

The Limited Capacity Model of Motivated Mediated Message Processing: Meta-Analytically Summarizing Two Decades of Research

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(LC4MP) aims to understand message processing dynamics. Despite 20 years of research, no meta-analysis has assessed LC4MP effects. We conducted a meta-analysis of the model to examine three theoretical research domains in the LC4MP: cognitive load, motivation, and memory. Results from 142 articles and 683 effects demonstrate that pooled effect sizes for research domain range from $r = .314 - .398$. Effect sizes vary by measurement modality with self-report resulting in the largest pooled effect size, followed by behavioral, and finally psychophysiological measures. We did not detect evidence of publication bias. These findings offer meta-analytic support for LC4MP research domains and are discussed in terms of falsifiability, predictive and explanatory power.

keywords: LC4MP, meta-analysis, cognitive load, motivation, memory, open science

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Modern communication science can trace its origins to an information processing perspective (Huskey et al., 2020; Schramm, 1955). The Limited Capacity Model of Motivated Mediated Message Processing (LC4MP; Lang, 2000, 2006, 2009, 2017) is a data-driven model that adopts an information processing approach for studying message selection, processing, and effects (Lang & Ewoldsen, 2013; Lang, Potter, & Bolls, 2008). The LC4MP has garnered more than 1000 citations¹ since its introduction in 2000. A systematic review of the literature showed that a total of 249 articles provide a direct test of the LC4MP, with 143 of those articles published within the last five years (Fisher, Keene, Huskey, & Weber, 2018). These studies span numerous research areas in quantitative communication science, including but not limited to: health communication, political communication, persuasion and social influence, gender roles and stereotyping, morality, news, media multitasking, educational media, media entertainment, and more (Fisher, Huskey, Keene, & Weber, 2018). Surprisingly, and despite nearly two decades of research, no meta-analysis of the LC4MP exists.

A meta-analysis of the LC4MP has both theoretical implications and methodological benefits. Using theoretical evaluation criteria common to communication science (for extended discussions of these criteria, see Chaffee & Berger, 1987; DeAndrea & Holbert, 2017; Popper, 1959/2002;

¹ Citations for Lang (2000) = 749, citations for Lang (2006) = 277. Data pulled from Web of Science™ on June 17, 2020.

Slater & Gleason, 2012), a meta-analysis offers a quantitative and empirically informed: (1) overview of a theory, (2) way to assess the accuracy of a theoretical model's predictive power, (3) test that evaluates if a theoretical component of the model can be falsified, and (4) method for evaluating the postdiction explanatory power of a theoretical model. In addition to these theoretical contributions, information about the distribution and magnitude of effect sizes in the LC4MP helps in planning future research studies, particularly for researchers interested in conducting *a priori* informed power analyses or *a posteriori* informed equivalence tests (Weber & Popova, 2012). Finally, a meta-analysis also allows researchers to test for evidence of publication bias (Carpenter, 2009; Levine & Carpenter, 2009).

Our meta-analysis of the LC4MP addresses these gaps in the literature. With these theoretical and methodological aims in mind, we now turn our attention to a brief overview of the LC4MP in which we discuss the model's theoretical research domains and how these research domains are commonly operationalized. We conclude with a series of *confirmatory* hypotheses and *exploratory* research questions that advance the aims outlined above.

Meta-Analyzing the LC4MP

One of the first issues to resolve when conducting a meta-analysis is specifying how key variables will be organized and grouped (Wilson, 2009). We argue that the first meta-analytic summary of the LC4MP should reach the widest possible audience while also testing core research domains within

the model. To that end, we expand on a recent LC4MP synthesis (Fisher, Keene, et al., 2018; Fisher, Huskey, et al., 2018) to meta-analytically summarize the model's three primary theoretical research domains: cognitive load, motivation, and memory (see also, Lang, 2009). The LC4MP uses self-report, behavioral, and psychophysiological measures, and the application of these measures varies by research domain (Lang, 2009). These measures have considerable differences in effect size magnitude and distribution with research consistently showing that psychophysiological measures have small effect sizes while behavioral measures show larger effects (Potter & Bolls, 2012). Accordingly, we also stratified our analysis by measurement modality. Together, our meta-analysis provides information about the magnitude and distribution of LC4MP effects, and evaluates if the magnitude and distribution of these effects is moderated by theoretical research domain and measurement modality. We also test if there is evidence of publication bias.

LC4MP Research Domains and Measurement Modalities

Research using the LC4MP typically encompasses one of three theoretical research domains (Lang, 2009): cognitive load, motivation, and memory. Research in the cognitive load domain is focused on understanding how the human information processing system, which is capacity limited, is impacted by message characteristics. For example, a cognitive load study might investigate the extent to which media messages are more or less cognitively

demanding based on formal message features (e.g., cuts and edits), thereby clarifying on how message characteristics influence attentional allocation (Lang, Bradley, Park, Shin, & Chung, 2006). Importantly, the LC4MP recognizes that motivation modulates these processes. For instance, a classic finding demonstrates that different emotional trajectories within a message elicit differential activation of the appetitive and aversive motivational systems, which ultimately influences message processing (Keene, Lang, & Loof, 2019; Lang, Sanders-Jackson, Wang, & Rubenking, 2013). Finally, the LC4MP offers clear predictions about how different message characteristics influence memory for a message. Both cognitive load and the motivational relevance of a message modulate message recognition (Keene & Lang, 2016).

