A Meta-Analytic Test of Trust Formation and Development in Swift Starting Action Teams

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Abstract

Trust is essential for operational and organisational effectiveness in high-stakes environments where cooperation and coordination among team members is key, particularly among swift starting action teams who are composed of individuals with little or no previous experience of working together. Wildman and colleagues (2012) developed a multilevel conceptual framework in which they characterised the formation and development of swift team trust according to an input-mediator-output-input model. We conducted a pre-registered systematic review of six electronic databases (Web of Science (core collection), Scopus, Business Source Complete, PsycInfo, and ProQuest Dissertations and Theses) to identify literature that could be used to test this conceptual model. From an examination of 19,249 potentially relevant items that studied swift starting action teams composed of adults (aged 18 years or more), we found no single comprehensive test of this model in its entirety nor a sufficient examination of key structural sections of Wildman and colleagues' model. Cumulating evidence from 53 primary studies via meta-analytic structural equation modelling (199 effects, N_{teams} = 2,380, $N_{individuals}$ = 9,975), we found that individual-level propensity to trust was positively related to one's perceptions of trust in their team; one's trust in their team was positively related to emotional reactions, team processes, and team performance; and team processes and performance were positively associated with individuals' subsequent trust in their team. We also revealed an indirect effect of trust perceptions on collective performance via team processes. Our findings underscore the need to consider innovative methodologies and technologies to study swift trust dynamics temporally in ways that permit empirical tests of multi-component conceptual models of trust formation and development.

Keywords: action team; meta-analytic structural equation modelling; STAT

A Systematic Review and Meta-Analytic Test of Trust Formation and Development in Swift Starting Action Teams

Swift starting action teams are composed of individuals with highly specialised knowledge, skills, and attributes with little or no previous collaborative experience who come together quickly and complete complex and time-pressurised tasks effectively in high-stakes environments (Mckinney et al., 2005). The deployment of these swift starting action teams, which is typically abbreviated to STATs to reflect their immediate and urgent nature, enables organisations to compete, innovate, and succeed when operating in dynamic and complex environments (Breuer et al., 2016; De Jong et al., 2016). Trust plays a critical role for operational effectiveness in high-stakes environments where cooperation and coordination among STATs members is key, yet ironically has little time to form due to the time-pressured and dynamic nature of the situation at hand (for a comprehensive review of trust, see Dirks & de Jong, 2022). Formally defined, trust is a psychological state in which individuals hold an attitude to accept vulnerability of others based on expectations that another person's intentions and behaviours will be beneficial or at least not detrimental (Rousseau et al., 1998). Little or no trust among STATs members can undermine their functioning and ultimately may lead to disastrous consequences across operational, political, and economical spheres. Thus, knowledge of factors that optimise trust formation and development among STATs and how best to translate this information into actionable strategies remains an important area of research for theory and practice.

The availability of a unifying conceptual framework of trust formation and development has the potential to foster systematic, coordinated, and accumulative efforts for researchers interested in the optimisation of team trust. Wildman et al. (2012) developed a multilevel conceptual framework in which they characterised the development of trust within STATs based upon an input-mediator-output-input model (IMOI; Ilgen et al., 2005). As depicted in Figure 2, trust is hypothesised to form via three inputs that team members bring with them into newly formed STATs, namely one's *propensity to trust* (i.e., generalized willingness to extend trust to others in the absence of prior knowledge about them; Burke et al., 2007), *surface-level cues* (i.e., overt demographic characteristics of others, such as age, race; Bell et al., 2011), and pre-existing knowledge imported from personal experiences and third-party information from trust sources (i.e., *imported information*) that is stored in one's memory (Wildman et al., 2012). The effect of surface-level cues and imported information on the development of individual level trust within the team is said to be mediated via trust-related schemas (i.e., patterns of thought or beliefs that characterise their perceived benevolence, integrity, and ability of the team; Williams, 2001) and situationally-activated emotional reactions upon first interaction with teammates, whereas propensity to trust has a direct influence on one's initial trust for the collective. The combination of these antecedent factors is said to underpin the emergence of team trust, which in turn has important implications for team processes (i.e., the 'doing' part of teamwork in which collectives translate inputs into salient outcomes such as behavioural coordination) and performance. Consistent with an IMOI perspective of teamwork, team performance converts from an output in one collaborative performance episode to an input for subsequent cycles of collaborative interactions over the lifecycle of a team, primarily as a source of feedback for trust development and learning. Relatedly, shared experiences in which members interact and observe each other's behaviour enacting team processes subsequently calibrates individuals' levels of trust in their team via enhanced awareness of deep-level cues that are salient in such circumstances (Milliken & Martins, 1996). Trust-related schema and deep-level cues are conceptually similar in content; the primary distinction reflects the time point at which the STAT is assessed. Essentially, trust-related schemas that serve as mediators of surface-level cues are based on one's life experiences broadly that inform individual member's initial perceptions of their team, whereas deep-level cues reflect an update of those initial schemas via the interactive experiences with the STAT.

