" and struggle to produce permanent behavioral change; and repeated use of the same intervention leads to diminishing returns through exposure effects. Consequently, uncritical and blind application of nudges not only fails to effectively guide citizen behavior but may even prove counterproductive [**?**, **?**, **?**]. These practical challenges have prompted scholars to reflect on the effectiveness of nudging and its boundary conditions, with meta-analyses of nudging intervention experiments representing a common approach. Existing research has either focused on evaluating specific nudging tools (e.g., default effects, information interventions) across policy domains [**?**, **?**, **?**, **?**], or compared different nudging measures within specific behavioral domains (e.g., dietary habits, vaccination) [**?**, **?**, **?**].

However, two key limitations persist. First, due to variations in effect size metrics, results across different meta-analyses lack comparability, preventing a comprehensive assessment of the overall effectiveness of different nudging tools across common behavioral domains. Second, a scientific and comprehensive classification of nudges is a prerequisite for evaluating their relative effectiveness. Most existing literature classifies nudges based on the psychological processes or intervention techniques used to construct decision-making contexts, yet this approach cannot encompass all nudging measures. Moreover, multiple cognitive pathways and intervention techniques often intertwine, making context-based classification inadequate for objectively assessing the true effects of different nudging interventions and unhelpful for resolving academic debates about nudge effectiveness under different cognitive pathways and transparency levels.

Addressing these limitations, this study draws on the analytical framework of Hansen and Jespersen [?], constructing a nudge classification framework based on two dimensions: whether the nudge relies on intuitive reflection and whether it is transparent. Using this framework, we first conduct a meta-analysis of 108 empirical results from 40 nudge studies published in *Behavioural Public Policy* (2017–2022) and *Behavioral Science & Policy* (2015–2022), integrating and analyzing the effect sizes of different nudging tools across common behavioral domains and exploring the sources of heterogeneity in nudge effectiveness. Second, we compare the relative advantages of nudging measures across different cognitive pathways and transparency levels. Finally, we examine the interactive effects among cognitive pathways, transparency, and heterogeneity factors influencing nudge effectiveness.

As the two most influential journals in behavioral public policy, *Behavioural Public Policy* and *Behavioral Science & Policy* feature editorial boards composed of leading scholars in behavioral economics and behavioral public policy. Since their inception, these journals have consistently focused on behavioral public policy theory and practice, particularly nudging, aggregating high-quality research and enjoying exceptional academic reputation and influence in the international behavioral public policy community. Moreover, compared with nudging experiments published in psychology and economics journals, behavioral public policy journals place greater emphasis on nudge effectiveness in real policy contexts, measuring intervention effects through citizens' behavior in authentic policy settings (mostly field experiments). This approach overcomes the "external validity dilemma" of traditional laboratory experiments, making findings more reflective of nudging's practical value. Therefore, by focusing on nudging research in the "behavioral public policy" domain and selecting studies from these two journals as our meta-analysis sources, this research provides a more targeted systematic evaluation of the overall effectiveness of different nudging tools across common behavioral domains.

This study's academic contributions are threefold: (1) The meta-analysis based on the dual perspective of "cognitive pathway" and "transparency" can disentangle the actual effects of multiple psychological processes and intervention techniques, facilitating objective understanding of different nudge types' true effects. (2) Our evaluation of different nudge types' effectiveness and variations not only addresses academic debates about whether nudge design should be transparent but also compares the effectiveness differences between the two cognitive pathways, providing empirical evidence for nudge tool selection in future policy practice. (3) Our analysis of the sources of heterogeneity in nudge effectiveness enriches the literature's explanation of influencing factors and boundary conditions for nudge effectiveness, contributing to knowledge accumulation in behavioral public policy science.

2. Theoretical Framework and Analytical Framework

A scientific and comprehensive classification is a prerequisite for evaluating the effectiveness of different nudging tools. Most existing meta-analyses of nudge effectiveness have followed the classic "MINDSPACE" framework [?]. While this framework classifies nudges based on the psychological processes underlying individual behavior, it cannot encompass all psychological factors driving behavioral change. For example, Keppeler et al. [?] attempted to guide COVID-19 vaccination by activating citizens' psychological ownership toward items—a psychological mechanism beyond the explanatory scope of the MINDSPACE framework. Furthermore, MINDSPACE's psychological drivers focus more on activating intuitive thinking (automatic system) while neglecting reflective thinking (reflective system), leaving many common educative nudges unclassifiable within this framework [?]. For instance, when hospitals provide patients with detailed information about different treatment options (including medical risks and financial costs), allowing patients to choose the most suitable option based on preferences, this behavioral intervention cannot be located within the MINDSPACE framework.

Thus, the MINDSPACE framework identifies common nudge types based on cognitive biases and psychological features corresponding to nudging measures but cannot encompass all possible nudging intervention tools, nor does it help resolve academic debates about nudge effectiveness under different cognitive pathways and transparency levels. Hansen and Jespersen [?] construct a nudge classification framework based on two dimensions: whether the nudge relies on intuitive reflection and whether it is transparent. Since nudges' cognitive pathways involve only System 1 or System 2, and transparency can be clearly categorized as transparent or non-transparent, any nudging measure can be unambiguously classified within this "cognitive pathway-transparency" two-dimensional framework. Drawing on this framework, this study establishes an analytical framework from the dual perspective of cognitive pathway and transparency, encompassing common nudging interventions in practice. Using this classification framework for meta-analysis allows comparison of effectiveness differences across nudge categories and provides comprehensive, objective evaluation of the true effects of nudging measures across different cognitive pathways and transparency levels.