Research testing components of the LC4MP is primarily conducted using self-report, behavioral, and psychophysiological measures (for an overview of the methodological toolbox of the model, see Lang, 2009). Self-report measures include, for example, valence (Keene & Lang, 2016) and arousal (Clayton, Leshner, Thorson, & Bolls, 2017; Clayton, Ridgway, & Hendrickse, 2017; Keene & Lang, 2016). Behavioral measures are not limited to, but include secondary task reaction time (Clayton, Leshner, Sanders-Jackson, & Hendrickse, 2020; Lang et al., 2006; Lang & Basil, 1998) and signal detection (Shapiro, 1994) procedures. Psychophysiological measures include heart rate (Clayton, Lang, Leshner, & Quick, 2019; Keene, Clayton, Berke, Loof, & Bolls, 2017), skin conductance (Clayton, Keene, Leshner,

Lang, & Bailey, 2020; Wang, Morey, & Srivastava, 2012), and facial electromyography at the corrugator supercilii muscle region (Leshner, Clayton, Bolls, & Bhandari, 2018; Rubenking & Lang, 2014), orbicularis oculi (Bailey, 2015, 2016) and zygomaticus major muscle region (Wang & Lang, 2012; Yegiyan & Bailey, 2016). A small handful of studies have investigated the neural basis of the LC4MP using electroencephalography (Stróžak & Francuz, 2016) or functional magnetic resonance imaging (Huskey, Mangus, Turner, & Weber, 2017; Seelig, et al., 2014); however, too few of these studies exist for conducting a meta-analysis, and therefore these approaches are excluded from further consideration in the present study.

Hypotheses

A systematic review of the LC4MP literature (Fisher, Keene, et al., 2018) showed that, even though some studies failed to find empirical support for a hypothesized relationship, the cumulative body of literature seemed to demonstrate robust support for each of the LC4MP's three theoretical research domains (cognitive load, motivation, memory). This was true regardless of how these theoretical constructs were methodologically operationalized (i.e., self-report, behavioral, psychophysiological). One limitation of this systematic review is that it did not empirically test these observed patterns in the literature.

Our meta analysis addresses this gap. We pre-registered two *confirmatory* hypotheses: (H1) that pooled effect sizes in each of the theoretical research domains (cognitive load, motivation, memory) will be

significantly different from zero, and (H2) that these effect sizes will differ by measurement modality with behavioral measures showing the largest effect and psychophysiological measures showing the smallest effect. We also evaluated two *exploratory* research questions that were not pre-registered: (RQ1) is effect size magnitude for each research domain is moderated by measurement modality, and (RQ2) is there evidence of publication bias in the LC4MP literature?

Open Science Practices and PRISMA PICOS Statement

Consistent with calls to adopt open science practices in communication research (Bowman & Keene, 2018; Dienlin et al., 2020; Lewis, 2020), the study rationale, hypotheses, code book, and analysis plan were pre-registered and are available on the Open Science Framework (OSF; https://osf.io/6j83h/?view_only=6c0c18c1c4ca40a9b366cc3a2e878c33).² A list of studies included in the meta-analysis, raw data, and code to reproduce the analysis is also on OSF (https://osf.io/dyfgw/?view_only=7a5026b41160424abba6c38736c423c1).

Our meta-analysis follows the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, & Altman, 2009). Below, we summarize the participants, interventions, comparisons, outcomes, and study designs (PICOS) included in our study (for the PRISMA checklist, see Supplemental Section 1).

² There is a typo in the pre-registration document (see e.g., table 1). This table shows that cognitive load can be recorded using self-report measures. However, this is inconsistent with Lang (2009), which argues that cognitive load can only be measured using behavioral or psychophysiological measures. Our codebook, also pre-registered on OSF, correctly shows that cognitive load was not coded if measured using self-report.

Participants

Our meta-analysis includes *participants* in all LC4MP research studies, regardless of any demographic or other profiling variables.

Interventions and Comparisons

Given our empirical goals, we applied broad *intervention or comparison* pre-selection criteria. Specifically, a study was included if and only if it contained a hypothesis or research question that was theoretically derived from the LC4MP. Post-hoc analyses were not eligible.

Outcomes

Our meta-analysis included *outcome* variables as specified by Lang (2009). These outcome variables were stratified by (a) research domain (cognitive load, motivation, memory) and (b) measurement modality (self-report, behavioral, psychophysiological). Given that combining effect sizes derived from categorical and continuous outcome variables introduces heterogeneity into a meta-analysis (Borenstein, 2009), we only included effect sizes where the outcome variable was continuous in nature.

Study Design

We extracted effect size data for all *study designs* including both experimental and survey data. Main and interaction effects were included as were between-subjects, within-subjects, and mixed designs. Effect sizes from mediation models were excluded as they are not directly comparable with common measures (Preacher & Kelley, 2011). In instances where an effect

size was not reported, effect sizes were calculated using the available data (e.g., *F*-statistic and degrees of freedom; Lakens, 2013).

Method

Our study builds on a recently published systematic review of the LC4MP (Fisher, Keene, et al., 2018). This review included a research article corpus that was current through March, 2018. This corpus was subsequently updated in June 2019. At both time points, searches were conducted by entering the terms: “LC4MP,” “LC3MP,” “Limited Capacity Model,” “Motivated AND Message Processing,” and “Motivated OR Mediated AND Message Processing.” into the following EBSCO databases: Communication and Mass Media Complete, Psychology and Behavioral Sciences Collection, and Sociology Source. Web of Science™ was also searched for articles citing the original LC3MP or LC4MP manuscripts. The first corpus contained a total of 669 articles. An additional 24 articles were added in June, 2019. From this corpus, articles were selected if they conformed to the PICOS guidelines discussed above. This filtering resulted in a final database of 142 unique articles, which the authors then coded (Figure 1).

Following best-practice recommendations from Wilson (2009), all study characteristics and effect sizes were independently extracted by two of the study authors for 100% of the articles. Two of the authors (RBC, JRC) who are experts in psychophysiological research extracted data from studies testing psychophysiological hypotheses. The other two authors (RWH, SW) extracted

data from the remaining studies. Disagreement among coders was resolved during joint consensus meetings which resulted in a final, unitized dataset.