Given the complexities of trust formation, maintenance, and development (e.g., multilevel, temporally salient, contextual variations), studying Wildman et al.'s (2012) conceptual model in its entirety via sufficiently powered studies will likely be costly and potentially ineffective with little foundational research to guide important methodological decisions (e.g., time course of key processes, Bayesian priors). If integrative conceptual models of organisational phenomena are never empirically tested, then we remain blind as to which factors and structural linkages between them are most salient for understanding such phenomena. There exists evidence on individual components of this conceptual model that can be leveraged to test its explanatory value, yet this evidence is fragmented across diverse literatures because the complexity of team trust development has not yet been empirically tested in an individual study to date. Thus, there remains a need to examine the empirical usefulness of this conceptual model of trust among STATs.

Conceptual and Empirical Contributions

We aimed to systematically review and statistically synthesise the literature of STAT trust via meta-analytic structural equation modelling, with the primary goal to identify evidence that can be employed to test the core propositions of Wildman et al.'s (2012) multilevel conceptual model of team trust development. In so doing, we generate new insights for the conceptual building blocks of trust development for STATs in three ways. First, we contribute to theory on trust formation and development by empirically examining an untested conceptual framework that incorporates individual-level inputs and mediators of trust development for team processes and outcomes, and feedback loops from these team-level outputs to individual-level determinants for future performance episodes. For this reason, our study is best characterised primarily as a 'tester' because it prioritises testing of existing theory rather than building new theory (Colquitt & Zapata-Phelan, 2007). This contribution is important because existing statistical syntheses of the trust literature capture antecedents or outcomes of trust only; for example, trust and performance broadly (De Jong et al., 2016) and in business teams specifically (Morrissette & Kisamore, 2020), trust and team effectiveness in virtual teams (Breuer et al., 2016), trust within the context of leadership and performance (Legood et al., 2021), and the antecedents of trust within the context of risk taking and job performance (Colquitt et al., 2007). Second, meta-analysis is ideally suited for testing theoretical sequences when no individual primary study has tested the model in its entirety

(Viswesvaran & Ones, 1995). Via our systematic review of the literature, therefore, we ascertain the extent to which this conceptual model has informed scholarly work on trust formation and development among STATs. In so doing, we shine a spotlight on the most prominently studied determinants and processes of trust formation and development in the literature to guide future research and interventions.

Our third contribution is adding an 'expander' perspective (Colquitt & Zapata-Phelan, 2007) to Wildman et al.'s multilevel conceptual model. We make two key extensions to the model, namely direct links from the execution of (i) team processes and (ii) team performance outcomes in one performance episode to one's subsequent trust in their team prior to any additional future performance episodes. Aligned with a temporal perspective of team trust (Grossman & Feitosa, 2018), this extension complements the original ideas of Wildman et al. that feedback loops update one's knowledge and expectations of performing in STATs (imported information) for future engagements in new contexts and teams involving different tasks and team members. We contend that such experiences provide knowledge of processes and results that also can serve to update team members' trust in their current STAT for scenarios where they are assembled to achieve a higher-order goal that encompasses multiple performance episodes (e.g., emergency room teams who care for multiple casualties or traumas across a shift spanning several hours; and newly assembled military teams who conduct multiple combat missions over several days) and which inform future interactions. Knowing that one will interact with their team across multiple performance episodes and rely on them to achieve an overall goal should enable them to extract trust-related information from such experiences and outcomes for future interactions (Saunders & Ahuja, 2006), regardless of the temporal stability of the team (De Jong et al., 2016). Empirically, there is evidence to suggest a mediating role of trust between past and future performances in basketball teams (Dirks, 2000), yet this expectation remains untested within the context of STATs.