2.1 Cognitive Pathways of Nudging: Intuitive Heuristics versus Deliberation

According to Kahneman's [?] dual-system theory, the human brain operates through two behavioral decision-making modes: fast thinking that is intuitive, uncontrollable, and unconscious (System 1), and slow thinking that is deliberate, conscious, and rational (System 2). In most situations, people lack sufficient time, resources, and motivation for fully rational deliberation, with most behaviors being unconscious, experiential decisions. Consequently, early perspectives held that nudging should act on System 1's automatic processes without engaging System 2 [?, ?, ?]. As Thaler and Sunstein [?] wrote in *Nudge*: "Homer Simpson forgot his rational thinking system… One purpose of this book is to explore how real-life Homers can live better" (pp. 26–27). Nudging was originally designed to cleverly exploit limitations in individuals' "irrational" behavioral characteristics to help them make correct decisions.

However, as nudging applications have deepened, scholarly understanding of its mechanisms has diverged. Some scholars maintain that nudging changes behavior solely through System 1's "heuristics" [?, ?], arguing that nudging guides behavioral change by exploiting individual cognitive deficiencies. The core lies in structuring environments to accommodate heuristic thinking and cognitive biases, thereby eliciting desired behavioral outcomes [?], and influencing behavior by preventing individuals from thinking about the pros and cons of alternative options [?]. Other researchers view "nudging" and "thinking" as two distinct pathways for behavior change: the former targets individuals with cognitive barriers who rely on experience and lack rational thinking, while the latter applies to individuals skilled in rational thinking, eager for knowledge, and capable of self-reflection [?]. Another group of scholars has begun exploring System 2's potential value in enhancing nudging intervention effectiveness. The UK Behavioural Insights Team [?] expanded nudging's cognitive pathways, arguing that both System 1 and System 2 are effective ways to guide behavioral change. Among nine common nudging measures, norms, defaults, salience, priming, and emotions relate to System 1, while messengers, incentives, commitments, and self-esteem involve System 2 more. Sunstein [?] distinguished between educative and non-educative nudges: educative nudges strengthen System 2 by increasing target groups' knowledge and capabilities, while non-educative nudges aim to evoke or activate System 1's automatic decision-making mechanisms without seeking to enhance individual capabilities. John and Stoker [?] proposed "nudge plus," suggesting that nudging processes should attempt to stimulate public autonomous reflection, freeing individual decisions from "paternalistic" interventions dominated by experts or elites to minimize infringement on individual autonomy. Incorporating elements that stimulate individual autonomous thinking into nudge design can strengthen nudge effectiveness [?].

Empirical analyses indicate that System 1 nudges have a slight edge in efficiency for changing individual behavior due to their low cost and ease of implementation [?], but System 2 nudges better respect individual autonomy. By strengthening individual agency to change behavior, they are more readily accepted by target groups and produce more durable intervention effects [?, ?, ?, ?]. In fact, the two cognitive processes do not operate independently: any nudging intervention triggers System 1's automatic mode, while System 2's reflective thinking must operate within the environment constructed by System 1's automatic mode. An experimental study on environmental facility selection also showed that default options—a nudging intervention—can function through both System 1 and System 2, with nudging measures across different cognitive pathways effectively guiding behavioral change [?]. Therefore, this study argues that the key to classifying nudges by cognitive pathway lies in identifying whether specific interventions involve reflective thinking. If an intervention's effectiveness presupposes individual deliberation, it can be classified as a System 2 nudge; otherwise, it is a System 1 nudge [?].

2.2 Transparency of Nudging Interventions: Silent Guidance versus Public Disclosure

Based on whether target groups are explicitly informed about intervention purposes, methods, and underlying psychological mechanisms during implementation, nudging interventions can be divided into transparent and non-transparent nudges [?, ?]. Non-transparent nudges advocate "silent influence," subtly changing target groups' choice architecture through covert means to guide their behavior quietly. Transparent nudges emphasize intervention information disclosure—making people aware of the intervention's existence and purpose, and informing them how nudges influence behavior [?].

Although non-transparent nudges often face controversy and criticism for violating transparency principles and allegedly manipulating individual behavior [?], Sunstein [?] notes that nudges often need to guide behavior in ways that people cannot detect. The reason for choosing silent intervention is that publicly declaring policy nudging intentions and forms will likely cause interventions to fail [?]. Whether people can recognize that their choices have been influenced is key to nudge effectiveness [?, ?]. Early meta-analysis results also confirmed that target groups' full awareness indeed triggers psychological defense mechanisms that reinforce original attitudes and behaviors [?], not only making nudging interventions inefficient or ineffective but also potentially triggering public reactance [?].