Finally, and based on recommendations from Levine and colleagues (2008), effect sizes were converted to a correlation coefficient (r). The r -value was transformed to Fisher's z in order to stabilize variance estimates during analysis (Borenstein, 2009). Results reported in this manuscript are transformed back to r to aid in interpretability.

Data Analysis

The analysis reported here was conducted using the *metafor* v2.1-0 package (Viechtbauer, 2010) in *R* v3.6.3 (R Development Core Team, 2012).

Hypothesis testing and model construction. Our study has two factors (research domain, measurement modality), each with three levels (cognitive load, motivation, memory; self-report, behavioral, psychophysiological). The two factors and their interaction were entered into the same model (see below) for testing H1, H2, and RQ1. Cognitive load and self-report were set as the reference level for their respective factors. The design is not fully crossed as Lang (2009) only identifies behavioral and psychophysiological measures of cognitive load, self-report and psychophysiological measures of motivation, and self-report and behavioral measures of memory. Lastly, a second model was constructed to test for publication bias (RQ2, see below).

A weighted random effects three-level meta-analysis model (Cheung, 2014) was constructed using the *rma.mv* function in *metafor* following

standard guidelines (Assink & Wibbelink, 2016). Individual effect sizes (which are conceptually understood as first-level data) were grouped within study at the second (within-study) level and then carried forward into the third (between-study) level. Parameters were estimated using a REstricted Maximum Likelihood estimation method (REML) model which has been shown to accurately estimate population heterogeneity in meta-analytic models (Viechtbauer, 2005). A Knapp and Hartung (2003) adjustment was applied during inference testing which helps mitigate type I error. H1 and H2 were evaluated by examining the model's main effects and RQ1 was tested by examining the model's interaction effect.

An Egger's test (Egger et al., 1997), which can be applied to three-level random effects models (Habeck & Schultz, 2015), was conducted to test for publication bias (RQ2). To conduct this test, we added the square root of the sampling variance for each effect as a term in the three-level model with moderators that is described above (for justification, see Sutton, 2009). When this term is added to the model, the intercept provides statistical information about the asymmetry of effect sizes in the literature, just as a funnel plot provides visual information about effect size asymmetry (Egger et al., 1997). A negative parameter estimate for the intercept indicates that there is effect size asymmetry (possible publication bias) with smaller sample sizes being associated with larger effect sizes (Sutton, 2009). An intercept that is not statistically different from zero indicates no evidence for publication bias.

Results

Descriptive Statistics

Our meta-analysis consisted of 142 unique articles and $k = 683$ individual effect sizes. Of these effects, 139 were for cognitive load, 152 for motivation, and 392 for memory. A total of 421 effects were measured using self-report, 95 using behavioral, and 167 using psychophysiological measures (see Table 1). The total number of participants across all studies was $n = 16,834$ ($M = 118.55$, $SD = 97.44$). Unweighted and weighted effect sizes are shown in Figure 2. The distributional characteristics of these data are reported in Supplemental Section 2.

The three level meta-analytic model demonstrated good fit relative to alternatives (Supplemental Section 3). The overall pooled effect size estimate was $r = .235$, 95% confidence interval (CI) [.187, .283]. A heterogeneity analysis showed that there was considerable variation across all effect sizes in the dataset, $I^2_{full\ model} = 79.9452$, $I^2_{third\ level} = 17.9329$, $I^2_{second\ level} = 62.0123$, $Q(682) = 4437.4654$, $p < .0001$. This indicates that moderator analyses are appropriate in order to investigate potential sources of heterogeneity (Levine & Weber, 2020).

Confirmatory Hypotheses and Exploratory Research Questions

A second analysis was conducted to evaluate the H1, H2, and RQ1. The research domain and measurement modality factors were added to the three-level model described above. Model fit was still good (Supplemental Section 4). The overall model was significant $F(4, 678) = 35.8246$, $p < .0001$.

The moderators did account for some, but not all, model heterogeneity, $I^2_{full\ model} = 79.6052$, $I^2_{third\ level} = 16.5354$, $I^2_{second\ level} = 63.9699$, $Q(678) = 4229.3730$, $p < .0001$.

The first hypothesis (H1) predicted a main effect for the theoretical research domains such that the effect sizes for each respective research domain should be significantly greater than zero. When the measurement modality factor is held at the reference level, the multi-level model revealed a significant main effect for domain, $F(2, 678) = 7.3653$, $p = .0007$. Cognitive load ($r = .326$, $t(678) = 9.9863$, $p < .0001$, 95% CI [.265, .384]), motivation ($r = .398$, $t(678) = 11.9091$, $p < .0001$, 95% CI [.327, .473]) and memory ($r = .314$, $t(678) = 11.8113$, $p < .0001$, 95% CI = [.259, .370]) were each significantly different from zero. Taken together, these results provide full support for H1.

The second hypothesis predicted that behavioral measures would show the largest pooled effect size and psychophysiological measures would show the smallest pooled effect size. When the domain factor is held at the reference level, a significant main effect for measurement modality was observed, $F(2, 678) = 46.6037$, $p < .0001$. Unexpectedly, self-report measures showed the largest pooled effect size ($r = .326$, $t(678) = 9.9863$, $p < .0001$, 95% CI [.265, .384]), followed by behavioral measures ($r = .252$, $t(678) = 8.8880$, $p < .0001$, 95% CI [.198, .304]). As predicted, psychophysiological measures had the smallest pooled effect size ($r = .139$, $t(678) = 4.7785$, $p < .0001$, 95% CI [.082, .185]). While all pooled effect sizes

are significantly different from zero, self-report and not behavioral measures elicited the largest pooled effect size, although inspection of the confidence intervals demonstrates that these two modalities are not statistically different from each other. Therefore H2 is partially supported.

Our first research question (RQ1) asked if the pooled effect size for the research domains in the LC4MP is moderated by measurement modality. An interaction effect was modeled to evaluate RQ1; however, the effect was not significant, $F(1, 667) = 2.2547, p = .1337$. Full cell means are reported in table 2.