Method

Transparency and Openness

We prospectively registered our study protocol on the 14th December 2020 via the Open Science Framework (OSF; https://osf.io/9egyt) using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses-Protocol template (PRISMA-P; Shamseer et al., 2015). All data, analysis code, and research materials are available at our OSF Project page (https://osf.io/69xwd/).

Literature Search

RL executed a systematic search on the literature from inception until 15th December 2020 using six electronic databases: Web of Science (core collection), Scopus, Business Source Complete, PsycInfo, and ProQuest Dissertations and Theses. The following combination of Boolean search terms formed the basis of our search strategy: (trust*) AND (team OR group OR collective OR crew OR unit OR squad) AND (swift OR action OR crisis OR swat OR project OR emergency OR temporary OR "ad hoc"). Full details of specific search protocols for each database are available in our preregistered PRISMA-P document. We also manually searched reference lists of eligible studies and all papers that had cited the final sample of papers with Web of Science.

Eligibility Criteria

We considered studies eligible for inclusion in the meta-analysis when they: (i) reported a quantitative summary of the association between an individual's trust of other team members or the team and at least one other variable captured in Wildman et al.'s (2012) conceptual model of trust development; (ii) studied STATs composed of adults (aged 18 years or more); and (iii) provided sufficient information in the published document to extract the required data, or this information was available by contacting the authors directly. We utilised Mckinney and colleagues' (2015) criteria for the characterisation of STATs: (i) composed of trained and/or professional members with limited or no knowledge of others on the team; (ii) the team must perform immediately; and (iii) the team faces high stakes from their inception. Given the overwhelming focus on student team samples within the scientific literature, we decided to apply these criteria liberally to accommodate such research for the purposes of this meta-analysis. We excluded primary studies when (i) they excluded a measure of trust as a study variable; (ii) the article was not written in English; (iii) the full-text was unavailable via our university library subscriptions or directly from the corresponding author; (iv) the information required for analysis was unavailable within the article and following direct requests to the corresponding author; (v) the article was a protocol, guideline, or a duplicate (e.g., conference proceedings of a published paper); or (vi) the results were published as a conference abstract rather than a full-text.

Article Screening

We exported all papers identified as potentially eligible via the database search process outlined above into Endnote for collation and subsequently into a web application for title and abstract screening. Research Screener is a cloud hosted machine-learning tool that semi-automates the abstract screening process (https://researchscreener.com). Simulation evidence with Research Screener indicates that systematic reviewers are highly likely to identify 100% of eligible studies when they have scanned up to 50% of the total pool of potentially eligible papers (Chai et al., 2021). In the first phase, RL and MTC screened 50% of the initial sample of potentially eligible articles after duplicates had been removed. In the second phase, RL reviewed full texts flagged for retention via phase one. A third member of the team [DG] discussed uncertainties with both screeners across phases one and two.

Data Extraction

RL extracted descriptive and statistical data from the final sample of eligible articles; DG assessed a random sample of 30% for accuracy and consistency, with discrepancies for specific items revisited across the entire pool of eligible studies. We contacted corresponding authors when key information required for the analysis was unavailable within the published article. Requests were sent via email on two occasions, separated by approximately two weeks. We extracted data on the nature of the eligible studies, participant characteristics, details of measures used, and effects that quantified the magnitude of association between theorised paths within the tested model. The full data extraction sheet is available on our OSF project page.

Coding of Studies

We developed a coding system to record key characteristics of the studies, samples, and study variables. In terms of study characteristics, we coded for type of publication (i.e., peer reviewed article vs thesis), study design (i.e., longitudinal vs cross-sectional), randomisation (i.e., yes vs no), team virtuality (i.e., geographically dispersed vs face-to-face), and study quality using a 9-item tool that covered domains most relevant to observational studies (sampling, operationalisation, confounding factors, reliability evidence, missing data, statistical analysis, selective reporting, conflict of interest, other threats to internal validity). The sample characteristics extracted from primary studies included the total sample size (continuous variable), number of teams (continuous variable), size of teams (continuous variable; the mean size was used for papers in which authors reported a range of team sizes), mean age of participants (continuous variable), and percentage of female participants in the sample (continuous variable). Finally, in terms of study variables, we coded how trust was operationalised (i.e., general trust, cognitive trust, and affective trust), process type, performance type, and the reliability of measures employed in the study.