These studies seem to suggest that nudge transparency and effectiveness cannot be reconciled, sparking widespread concerns about transparent nudge effectiveness [?]. However, Sunstein [?] points out that transparent nudges are not necessarily doomed to fail in theory; their effectiveness depends on the degree to which people perceive their autonomous choice as restricted. If people believe that publicly disclosed nudging measures do not threaten their freedom of choice (e.g., providing information, reminders, warnings), transparency does not negatively affect nudge effectiveness. Conversely, if public nudging interventions make individuals feel clearly manipulated (e.g., default options, social norms), they trigger rejection. Additionally, citizens' trust in choice architects (policymakers) and individuals' "rebelliousness" levels also affect transparent nudge effectiveness. Since then, increasing empirical analyses have supported transparent nudge effectiveness. For example, experimental analyses by Loewenstein et al. [?] and Steffel et al. [?] on transparent versus non-transparent default options show that transparent defaults are equally effective; whether intervention information is concealed does not affect intervention effectiveness, and default options can still guide behavioral change even when subjects know the intervention is unethical. Kroese et al.'s [?] study manipulating shelf product placement (displaying healthy foods in prominent sight) also indicates that the public still chooses to purchase healthy foods even when aware they are being guided.

It should be noted that existing literature further subdivides transparent nudges based on the content of disclosed intervention information (intervention methods, purposes, expected outcomes) and compares their relative effectiveness [?, ?]. This study does not adopt this approach for two reasons: First, most comparative studies on transparent versus non-transparent nudge effectiveness have focused on default options [?], lacking examination of other interventions. Second, behavioral domains also affect transparency effectiveness, yet existing research has focused primarily on consumer decision-making, neglecting other behavioral domains. Therefore, to analyze and compare the intervention effects of transparent versus non-transparent versions of multiple common nudging measures across broader behavioral domains, and considering meta-analytic feasibility and variable operability, this study does not conduct overly detailed analysis of transparent nudge subtypes. Instead, we distinguish transparent from non-transparent nudges based solely on whether intervention information (any type) is disclosed in ways that target groups can fully detect, comprehensively considering their effectiveness and differences.

2.3 Variations in Nudge Effectiveness and Their Causes

The heterogeneity of nudge effectiveness across decision-making contexts has received substantial empirical support [?, ?, ?]. Discussions of these variations have followed two main approaches: first, using specific elements as benchmarks (e.g., behavioral domains, experimental design) for meta-analysis to compare nudge effectiveness across contexts [?, ?]; second, conducting regression analysis that synthesizes various potential influencing factors to compare their effects on nudge effectiveness [?, ?, ?, ?]. This study follows the second approach to explore the roots of heterogeneity in nudging effects. Beyond nudge category differences, factors influencing nudge effectiveness can be categorized into three types: research design, behavioral characteristics, and behavioral domains.

(1) Research Design. Experimental type, sample size, and variable data type in research design may all affect nudge effectiveness. Regarding experimental types for nudging interventions, because different experimental types vary in their degree of experimental condition control, laboratory experiments are considered to best avoid external interference and thus produce better effects [?], with more generalizable conclusions [?]. Some scholars find that field experiments produce better effects, possibly because field experiments are generally preceded by pilot studies, where researchers select results showing larger effect sizes for experimentation, while laboratory experiments are mostly exploratory and harder to detect actual effects [?]. However, recent empirical analyses have not found differences in effect sizes across experimental types, suggesting that which experimental type is more suitable for exploring behavioral intervention effects requires more empirical analysis [?, ?].

Based on subject numbers, randomized controlled experiments can be divided into large-scale experiments (sample size $\geq$ 1000) and small-scale experiments (sample size $<$ 1000) [?]. When examining how sample size (total subjects in control and treatment groups in a single experiment) affects effect size, existing literature typically uses this as a classification criterion to compare effect size differences across studies with different sample sizes [?]. Meta-analyses in medicine, education, and other disciplines have consistently concluded that small-scale experiments usually have larger effect sizes than large-scale experiments [?], yet scholars in behavioral public policy have not reached consensus on sample size's effect. For example, Nisa et al.'s [?] meta-analysis of environmental behavior intervention experiments shows that small-scale experiments have larger effect sizes than large-scale ones, but Jachimowicz et al.'s [?] meta-analysis of default effects indicates no significant difference between large-scale and small-scale experiments, suggesting that sample size's influence in nudging experiments requires continued investigation.

Meta-analytic effect size calculation depends on the variable type selected in different experimental studies. Continuous variables (e.g., "donation or investment amount") and dichotomous variables (e.g., "yes or no") represent different response modes for subjects, with subjects facing different decision-making contexts across response modes. Although statistical methods can convert effect sizes calculated from different variable types to the same dimension for comparison [?, ?], whether different decision-making contexts affect behavioral intervention effectiveness remains to be empirically explored [?, ?].

(2) Behavioral Characteristics. According to behavioral science knowledge, behavioral motivation and whether behavior involves monetary changes affect nudging measures' actual effectiveness. Theoretically, when people realize their prosocial behavior is guided rather than spontaneous, nudging intervention effectiveness diminishes significantly [?, ?], yet experimental studies have not found effectiveness differences when using nudges to guide self-interested or altruistic behaviors [?, ?]. Therefore, some scholars suggest that behavioral motivation's effect on intervention effectiveness may relate to nudge transparency and behavior's public nature [?]. Furthermore, rational individuals' decision-making follows utility maximization principles, with actual monetary changes being easier to perceive and calculate, more likely to activate System 2's reflective thinking. However, for nudging measures like default options, effectiveness depends more on changing choice architecture and relying on System 1's automatic thinking, so when nudging measures adjust behaviors involving monetary changes, System 1 cognitive pathway-dependent nudging interventions may not achieve expected effects [?]. Additionally, according to motivation crowding theory, monetary incentives increase extrinsic behavioral motivation but may decrease intrinsic motivation [?, ?]. Therefore, whether behaviors involving monetary changes affect intervention effectiveness, and whether the underlying mechanism operates through cognitive pathways or internal/external motivation, requires further empirical analysis.