Our second research question (RQ2) probed for evidence of publication bias. An Egger's test (Egger et al., 1997) was conducted where the square root of the sampling variance was added as a parameter in the three-level model with moderators that is described above. The overall model was significant $F(5, 677) = 33.4576, p < .0001$. The model still showed considerable heterogeneity, $I^2_{full\ model} = 77.3645, I^2_{third\ level} = 17.7537, I^2_{second\ level} = 59.6108, Q(677) = 3956.7687, p < .0001$. Nevertheless, the intercept, which is interpreted as a measure of effect size asymmetry and therefore potential publication bias, was not significantly different from zero ($b = .1108, t(677) = 1.9487, p = .0517, 95\% \text{ CI } [-.001, .222]$). This demonstrates there is no statistical evidence for publication bias within the LC4MP literature.

Following guidelines from Greenhouse and Iyengar (2009), a number of sensitivity analyses were also conducted (Supplemental Sections 5 - 6).

These analyses show the same pattern of results, even when: (a) outliers are removed, (b) potential sources of heterogeneity are removed, and (c) when missing data - based on incomplete reporting, which is a type of publication bias - are replaced with effect size = 0. These tests all show a pattern of results that is consistent with the main analysis. This provides additional confidence in our study's findings.

Discussion

By meta-analytically synthesizing 19 years of LC4MP research across 142 articles and 683 unique effect sizes, we empirically investigated the pooled effect size estimates for each theoretical research domain (cognitive load, motivation, memory) and measurement modality (self-report, behavioral, psychophysiological) used to operationalize these theoretical constructs. For both domain or measurement modality, pooled effect sizes are statistically greater than zero. Therefore, the core theoretical research domains in the LC4MP receive meta-analytic support.

In the introduction, we drew on classic frameworks for evaluating a theoretical contribution to communication science (Chaffee & Berger, 1987; DeAndrea & Holbert, 2017; Popper, 1959/2002; Slater & Gleason, 2012) in order to conduct the first ever meta-analysis of the LC4MP. Specifically, we argued that a meta-analysis of the LC4MP would (1) provide a quantitative overview of the model, (2) evaluate the accuracy of the model's predictive power, (3) test if a research domain in the LC4MP can be falsified, and (4) interrogate the model's postdiction explanatory power. The discussion

section is primarily organized around these theoretical contributions. We also include a discussion of publication bias and methodological issues in the LC4MP. Finally, we conclude with a reflection on our study's limitations and core conclusions.

Criterion #1: Theoretical Overview

Using a meta-analysis to address this criterion requires asking two questions: are the pooled effect sizes statistically different from zero and, if yes, what is the magnitude of the effect size and what does that magnitude mean? The answer to the first question is an unequivocal yes. Our meta-analysis shows that, regardless of research domain, measurement modality, or sensitivity test, effect sizes in the LC4MP are statistically different from zero.

Answering the second question requires a more indepth treatment. Cohen's (1988) framework for evaluating effect size magnitude is well-known (small, $r = .10$; medium, $r = .30$; large, $r = .50$). Cohen, however, came to disavow the framework as arbitrary and not sufficiently useful for answering the crucial "compared to what" question (Funder & Ozer, 2019). Indeed, Funder and Ozer argue that effect sizes are much more meaningfully interpreted against other empirical benchmarks. To that end, we contextualize our findings within a recent study that meta-analyzed 149 meta-analyses constituting 60 years of quantitative communication research (Rains, Levine, & Weber, 2018).

This Rains and colleagues meta-meta-analysis found that the mean effect size for the field of communication is $r = .21$. Drawing from Berlo (1960), Rains and colleagues noted that higher-order communication processes are highly contextualized, multi-determined, and may inherently yield small effect sizes. By comparison, the LC4MP is largely focused on the domain-general, lower-order, cognitive, and biological processes that underpin message processing and effects. Lang and colleagues (e.g., Geiger & Newhagen, 1993; Lang, 2013; Lang & Ewoldsen, 2013) have long argued that lower-order process-oriented models of communication yield more explanatory power. In our study, we observed that pooled effect sizes for the theoretical research domains (all r 's $\geq .314$) exceed the mean effect size reported by Rains and colleagues (2018). This supports Lang and colleague's assertion.

One limitation of using a meta-analysis to address this criterion is that, as Slater and Gleason (2012) note, "a meta-analysis may provide only a pixelated image of the state of knowledge on a given topic" (p. 229). Indeed, while our meta-analysis provides high-level support for the LC4MP's theoretical research domains, it does not investigate the numerous sub-processes, or interactions between these sub-processes, that the model predicts. For instance, the LC4MP has long held that cognitive-load interacts with motivation to influence memory for a message. Our meta-analysis does not, and can not, test this theoretical assertion. With that said, this is less of a limitation and instead represents a clear starting point for future research.

Given that this was the first meta-analysis of the LC4MP, our aim was to see if there was empirical support for the model's core theoretical research domains. If we failed to find support for these domains, then more narrowly focused investigations of the model's subcomponents would be unnecessary. Instead, our study provides an empirical foundation on which future meta-analyses of the LC4MP might build.

Criterion #2: Predictive Power Accuracy

DeAndrea and Holbert define this criterion as "The extent to which a theory offers predictions that turn out to be right: There is little utility in a theory's predictions if they are not revealed in the data" (p. 176). In our study, we investigated if there was meta-analytic support for each of the three theoretical research domains in the LC4MP, or not. In short, the answer is yes. For cognitive load ($r = .326$), motivation ($r = .398$), and memory ($r = .314$), the pooled effect sizes revealed in our meta-analysis shows that the LC4MP is a model capable of generating accurate, theoretically-derived predictions. Importantly, the effect size magnitudes for research domain are observed when evaluating the main effect in a full meta-regression model that also included a term for measurement modality. This analytic decision means that, independent of the type of measurement used to operationalize a theoretical construct in the LC4MP, the model is capable of generating accurate predictions that are statistically different from zero for each of its three theoretical research domains.