Statistical Analyses

Registered approach. Given our primary interest in testing a theoretical sequence, we planned to synthesise data from primary studies statistically within a meta-analytic structural equation modelling (MASEM) framework (Cheung, 2015; Jak et al., 2021). A statistical test of Wildman et al.'s (2012) model in its entirety requires at least one observed correlation coefficient between each of the variable pairs in the averaged correlation matrix (Jak et al., 2021). With 20 variables in the hypothesised theoretical sequence (including feedback loops to inputs and mediators; see Figure 2), there are 190 possible bivariate correlations that required at least one data point to run MASEM. Unfortunately, owing to the unavailability of data in the published literature, we were unable to test the model in its entirety because of the absence of correlational data for numerous pairs of elements among specific paths of the theoretical sequence.

Deviated approach. As a methodological compromise, we split the theoretical sequence of trust formation and development into eight individual components based on the availability of data within the literature (see Figure 3). Two of these models were univariate in nature because they captured the association between two variables only, namely propensity to trust → trust (Model 1) and trust → emotional reactions (Model 4). Six of the models were multivariate in nature because they captured the associations between three or more variables (Models 2, 3, and 5-8). We analysed these six models using a three-level, multivariate mixed-effects weighted meta-regression modelling approach to account for dependencies between effect sizes from the same sample (Wilson et al., 2016). Effect size dependencies in our data occurred because of assessments of different types of trust, multiple experimental groups, and multiple measures of team processes or team performance. Accordingly, we followed the five-step process advocated by Wilson et al. (2016) to account for non-independence among effects within our statistical model. First, we estimated an unadjusted pooled correlation matrix via a no-intercept model using a dummy variable for each correlation to identify its position in the correlation matrix (e.g., each correlation between trust and performance was coded with a 1 and all others coded as a 0, representing one of the off-diagonal matrix cells). The synthesised correlation coefficients were weighted by the inverse of their sample size (Schmidt & Hunter, 2015). Second, we executed a meta-regression model incorporating adjustments for eight moderator variables where available in primary studies (type of publication, study design, sex, age, team size, virtuality, randomisation, and trust type) to estimate coefficients and residuals that are used to create a set of adjusted correlation coefficients that replace the observed correlations. The coefficients and residuals obtained in step 2 are used to create covariate-adjusted correlations (step 3) and estimate an adjusted pooled correlation matrix (step 4). We conducted these analyses using the *rma.uni* and *rma.mv* functions of the *metafor* package (Viechtbauer, 2010) in the R statistical platform (R Core Team, 2020). In the final step, the unadjusted and adjusted pooled correlation matrices are utilised to examine the multivariate structural sequences among study variables depicted in Figure 2 using weighted least squares (WLS) via the *metaSEM* package (Cheung, 2015). For model 3, we estimated the indirect effect of one's perceptions of their team on collective performance via team processes (i.e., product of the direct effects that constitute the mediation pathway). Simulation evidence indicates that MASEM is among the best methods for examining indirect effects meta-analytically in terms of bias, precision, and coverage (van Zundert & Miočević, 2020). We imputed missing data on the age and sex variables using the *mice* package in R (Buuren & Groothuis-Oudshoorn, 2011) to maximise the data available for the main analyses. Owing to inconsistency in the reporting of reliability estimates for study variables within primary studies, we executed a series of sensitivity analyses in which we applied measurement reliability corrections (.70, .80, .90) to the predictor and criterion variables each of the models depicted in Figure 2 using established formulas (Wiernik & Dahlke, 2020); the results of these analyses are available on the OSF (see Table S2).