(3) Behavioral Domains. The heterogeneity of nudge effectiveness across behavioral domains is a hot topic in behavioral public administration research, with most relevant work focusing on comparing nudge effectiveness across health, consumption, finance, and public interest domains [?]. For example, Jachimowicz et al. [?] found that default options have higher intervention effects in consumption domains and lower effectiveness in environmental domains, but found no differences between health and other domains. However, DellaVigna and Linos's [?] analysis shows that nudging interventions have higher effects in health and public interest domains and poorer effects in consumption domains. This discrepancy may stem from different analysis objects: the former focused only on default options, while the latter covered multiple nudge types. Similarly, Hummel and Maedche's [?] meta-analysis shows nudging has higher effects in finance than health domains, but Mertens et al.'s [?] meta-analysis reaches the opposite conclusion, possibly because different studies used different literature screening criteria (e.g., health domains can be further divided into medical health, dietary health, etc., with potentially different intervention effects). This indicates that while existing research has confirmed nudge effectiveness differences across behavioral domains, comparative analyses of nudge effects across domains have not reached consistent conclusions.

2.4 Interactive Effects of Cognitive Pathway, Transparency, and Heterogeneity Factors

The academic community has long debated the relative advantages of System 1 versus System 2 nudges and transparent versus non-transparent nudges [?]. This controversy likely arises because most existing research compares based on a single dimension without fully considering that the applicability of different cognitive pathways or transparency levels varies across contexts—differences manifested through interactions among cognitive pathways, transparency, and heterogeneity factors.

Existing literature has explored applicable contexts for different cognitive pathway nudges from theoretical and empirical perspectives. Theoretically, using System 2 for decision-making requires effortful self-control; individuals lacking self-control are more likely to give up when facing complex cognitive tasks. System 1 decision-making requires no citizen effort, making System 1 nudges more effective for citizens with weak self-control. Additionally, according to Cognitive Load Theory, people face memory capacity limitations when processing information; when cognitive tasks exceed memory capacity limits, citizens' probability of making wrong decisions increases. Since System 1 decision-making uses intuitive thinking with lower cognitive demands, some scholars believe System 1 nudges outperform System 2 nudges under high cognitive load [?]. Empirical studies also confirm differential intervention effects of System 1 and System 2 nudges across contexts. For example, when nudging behaviors relate to citizen interests (e.g., guiding citizens to purchase flood insurance, disability insurance), activating citizens' reflective thinking (System 2 nudges) works better [?]; when target groups' personal preferences oppose nudging's expected behavioral direction, System 1 nudges are more applicable [?].

The effect of transparency on nudge effectiveness also varies under different conditions. Scholars generally agree that the degree of threat different interventions pose to personal autonomy is key to transparent nudge effectiveness. Sunstein [?] proposes that transparent nudge effectiveness depends on the degree to which people perceive their autonomous choice as restricted; when citizens believe nudging measures threaten their autonomous choice, covert intervention works better. Empirical results also show that interventions strongly invasive of citizen autonomy (e.g., reducing plate sizes in cafeterias) should remain covert, while less invasive interventions (e.g., default options) can be publicly disclosed by governments to strengthen citizen trust and enhance intervention effectiveness [?]. Additionally, transparent nudge effects show obvious heterogeneity across behavioral domains. For example, Kroese et al.'s [?] study manipulating shelf product placement found that publicly disclosing intervention information could still effectively guide citizens to purchase healthy foods. Gråd et al.'s [?] study on default options' effect on donation behavior found transparent default options significantly less effective than non-transparent ones. Therefore, some scholars infer that transparent nudges work better when expected behaviors benefit citizens themselves [?].

These studies show that different cognitive pathways or transparency levels produce different effects in specific contexts, and comparisons cannot be divorced from intervention contexts. Therefore, analyzing possible interactive effects among cognitive pathways, transparency, and heterogeneity factors helps address academic controversies about nudge effectiveness under different cognitive pathways and transparency levels.

3.1 Research Method

Meta-analysis, also known as 荟萃分析, is a statistical method for systematically evaluating existing empirical research results. Effect size metric selection is crucial in meta-analysis, with its magnitude indicating the strength of nudging behavioral intervention effects across studies. Based on behavioral intervention experiment characteristics, standardized mean differences better capture differences between control and treatment groups in behavioral science [?]. When all data are transformed to a scale where between-group standard deviations equal 1, standardized mean differences have high comparability across studies. Therefore, this study selects standardized mean difference as the effect size estimate, commonly known as Cohen's d coefficient, where larger coefficient values indicate better intervention effects [?]. We use Comprehensive Meta-Analysis 2.0 software to calculate effect sizes.

3.2 Data Sources

This study conducts meta-analysis on nudging intervention experiments published in the authoritative behavioral public policy journals *Behavioural Public Policy* (2017–2022) and *Behavioral Science & Policy* (2015–2022), screening 40 articles yielding 108 research results. During literature searching, all articles from both journals were included (totaling 330 articles), then screened individually by reading full texts. The meta-analysis literature search and screening process is shown in [Figure 1: see original paper].