With that said, our meta-analysis addresses predictive power at a very high, or “pixelated”, level. Future researchers might build upon our findings to resolve current theoretical ambiguities in the LC4MP. For example, the LC4MP has long held that cognitive resources are drawn from one unitary pool that does not distinguish between visual and auditory information in a message (Lang, Potter, & Bolls, 1999). However, twenty years of research results have provided mixed support for this assumption, which led Fisher and colleagues (2018) to propose that the model would benefit from assuming that cognitive resources can be drawn independently from visual and auditory pools (see also, Keene & Lang, 2016). This means that, even if a message heavily loads resources in the visual pool, there should be sufficient resources for processing auditory information in a message.

While this update to the LC4MP helps explain conflicting findings in the cognitive load research domain, it has yet been subject to just one empirical test (Fisher et al., 2019). As evidence accumulates, future meta-analysis could code if an effect size corresponding to a cognitive load measure (e.g., a secondary task response time) was in the same or different modality as the primary task. If Fisher and colleagues are right, effect sizes corresponding to different levels of cognitive load in a message will be statistically different from zero when both the primary and secondary task are in the same modality, but will be indistinguishable from zero if they are in different modalities. Our meta-analysis sets the foundation for clarifying these important components of the model.

Criterion #3: Falsification

Meta-analyses are fundamentally about theoretical falsification. The analysis accomplishes this goal by collecting all available effect sizes within a literature, aggregating these effect sizes, and statistically testing to see if they differ from zero. A meta-analysis might endeavor to falsify one or several sub-components of a theory or model (e.g., Banas & Rains, 2010; Carpenter, 2010; Huang & Shen, 2016), or a study might aim to meta-analytically summarize results within a given research domain (e.g., Anderson & Bushman, 2002). There is certainly no “right” way to do a meta-analysis and it is worth noting that each approach imposes important constraints on theory falsification.

For instance, a meta-analysis focused on individual mechanisms of a theory or model might very well falsify one mechanism while leaving the overall model largely intact (see, e.g., Braddock & Dillard, 2015). This approach can resolve controversies surrounding a given theoretical mechanism. However, a single study that adopts this approach is unlikely to ever falsify a theory in its entirety. By comparison, a more broadly scoped meta-analysis might recognize that there are several null findings within a literature and ask if those null findings are sufficiently numerous to overturn that literature (see e.g., Anderson & Bushman, 2002; Prescott, Sargent, & Hull, 2018). Our meta-analysis adopted this second approach and found that, despite the null or otherwise unexpected results in the LC4MP literature (for a review, see Fisher, Keene, et al., 2018), these null findings are not

sufficiently numerous to falsify the core theoretical research domains within the LC4MP.

With that said, and as we have emphasized above, there are areas of mechanistic controversy in the LC4MP (for a more in-depth treatment, see Fisher, Huskey, et al., 2018b). Future meta-analyses might narrow their focus on these controversies. We provide our code book, raw data, and analysis code on the project's OSF repository. This means that we have given future researchers a head-start in their empirical efforts. Instead of starting from scratch, future researchers might simply take our existing materials and dataset, classify the effect sizes we provide according to a new theoretical moderator of interest, slightly modify our analysis code (to reflect the new moderator), and return an empirical result. In this way, our meta-analysis serves as a jumping off point for future theoretical inquiry.

Criterion #4: Postdiction Explanatory Power

Finally, DeAndrea and Holbert define postdiction explanatory power as “The extent to which explanations are consistent with existing empirical data” (p. 176). As already discussed above, the postdiction explanatory power for each theoretical research domain seems robust in comparison to many research areas in quantitative communication science. We will not belabor this point here again.

Instead, we turn to measurement. One component of explanatory power is related to the methodological operationalization of theoretical research domains in the LC4MP. Measurement validity and reliability play a

critical role in explanatory power (Spearman, 1904). In addition, there has been heated debate about what types of measurements yield valid inferences. Self-report measures are often maligned as being subject to social-desirability bias, confirmation bias, post-hoc reflection, and more, especially when compared to behavioral measures (Lang et al., 2006; Nisbett & Ross, 1980; Shapiro, 1994). Other researchers have argued that biological measurements such as psychophysiology and electroencephalography (Clayton, Keene, et al., 2020; Keene et al., 2017; Potter & Bolls, 2012) as well as neuroimaging (Falk et al., 2015; Turner, Huskey, & Weber, 2018; Weber, Fisher, Hopp, & Lonergan, 2017; Weber, Mangus, & Huskey, 2015) are useful for overcoming the limitations imposed by both behavioral and self-report measures. All these methodological approaches have been utilized to test the LC4MP. Our meta-analysis lets us ask: how well does the LC4MP methodological “toolbox” (see Lang, 2009) work? If effect sizes are a measure of prediction accuracy (Funder & Ozer, 2019), then investigating the effect sizes corresponding to different measurement modalities in the LC4MP provides an answer.

Here again, the “compared to what” question becomes critically important. Returning to the Rains and colleagues (2018) meta-meta-analysis, these scholars questioned if the communication science methodological toolbox is sufficiently sensitive to detect anything beyond what Cohen (1988) would classify as small effects. Our results cannot speak to the field at large, but the answer is clear for the LC4MP. Self-report measures ($r = .326$)

provide larger effect sizes than behavioral ($r = .252$) or psychophysiological measures ($r = .139$). Communication scientists have long-known that psychophysiological measures are low signal, high noise (Potter & Bolls, 2012). This suggests that such measures are still best suited to evaluating the biological underpinnings of communication processes. We do not wish to discount the importance of behavioral measures (Krakauer, Ghazanfar, Gomez-Marin, Maciver, & Poeppel, 2017), however, we are encouraged to see that low-cost, easy-to-collect, and well-validated self-report measures have considerable explanatory power in the LC4MP.