Deviations from Pre-Registered Protocol

In addition to those changes with our analytical protocol outlined above, we deviated from our registered protocol in three other ways. First, owing to the unavailability of data within existing literature, we were unable to test the entire model of trust development as originally proposed by Wildman et al. (2012). Thus, we examined a reduced model that excluded (i) surface-level cues and imported information as determinants of individuals' trust in their team, (ii) trust-related schema and emotional reactions as psychological mediators of the effects of propensity to trust, surface-level cues, and imported information on individuals' trust in their team, and (iii) deep level cues as mediators of the feedback loop from team processes to initial inputs and psychological mediators. Owing to their availability in the literature, we also added (i) direct paths from deep-level cues after a performance episode to propensity to trust, trust-related schema, and an individuals' subsequent trust in their team, and (ii) direct paths from team processes enacted during a performance episode and team performance to an individuals' subsequent trust in their team. Second, rather than independently testing the effects of each moderator on individual structural paths, we calculated a correlation matrix that was adjusted by the inclusion of these covariates in the model (see step 2 above). Third, given our interest in initial perceptions of trust among STATs, we used the first assessment of a variable in studies that included two or more assessments of them for the forward loop of the model (solid black lines of Figure 2); for variables encompassed in the feedback loop (solid grey lines of Figure 2), we utilised the second assessment of the study variable in the temporal sequencing of the primary study design. Hypothesis 8, for example, leveraged correlations between (updated) trust assessed after one's team had performed a task (see Model 5, Figure 3).

Results

Literature Search Overview

An overview of the search and study selection process is depicted in Figure 1. In total, we identified 67 eligible studies of which 14 were excluded from the final analysis because we were unable to access data from the paper or corresponding author. The 53 eligible studies were published between 1996 and 2020, and yielded a total of 199 usable effect sizes of which the majority operationalised trust via generalised forms (n = 156) followed by affective (n = 23) or cognitive elements (n = 20). The final sample included 9,975 participants who were members of 2,380 teams (range of 2 to 12 members per team). Participants were, on average, 25 ± 4 years of age, with females accounting for approximately 48% of participants. A full overview of synthesised studies including assessments of methodological quality is provided on the OSF (see Table S1).

Compartmentalised Assessment of Trust Development Theoretical Sequence

Parameter estimates for unadjusted and covariate-adjusted analyses are presented in Table 1. We found that most eligible work identified via our systematic review of the literature targeted individual-level propensity to trust as a key determinant of individuals' perceptions of trust in their team, as well as individuals' trust perceptions of their team as an antecedent of team process and performance. We also revealed emotional reactions as a common outcome of one's initial evaluation of trust in their team, which contrasts directly to the original proposal by Wildman et al. (2012) as a situationally activated state upon first interaction with teammates. In terms of the feedback loop, most of the available evidence captured the flow-on effects of team processes and performance on individuals' subsequent trust in their team. There were minor differences between these unadjusted and covariate-adjusted analyses in terms of the effect size estimate (Δ ± 0.04) and the 95% confidence interval (95% CI = ± 0.08); accordingly, we rely on the covariate-adjusted model for interpretation purposes. Analyses revealed non-zero parameter estimates for the associations between propensity to trust (r = .38, 95% CI = .30, .46) and individual-level emotional reactions (r = .49, 95% CI = .39, .59) with one's trust in their team, which in turn was associated with team processes (β = .39, 95% CI = .33, .45) and team performance (β = .19, 95% CI = .11, .26). The indirect effect of one's trust in their team on collective performance via team processes was small yet statistically meaningful (β = .04, 95% CI = .005, .07). Regarding feedback loops, analyses revealed non-zero associations between team processes (β = .20, 95% CI = .08, .38) and team performance (β = .16, 95% CI = .03, .29) with individuals' subsequent trust in their team. All three components of deep level cues evidenced non-zero associations with subsequent assessments of ability and benevolence but not integrity dimensions of trust-related schema (.35 > β < .56).

Discussion

We empirically quantified the associations among factors considered salient for trust formation and development among STATs via a systematic review of the literature and meta-analysis of primary data. Using data from 53 studies involving 2,380 teams and 9,975 participants, we found that no single study has empirically examined Wildman et al.'s (2012) multilevel conceptual framework of trust formation and development within STATs in its entirety. In terms of the statistical estimates of structural pathways of the model, individual-level propensity to trust was positively related to one's perceptions of trust in their team; one's trust in their team was positively related to emotional reactions, team processes, and team performance; and team processes and performance are positively associated with individuals' subsequent trust in their team. All other paths were non-zero but statistically inconsequential.