Among the 40 sample articles, most focus on behaviors in health, consumption, and public interest domains. Experimental types are primarily field experiments (25 articles) and online experiments (11 articles). Thirty-nine articles use randomized controlled designs, with only one using a pre-post design. Most articles focus on the actual effects of interventions like norms, salience, and messengers. Sample sources are predominantly Western countries, with many studies using subjects from the UK, US, Germany, and the Netherlands. Sample sizes across articles range from a minimum of 88 to a maximum of 11,157,069, showing substantial variation (see).

4.1 Nudging Effect Size Estimation

Considering sample size differences across studies, using fixed-effect models with sample size as the weighting standard would produce substantial errors, so we adopt random-effects models to synthesize effect sizes. Following Cohen's [**?**] criteria, we use $d = 0.2$, $d = 0.5$, and $d = 0.8$ as cutoffs for small, medium, and large effect sizes, respectively. Results show (see [Figure 2: see original paper]) that the comprehensive effect size for nudging intervention effectiveness is $d = 0.21$, 95% CI = [0.19, 0.23], indicating a small observed effect. Six studies show effect sizes below 0, 47 studies show effect sizes between 0 and 0.2, and 55 studies show effect sizes ≥ 0.2, with significant variation across studies.

Heterogeneity test results show $I^2 = 99.5\%$. The I^2 statistic represents the proportion of variation due to true differences; $I^2 = 0$ indicates all observed variation is due to random error, while values $> 75\%$ indicate high heterogeneity requiring further exploration of other factors affecting effect values. Below, we analyze heterogeneity sources from nudge type, research design, behavioral characteristics, and behavioral domains, then further distinguish the true effects of different nudge categories from cognitive pathway and transparency dimensions.

4.2 Transparency and Cognitive Pathway Effect Size Analysis

Drawing on Hansen and Jespersen's [**?**] framework, this study classifies all 108 nudging methods across the two dimensions of "cognitive pathway-transparency" (see [Figure 3: see original paper]). Cognitive pathway classification depends on whether specific interventions involve reflective thinking: if effectiveness presupposes individual deliberation, it is classified as System 2 nudging; otherwise, it is System 1 nudging. Transparent versus non-transparent nudges are distinguished by whether intervention information is disclosed in ways target groups can fully detect; if subjects can perceive intervention methods, purposes, or expected outcomes (any one suffices), it is a transparent nudge; otherwise, it is non-transparent. Coding only classifies intervention types without scoring transparency or reflectiveness degrees. Two researchers independently completed classification coding, with Cohen's Kappa = 0.92, indicating high reliability. Forty studies used non-transparent System 1 nudges, 12 used non-transparent System 2 nudges, 16 used transparent System 1 nudges, and 40 used transparent System 2 nudges, showing that non-transparent System 1 and transparent System 2 nudges are current academic foci.

It should be noted that under Hansen and Jespersen's [?] classification, default options should belong to non-transparent System 1 nudges, and social norms should belong to transparent System 2 nudges. However, due to different experimental contexts and human manipulation, these two nudging methods appear across multiple categories in sample literature classification. For example, Paunov et al.'s [?] analysis of course selection behavior and Boruchowicz et al.'s [?] study on contact tracing app installation both manipulated default option transparency, while Kantorowicz-Reznichenko et al.'s [?] experimental study on COVID-19 vaccination intentions manipulated social norm transparency. Overall, these exceptional cases do not affect the classification framework's rationality and feasibility.

Meta-analysis results for the four nudge categories (see) show that non-transparent System 1 and transparent System 2 nudges are more effective, while transparent System 1 and non-transparent System 2 nudges have significantly smaller effect sizes. Examining single dimensions, non-transparent System 1 nudges outperform transparent ones, while transparent System 2 nudges outperform non-transparent ones; transparent nudges stimulating active thinking outperform intuitive thinking, and non-transparent nudges using intuitive thinking achieve better intervention effects.

4.3.1 Analysis of Factors Influencing Nudging Effect Heterogeneity

Using sample literature's Cohen's d values as the dependent variable, we explore effect size influencing factors from four dimensions: nudge type, research design, behavioral characteristics, and behavioral domains. Variable operationalization and coding are as follows (see). Among nine articles, 24 research results involve decision-making behaviors across multiple domains. Two coders independently coded each study's behavioral domain, with Cohen's Kappa = 0.95, indicating high reliability. To avoid the dummy variable trap (multicollinearity), we use non-transparent System 2 nudges as the baseline group in model specifications, defining only the other three nudge types in the table.

Among Models 1–6 (see), Model 4 has the largest F-statistic and adjusted R^2, indicating optimal model fit. Model 4 results show that, regarding research design, sample size has a significant negative effect on effect size ($\beta = -0.52$, $p < 0.001$), indicating that experiments with ≥ 1000 subjects show significantly lower behavioral intervention effects than those with < 1000 subjects. Experimental type and data type do not affect nudging intervention effectiveness. Among behavioral characteristic variables, neither behavioral characteristics nor monetary changes significantly affect effect size, indicating that whether decision-making is self-interested or altruistic, or involves actual monetary changes, does not affect nudging intervention effectiveness. Regarding behavioral domains, health domain ($\beta = 0.23$, $p < 0.1$) and finance domain ($\beta = 0.26$, $p < 0.1$) have significant positive effects on effect size, indicating better nudging effects in health and finance domains. These results show that nudge effectiveness is influenced by research design and behavioral domains, with heterogeneity explainable by experimental sample size differences and whether nudging behaviors involve health or finance domains.