Important questions remain for future meta-analyses of the LC4MP. For instance, researchers have long argued that behavioral measures of memory (e.g., signal detection) are more valid than self-report measures (e.g., cued recall; Shapiro, 1994). Our meta-analysis cannot address this question directly, but future research might. Similarly, a growing body of research shows that, in instances where self-report measures are particularly less accurate, biological measures can be illuminating (Berkman & Falk, 2013; Turner et al., 2018; Schmälzle & Meshi, 2020; Weber et al., 2015). There are already hints that this may be the case for research in the LC4MP (e.g., Clayton, Lang, et al., 2019; Clayton, Leshner, et al., 2020). Future meta-analyses of the LC4MP might investigate this issue.

Publication Bias

Despite evidence of publication bias in communication research (Levine & Carpenter, 2009), publication bias analyses are still quite

uncommon in communication research (Levine & Weber, 2020; Sun & Pan, 2020). Our study conducted two types of analyses to search for publication bias. In our main analysis, we used an Egger's test (Egger, et al., 1997) to search for evidence of effect size asymmetry in the literature. In a supplemental analysis (Supplemental Section 6), we investigated if missing effect sizes, which were overwhelmingly not reported because the statistical test associated with the effect was not significant, represented another source of bias. We briefly discuss both analyses, below.

An Egger's test evaluates if there is statistical evidence for asymmetric effect sizes in the literature. Said differently, the Egger's test looks to see if small sample studies with large effect sizes are published while small sample studies with small effect sizes are not published. This analysis is contingent on the fact that uncertainty around an effect size (or the precision of effect size estimation) is determined in part by sample size. All things being equal, effect sizes observed in small samples have wider confidence intervals than effect sizes observed in larger samples. If small effect sizes from small sample studies are not observed in the meta-analytic data set, this suggests that such studies exist, but were never published because the result was not significant. Our analysis did not show support for this type of publication bias.

Sterne, Egger, and Smith (2001) argue that an Egger's test is best conceptualized as an investigation into "small study effects" (p. 101), and that the test is not well suited for investigating other potential sources of

publication bias. Indeed a wealth of alternative tests exist, each with their own strengths and weaknesses (for reviews, see Sun & Pan, 2020; Sutton, 2009). One complication of our study is that these tests are developed and validated on two-level (and *not* three-level) meta-analytic models. In fact, with the exception of the Egger's test, these analyses have not been extended to three-level meta-analytic models (like the one we employed in this study), and their validity for evaluating publication bias in three-level models is currently unknown (Assink & Wibbelink, 2016).

The Egger's test is also typically underpowered (Sutton, 2009) and for small meta-analyses, Egger and colleagues (1997, 2001) recommend a p -value cutoff of .10. Exactly when a meta-analysis becomes sufficiently powered for a more conventional cutoff of $p < .05$ is not clear. In our study, we collected a total of 683 unique effect sizes, which is considerably larger than the original studies Egger's test was validated on. The p -value observed in our Egger's test analysis was $p = .0517$. If a $p < .10$ cutoff is applied, then this suggests potential publication bias. We believe, given the large number of effect sizes included in our analysis, that our study is comparatively well-powered and the more conventional $p < .05$ cutoff is appropriate.

Our study also investigated a second source of publication bias, that is, effects that are not missing at random (NMAR; Pigott, 2009). NMAR effects are those that are systematically not reported in the published literature, usually because they are associated with a non significant result. There are no perfect methods for dealing with NMAR bias, especially for three-level

models (Assink & Wibbelink, 2016; Pigott, 2009), but the most-common procedure is a single-value imputation strategy where missing effects are replaced with a value of zero. Our results (Supplemental Section 6) show that even when 181 missing effect sizes are replaced with zero, this is not sufficient to overturn support for our hypotheses.

This approach is conceptually similar to a *Fail Safe N* analysis for publication bias (Rosenthal, 1979), which asks how many studies showing a null-result it would turn to overtake a meta-analytic result. Regrettably, there is no known application of *Fail Safe N* to three level models, but we can say that even by increasing the null effect size count by 25%, all with values of zero, our hypotheses still hold. There are, of course, several limitations to a single-value imputation strategy. These include (1) strong assumptions about *why* an effect size was not reported, (2) artificially making the data bimodally distributed, and (3) underestimating variance among effect sizes (Pigott, 2009). This means that this NMAR analysis should be taken as one additional piece of evidence against publication bias, rather than a conclusive answer.

We should point out that our toolbox for evaluating publication bias was limited by the multi-level nature of our data. We applied the tools at our disposal, although these tools come with several important limitations. Nevertheless, our findings appear to at least tentatively suggest that publication bias is not common among LC4MP research. Future research should more explicitly investigate the extent to which publication bias is a

problem for the LC4MP using state-of-the-art analytical techniques (for reviews, see Sun & Pan, 2020).

Methodological Observations

Our meta-analytic summary allows us to observe several data-driven trends in the LC4MP literature. We see that the literature has a strong emphasis on memory (392 effect sizes). Although, and despite recent calls for behavioral memory measures (Fisher, Huskey, et al., 2018), memory research in the LC4MP is most commonly evaluated using self-report data (347 effect sizes). This could reflect that a large amount of LC4MP literature is organized around persuasive message processing where memory for a message is a key outcome variable (Fisher, Keene, et al., 2018; Cappella, 2006). By comparison, just 139 effect sizes correspond to questions about cognitive load, and 152 effect sizes are related to motivation.

We also see that self-report measures (421) are the most common technique in the LC4MP toolbox (see Lang, 2009), accounting for 62% of all observed effect sizes. In our study, we observe that self-report measures had the largest pooled effect size followed by behavioral measures (although this difference was not statistically significant). One unknown question in the LC4MP is just how well correlated self-report measures are with their behavioral counterpart. For instance, to what extent do self-report measures of memory correspond with behavioral measures? There is some reason for concern as growing evidence shows that there is often a weak correlation between these two measurement modalities (Dang et al., 2020). One

opportunity for refining the LC4MP toolbox is a more careful investigation into the relationship between self-reported and behavioral measures of constructs in the LC4MP.

We also see some interesting patterns in the data suggesting that LC4MP research is becoming more accurate over time. A simple Pearson correlation between study year and effect size shows a negative relationship ($r(681) = -.38, p < .0001$, two-tailed). A negative Pearson correlation is also observed between study year and sampling variance ($r(681) = -.21, p < .0001$, two-tailed) while sample sizes increase with year ($r(681) = .29, p < .0001$, two-tailed). Together, these results show that sample size is increasing in LC4MP research, which seems to be exerting downward pressure on effect sizes, but also improving uncertainty around the effect size. These are all good trends in the literature.

At the same time, we do observe some troubling patterns. Nearly 20 years have passed since Levine and Hullett (2002) advised communication scientists against reporting η_p^2 in favor of η^2 , but the reporting of η_p^2 still persists. A total of 186 effect sizes report η_p^2 which can bias the true effect size value. Moreover, it is not always possible to convert between a reported η_p^2 value and the more accurate η^2 estimate without additional information about the data (Lakens, 2013). Of the 186 effect sizes we observed that reported η_p^2 , 109 were in studies published since 2010. This sort of reporting hampers synthesis efforts. Authors need to start reporting more accurate

effect sizes, and journal reviewers and editors need to be more diligent in requiring this during the peer-review process.

Finally, we attempted to conduct an analysis of the gray literature (Rothstein & Hopewell, 2009). We directly contacted every corresponding author for the articles in our corpus ($n_{authors} = 80$) asking for unpublished research. Of these, just two responded, making a meaningful analysis of the gray literature impossible. The vast majority of LC4MP studies still do not make their data and analysis code publicly available on repositories such as the OSF. Between low response rates from primary study authors and limited data availability, the quality and accuracy of data included in our meta-analysis are constrained by the overall quality and accuracy of the published LC4MP literature.

In some ways, it appears that the LC4MP literature can improve. Authors can heed calls for practicing open science (Bowman & Keene, 2018; Dienlin et al., 2020; Lewis, 2020) by making their data and code available, which will aid future meta-analytic investigations. Authors can also be more precise in their reporting of effect sizes, and report complete statistics for all tests (including zero order correlations where appropriate), even for tests that are not significant. At the same time, there is reason for optimism. Sample sizes are increasing in the LC4MP, effect sizes are more accurately measured, and there is good evidence that the LC4MP toolbox is valid.

Limitations

There are two important limitations that are necessary to discuss in order to correctly interpret the results discussed in this study. First, we extracted 683 effect sizes from the published literature. Just 66 effect sizes showed directional information (e.g., r , Cohen's d), of these, nearly all were positively signed. The remaining effect sizes were extracted from statistics that limit directionality information (e.g., η^2). Given that our hypotheses are about overall magnitude, and *not* directionality, we believe this is an acceptable constraint on our meta-analysis. However, future meta-analyses of the LC4MP should take this into consideration when planning their data extraction.

A second limitation in our study is related to what is sometimes pejoratively called the *fruit salad* approach to meta-analyses (Carpenter, 2020). This problem arises when there is construct invalidity in the meta-analysis, meaning that multiple constructs are grouped under one larger "class" of construct. As Carpenter's excellent essay (2020) shows, this construct invalidity can hamper theoretical tests for a variety of theoretical and methodological reasons. And, as others have discussed (e.g., Levine & Weber, 2020), construct invalidity can introduce unexplained or unexplainable heterogeneity into a meta-analysis, which presents important validity challenges. These critiques are rightly applied to our meta-analysis.

We are compelled to point out that we intentionally set-out to design such a meta-analysis, and such meta analyses already exist in the field of communication (e.g., Rains, Levine, & Weber, 2018). So long as researchers

are honest about the uncertainty this approach introduces and clear about limitations, fruit salad meta-analyses can be informative (Wood & Eagly, 2009). We believe we meet these criteria. In our study, we set out to design a meta-analysis that would let us broadly investigate the LC4MP research while setting the stage for future meta-analytic inquiry. We are under no illusion that constructs in the LC4MP (e.g., memory which can be subdivided into encoding, storage and retrieval) or their measurement modalities (e.g., recognition, free/cued recall, signal detection) are all one unified construct. Readers should not be under this illusion, either.

However, it is now possible for LC4MP researchers to have an empirically defined, with some caveats, effect size that is useful in power analyses and equivalence testing (Weber & Popova, 2012). And, as we've discussed above, our meta-analysis does make important theoretical and methodological contributions to the LC4MP. We admit that future work is necessary to test explicit mechanisms in the LC4MP and we hope that our meta-analysis, and the open data and code that we provide, serves as a jumping-off point for such inquiry.

Conclusion

Given the longevity and ubiquity of the LC4MP in communication science, a meta-analysis of the LC4MP was long overdue. While a qualitative assessment of existing research generally supports the model's core predictions (Fisher, Keene, et al., 2018), our results provide meta-analytic

support for the model's core theoretical research domains while also demonstrating that effect sizes within the LC4MP vary depending on measurement modality. Using four common theory evaluation criteria (discussed above) our meta-analysis provides an empirical overview of the overall model, demonstrates that the LC4MP has both predictive and explanatory power, and provides evidence showing that null or otherwise unexpected results in the LC4MP literature do not falsify the model. Our results do not suggest publication bias impacts the LC4MP literature. Moreover, our results provide researchers another tool for conducting power analyses and equivalence tests which assist in future theoretical inquiry, while also pointing to ways in which LC4MP research can improve, and ways it already has. No single study, including our meta-analysis, can address all research questions. We have pointed out pressing questions that future researchers might address while also providing data and code that might help facilitate these empirical efforts. It is our hope that future meta-analysts will further interrogate specific mechanisms within the LC4MP, which will further expand knowledge.