4.3.2 Interactive Effect Analysis of Different Nudge Types and Heterogeneity Factors

(1) Model Specification. To analyze interactions among transparency, cognitive pathways, and research design, behavioral characteristics, and behavioral domains, and further explore why existing literature's single-dimension classification comparisons produce conflicting conclusions, this study constructs the following interactive effect model:

In the model, represents each study's effect size; when examining cognitive pathway interactions, represents each experiment's nudge cognitive pathway (System 1 = 1, System 2 = 0); when examining transparency interactions, represents each experiment's nudge transparency (transparent = 1, non-transparent = 0), represents specific categories of research design, behavioral characteristics, and behavioral domains (sample size, field experiment, data type, behavioral motivation, monetary change, health, consumption, finance, public interest), and represents interaction terms.

(2) Results Analysis. Overly low adjusted R^2 indicates insufficient explanatory power of independent variables; negative values indicate poor goodness-of-fit relative to degrees of freedom [**?**]. Due to limited dependent variable numbers, constructing interactive effect models with all variables simultaneously would produce large biases. Therefore, this study examines interactive effects for each variable separately, which also limits independent variable explanatory power. Below, we discuss only models with significant F-statistics and regression coefficients.

Cognitive pathway interactive effect regression results (see) show that from the sample size interaction term model (Model 1) ($\beta_1 = -0.27$, $p < 0.01$; $\beta_2 =$

-0.56, $p < 0.001$; $\beta_3 = 0.29$, $p < 0.1$), when total subjects in control and treatment groups ≥ 1000, System 1 and System 2 nudge effects show no significant difference; when total subjects < 1000, System 2 nudge effects exceed System 1 effects ($\beta_1 < 0$) (see [Figure 4a: see original paper]).

Transparency interactive effect regression results (see) show that from the behavioral motivation interaction term model (Model 4) ($\beta_3 = 0.38$, $p < 0.1$), when nudging interventions are self-motivated, transparent nudge effects exceed non-transparent nudges ($\beta_1 + \beta_3 > 0$); when altruistically motivated, non-transparent and transparent nudge effects show no significant difference (see [Figure 4b: see original paper]). From the health interaction term model (Model 6) ($\beta_3 = 0.42$, $p < 0.1$), when nudging interventions belong to health domains, transparent nudge effects exceed non-transparent nudges ($\beta_1 + \beta_3 > 0$); when not in health domains, non-transparent and transparent nudge effects show no significant difference (see [Figure 4c: see original paper]). From the public interest interaction term model (Model 9) ($\beta_1 = 0.36$, $p < 0.01$; $\beta_3 = -0.40$, $p < 0.1$), when nudging interventions involve public interest, transparent nudge effects are smaller than non-transparent nudges ($\beta_1 + \beta_3 < 0$); when not involving public interest, transparent nudge effects exceed non-transparent nudge effects ($\beta_1 > 0$) (see [Figure 4d: see original paper]).

5.1 Research Conclusions

Based on the dual perspective of "cognitive pathway" and "transparency," this study meta-analyzes 108 empirical results from 40 nudge studies in *Behavioural Public Policy* (2017–2022) and *Behavioral Science & Policy* (2015–2022), comparing the relative advantages of nudging measures across different cognitive pathways and transparency levels, and exploring interactive effects among nudge cognitive pathways, transparency, and heterogeneity factors. Findings show:

(1) Nudging research in behavioral public policy shows small overall effects and faces failure risks in practice. Compared with most existing nudging intervention meta-analyses [**?**, **?**, **?**, **?**], this study observes relatively smaller overall effects. The forest plot distribution shows some nudge studies even have negative effect sizes. This may be because, relative to other meta-analyses that estimate effect sizes mostly from citizens' choices in experimental contexts, research focusing on behavioral public policy domains mostly measures nudging intervention effects through citizens' behavioral decisions in real policy contexts, and choices in experimental contexts do not necessarily translate into real-life behaviors [**?**], leading to smaller overall effect sizes in this study. Nisa et al.'s [**?**] meta-analysis also shows that nudging effects in real policy contexts are lower than expected. Some scholars argue that even small overall effects can produce substantial impacts when target group sizes are large [**?**].

Furthermore, although a few measures like default options have strong nudging effects in promoting or improving individual behavior [**?**], nudging as a whole toolbox of behavioral public policy tools does not always achieve "leveraging small forces for large effects" in solving "behavioral failures" and faces failure risks in practice. Sunstein [?] comprehensively analyzed reasons for nudging inefficiency or underperformance, arguing that target groups' strong prior preferences and nudging actors' self-interest motivations may cause nudge failure. If people cannot understand nudging-relevant information or misunderstand policy measures, or if citizens strongly resist official policy guidance, nudging intervention effects will be greatly reduced. Tor [?] identified three types of failed nudges: (1) technically flawed nudges requiring design optimization; (2) insufficient nudges that cannot effectively promote behavioral change and require mandatory interventions; and (3) unsuitable nudges that should not be applied to certain target groups or behavioral domains. Additionally, some scholars argue that nudge effectiveness evaluation should not only satisfy statistical significance but also consider sufficiency in problem-solving, scalability to intervention populations, and subjectivity of intervention measures [?]. Future research should continue in-depth analysis of nudge failure causes to provide more empirical evidence for nudging tool optimization.