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Table 1

Number of effect sizes for each level of research domain and measurement modality

	<u>Self-Report</u>	<u>Behavioral</u>	<u>Psychophysiological</u>	<u>Total</u>
Cognitive Load	—	50	89	139
Motivation	74	—	78	152
Memory	347	45	—	392
Total	421	95	167	683

Table 2

Pooled effect size (r) and 95% CI for the research domain x measurement modality interaction

	<u>Self-Report</u>	<u>Behavioral</u>	<u>Psychophysiological</u>
Cognitive Load	—	.242 [.186, .296]	.151 [.093, .208]
Motivation	.371 [.315, .425]	—	.173 [.112, .232]
Memory	.291 [.244, .337]	.240 [.173, .304]	—

Figure 1

Flow of information when selecting 10073g documents for inclusion in the meta-analysis.

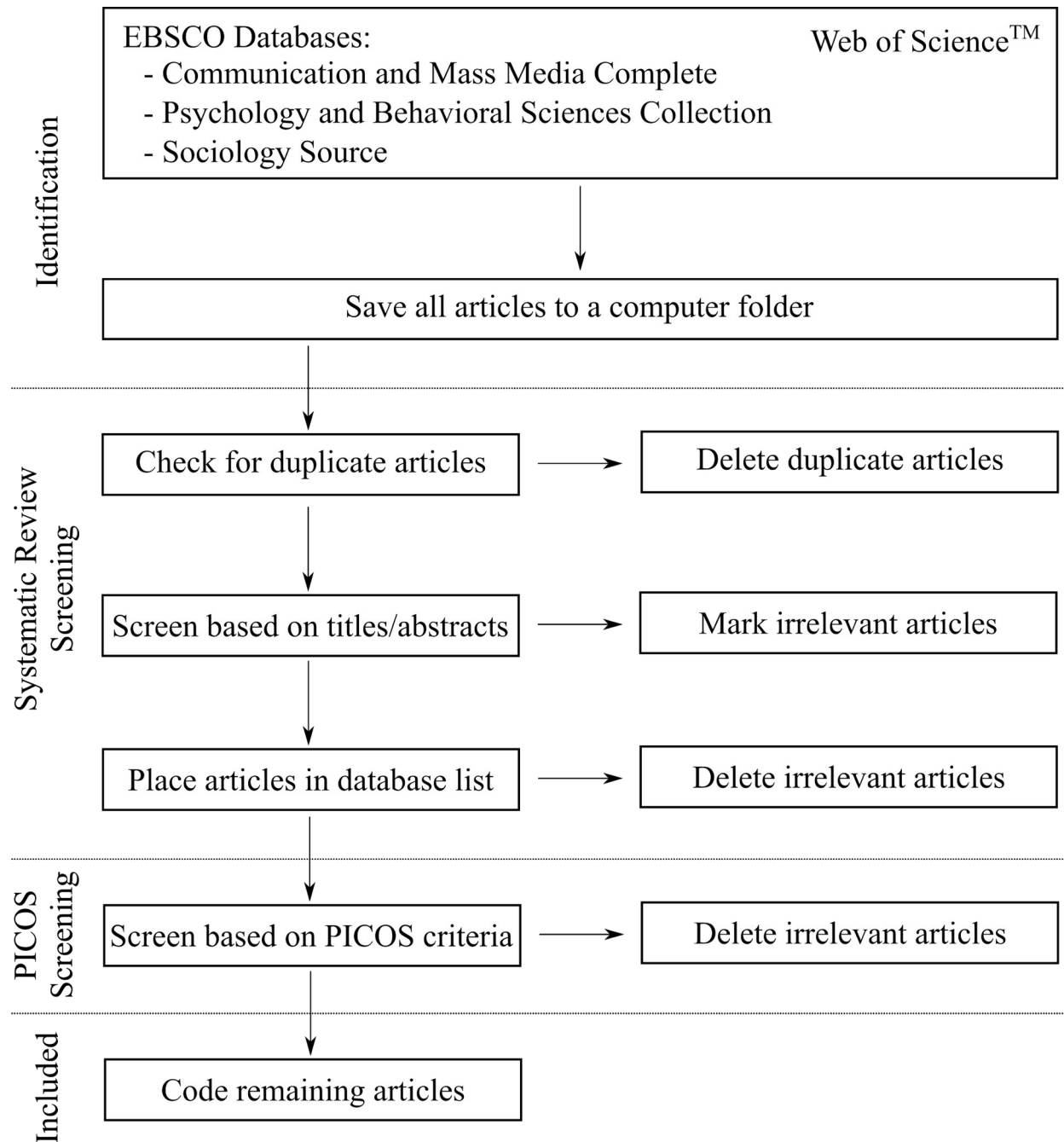


Figure 2

Forest plots of all effect sizes included in the main analysis. The first column shows study's lead author and publication year as well as the research domain, measurement modality, and study/effect ID (all of this information can be cross referenced with the raw data, which is hosted on the OSF (https://osf.io/dyfgw/?view_only=7a5026b41160424abba6c38736c423c1)). The middle column shows information about the effect size. Black squares represent raw unweighted effects and their 95% confidence intervals. Gray diamonds represent the fitted value for each effect and its 95% confidence interval. The final column includes the weight applied to the unweighted effect, the unweighted effect size, and its 95% confidence interval. Studies are organized according to publication year, effects are shown in the order they appear in the manuscript. All effect sizes are shown in Fisher's Z.