(2) Nudging can reconcile transparency and effectiveness, with interactive effects between cognitive pathway and transparency on nudge effectiveness. This study's results show that non-transparent System 1 and transparent System 2 nudges are more effective, while transparent System 1 and non-transparent System 2 nudges have significantly smaller effect sizes. Our conclusions reaffirm that nudge transparency and effectiveness are not incompatible [?, ?, ?, ?, ?]; not only covert interventions can work. Therefore, if policymakers can reasonably disclose intervention information when using nudging tools, meeting Thaler and Sunstein's [?] "publicity principle," this will help resolve long-standing controversies about nudging allegedly manipulating citizen behavior.

Additionally, this study finds interactive effects between cognitive pathway and transparency on nudge effectiveness, manifested as non-transparent System 1 nudges outperforming transparent System 1 nudges, and transparent System 2 nudges outperforming non-transparent System 2 nudges. This result can be explained from two angles based on cognitive pathway mechanisms. First, why System 1 nudges suit covert interventions: Since System 1 nudges use intuitive thinking to guide citizens toward expected behaviors, these methods mostly threaten citizens' autonomous choice, and disclosing intervention information triggers opposition [?]. Second, why disclosing intervention information can enhance System 2 nudge effectiveness: Because System 2 decision-making depends on citizens' reflective thinking, disclosing intervention information provides more decision-making basis for citizen deliberation, reduces unnecessary cognitive burden, and lowers the effort required for active thinking. Under low cognitive load, System 2 nudges outperform System 1 nudges [?]. The interactive effect between cognitive pathway and transparency is an exploratory finding of this study, offering a new explanatory path for controversies about intervention effects across different transparency or cognitive pathway levels.

(3) Nudging intervention effects are influenced by research design and vary across behavioral domains. First, regarding research design, overly large sample sizes reduce nudging intervention effectiveness. This indicates that the "small sample-large effect" phenomenon common in medical and educational experimental research [?] also exists in behavioral public policy. On the other hand, it shows that large-sample experimental results are more reliable than small-sample result variability [?, ?].

Second, nudging effects differ across behavioral domains, with better effects in health and finance domains. This finding differs substantially from existing analyses. For example, Jachimowicz et al. [?] and 赵宁等 [?] did not find better default option effects in health domains, and Mertens et al. [?] did not find significantly higher nudging effects in finance domains. In fact, existing meta-analyses on nudge effectiveness across behavioral domains often reach conflicting conclusions (e.g., Hummel and Maedche [?] versus Mertens et al. [?] on finance and health domain comparisons have opposite conclusions). These differences may arise because: (1) meta-analyses target different nudging measures—Jachimowicz et al. [?] and 赵宁等 [?] focused only on default options, while this study examines comprehensive effects across multiple nudging measures, reducing comparability; (2) meta-analyses include different subcategories of behavioral domains (e.g., financial behavior can be subdivided into saving, borrowing). This study's financial behaviors mostly involve saving and insurance purchasing, but we cannot know Mertens et al.'s [?] financial behavior subcategories, nor can we determine whether nudging effects are identical across subcategories (e.g., saving versus borrowing in finance domains), especially since 赵宁等 [?] have proven that nudging effects differ significantly across environmental domain subcategories (self-interested versus altruistic). This suggests future research on nudging in health, finance, and other domains should further refine categories to increase comparability across studies.

(4) Complex interactions exist among the cognitive pathways through which nudging operates, nudge design transparency, and heterogeneity factors influencing effect sizes. Results show significant interactions between cognitive pathway and sample size, and between transparency and behavioral motivation, health domain, and public interest. These interactive effects reflect differences in the applicability of different cognitive pathways or transparency levels across contexts.

Regarding applicability differences between System 1 and System 2 nudges, existing research suggests influencing factors include citizens' cognitive abilities, behavioral preferences, and nudging behavioral domains [?, ?]. First, this study did not find interactive effects between nudge cognitive pathway and behavioral domain, and Banerjee and John's [?] claim that System 2 nudges are more effective for behaviors involving citizen self-interest requires more empirical verification. Second, this study finds that System 2 nudges work better in small-scale experiments, indicating that differences in experimental design sample sizes lead to differential intervention effects for System 1 and System 2 nudges. This can be explained by experimental type differences: 70% of small-scale experiments in this study's sample are online experiments, while 82% of large-scale experiments are field experiments. Compared with the complexity of real decision-making contexts, online experiments' virtual contexts help citizens concentrate and activate System 2 for deliberation, making System 2 nudges more applicable than System 1 nudges in small-scale experiments. However, limitations of this study's interactive effect models prevent further exploration of citizens' cognitive abilities or behavioral preferences' potential roles, providing new directions for future research.

Regarding applicability differences between transparent and non-transparent nudges, existing research has explored transparent nudge applicable contexts from behavioral domain and perceived autonomy invasion perspectives. This study's conclusions show that when nudging behaviors closely relate to citizens' own interests (self-interested motivation, health domain, not involving public interest), disclosing intervention information can enhance nudge effectiveness, highly consistent with existing findings [**?**, **?**, **?**]. Additionally, existing research shows that the degree to which people perceive their autonomous choice as restricted is also key to whether transparency works [**?**], but measuring citizens' perceived autonomy invasion is difficult, preventing assessment of transparency's actual impact on this factor in this study. Overall, this study's analysis of interactive effects among cognitive pathways, transparency, and heterogeneity factors proves that nudge cognitive pathways and transparency have differential applicability across contexts.

5.2 Policy Implications

These findings not only address academic controversies about nudge effectiveness under different cognitive pathways and transparency levels, providing objective and accurate evaluation of different nudging interventions' true effects, but also offer the following policy implications for enhancing nudging tool effectiveness.

First, policy departments should fully recognize potential nudge failure risks, maintain prudent attitudes when applying nudging interventions, and actively take measures to address nudge failure. In recent years, as behavioral public policy has demonstrated enormous potential in Western developed countries' policy practice, governments worldwide have followed suit, even showing blind trend-following tendencies. However, this analysis shows that overall, various nudging measures are not as remarkably effective as expected. Therefore, policy departments should form rational expectations about behavioral effects when attempting to use nudging interventions, fully recognizing possibilities of low or no effectiveness. Nudging and traditional policy tools are not mutually substitutive but complementary; relying on single tools cannot guide citizen behavior, and combining nudging with traditional tools works better [**?**]. Facing nudge failure, policymakers can adopt these strategies: (1) respect citizens' free choice and make no changes; (2) select alternative solutions; or (3) change rules, frameworks, and personalized settings, or switch to traditional policy tools like incentives and bans [?].

Second, in designing nudging measures, decision-makers should emphasize cultivating and enhancing individuals' reflective decision-making abilities through more transparent policy design. Decision-makers often face dilemmas when selecting nudging tools: silently guiding public behavior turns policy design into "trickery" and provides legitimacy for government manipulation of citizen actions, but publicly declaring policy nudging intentions and forms will likely cause interventions to fail. This study's analysis shows that nudge transparency and effectiveness are not in conflict: transparent nudges stimulating active thinking outperform intuitive heuristics, while non-transparent nudges using intuitive heuristics achieve better intervention effects. Stimulating target groups' autonomous thinking can improve their cognitive levels and decision-making abilities and help maintain long-term behavioral intervention effects. Therefore, decision-makers should help individuals improve their decision-making abilities by changing cognitive or decision-making environments, using "educative nudges" to "empower" individuals [?, ?]. During policy formulation, proactively disclose policy goals and implementation means to target groups who hold resistant attitudes toward government intervention to gain public support. During policy implementation, when facing potential conflict-of-interest situations (e.g., doctor-patient communication, urban management law enforcement), providing detailed decision-making information can enhance public cognitive abilities, guide citizens toward rational behavioral decisions, alleviate conflicts, and promote smooth policy implementation.

Third, policy formulation departments should fully consider nudging applicability and formulate differentiated, personalized nudging measures based on behavioral domains and characteristics, leveraging various emerging technologies to enhance policy effectiveness. When selecting policy tools for health and finance domains, prioritize nudging interventions to guide behavioral change. When public policies more closely relate to citizens' own interests, policy design should focus on increasing people's knowledge reserves and ability to distinguish right from wrong to encourage active, welfare-promoting behaviors, using government information disclosure to enhance policy process transparency and fully protect citizens' right to know. When policy content concerns public interest, government departments should use clever designs to subtly utilize or overcome individuals' "irrational" psychological factors and cognitive biases to guide people toward policy-desired behaviors. Furthermore, organically integrate emerging technologies with behavioral science knowledge, use big data analytics of individual behavior to optimize individual choice architecture [?], and explore evidence-based nudging policies based on big data. Policy formulation departments can combine emerging technologies like virtual reality, social robots, game design, self-quantification, and behavioral informatics with behavioral science to design personalized choice schemes and nudging methods based on target group characteristics [?].

5.3 Research Limitations and Future Directions

This study's limitations mainly include: (1) Most meta-analysis sample literature interventions concentrate in health and consumption domains, preventing examination of heterogeneity in more behavioral domains. (2) Since *Behavioural Public Policy* and *Behavioral Science & Policy* nudging intervention experiment samples mostly come from Western countries, with relatively few studies using Eastern country subjects, this study cannot conduct cross-cultural analysis of nudge effect heterogeneity. (3) Limited by sample literature numbers, too many interactive variables would cause large model estimation errors, so this study does not examine interactive effects among heterogeneity factors. (4) The effects of the four nudge categories under the "cognitive pathway-transparency" two-dimensional classification framework are affected by sample sizes, and the interactive effects between nudge cognitive pathways and transparency require more empirical evidence.

Future research should pay more attention to nudging actual effects in other behavioral domains, further refining target behavior categories to study nudge effect heterogeneity. Existing research shows that default option effects are significantly higher in Western than Eastern cultural contexts [**?**]; future research can further analyze effectiveness differences and reasons for other nudging measures across cultural contexts. Interactive effect studies on nudge effectiveness can better reveal heterogeneity roots; future research should design more diverse interactive effect models to explore possible interactive effects among more heterogeneity factors. Additionally, intervention effects of different transparency or cognitive pathway nudges require testing with larger sample sizes.

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Note: Figure translations are in progress. See original paper for figures.