Conceptual and Empirical Contributions

Our primary objective to examine Wildman et al.'s (2012) multilevel conceptual framework relied on the availability of a sufficient body of work from which to synthesise empirical evidence on the structural elements of this framework. Via a systematic review of approximately 19,000 potentially relevant items in the literature, we found no single comprehensive test of this model in its entirety nor a sufficient examination of key structural sections (e.g., initial inputs → psychological mediators → trust). In the organisational sciences, there exists a “fetish for new theory” (Antonakis, 2017, p. 7) or papers that can be characterised primarily as ‘builders’ where authors propose new or amended theories or conceptual models integrating several factors to explain a phenomenon (Colquitt & Zapata-Phelan, 2007), yet such models are rarely (~10%; Kacmar & Whitfield, 2000) or never tested in their entirety (Edwards et al., 2014). Consistent with these previous findings and perspectives, there appears to be a lag in empirical tests of Wildman and colleagues’ integrative conceptual exposition of trust formation and development in STATs, despite the importance of such collectives for the safety, health, security, and success of societies and their citizens worldwide (e.g., McLaren & Loosemore, 2019; Zakaria & Mohd Yusof, 2020) and the salience of trust for optimising their functioning (Mckinney et al., 2005; Rousseau et al., 1998). Of course, it is important to acknowledge that less than one decade has passed since the publication of Wildman and colleagues’ multilevel conceptual framework of trust. Equally, studying teams in ways that maximise operationalisation with concept is challenging, particularly with regard to process dynamics (Kolbe & Boos, 2019), and likely amplified when interested in STATs (e.g., experts with no previous collaborative experiences assembled to achieve a specific objective in high-stakes settings). We encourage researchers to leverage recently articulated guidelines (Maynard et al., 2021) and advancements in technologies (Klonek et al., 2020) to think innovatively about how best to study teams in ways that can permit empirical tests of multi-factorial conceptual models (e.g., unobtrusive measurement of the content and frequency of communication patterns between members during dynamic interactions in the lab or field to operationalise key psychological concepts).

Of the three broad categories of key determinants of individual-level perceptions of trust in one’s team, we found that researchers have empirically examined propensity to trust but not surface-level cues or imported information. Propensity to trust is most salient in social contexts where *a priori* knowledge of trustee(s) is unavailable (Alarcon et al., 2016; Gill et al., 2005), with the importance of such individual differences on trust dynamics dissipating over time (Jones & Shah, 2016). Thus, it is unsurprising that scholars have prioritised examinations of this individual difference variable as a determinant of one's initial evaluations of trust in their team within the context of STATs where team members are unknown to each other. Our findings confirmed the importance of individual differences in propensity to trust as a direct determinant of one's evaluation of trust in their team. The effect size magnitude reported here (r_c = .38) is comparable to previous meta-analytic data (Colquitt et al., 2007) that summarised the association between propensity to trust and trust in coworkers (r_c = .37), yet our estimate (r_c = .38) is larger when leaders are the referent of one's trust assessment (r_c = .21). Propensity to trust is also positively associated with trust in non-human entities such as m-commerce (r = .32, Sarkar et al., 2020) and x-ray machines (β = .21, Merritt & Ilgen, 2008). Considered collectively, the degree of trust propensity that one brings with them to the formation of new teams involving humans only or with machines or technology, particularly STATs, sets the stage for the initial trust judgments they make of their team. Practically, dispositional aspects of trust are an important consideration for understanding the maladaptive outcomes of breakdowns or failures in trust between members (Ferguson & Peterson, 2015). Nevertheless, in the absence of data on the salience of surface-level cues and imported information, the relative importance of these three initial inputs to the formation of swift trust remains unknown and therefore represents an important consideration for future research.

Consistent with existing meta-analytic data (Breuer et al., 2016; Colquitt et al., 2007; De Jong et al., 2016; Morrissette & Kisamore, 2020), our findings confirmed the salience of members' trust perceptions of their team for enhancing collective processes and outcomes and extend this perspective to STATs. In so doing, we provide the first meta-analytic estimates of the direction and magnitude of associations between swift trust in one's team and collective processes and outcomes, thus revealing direct and indirect effects between these concepts. This contribution is important because it initiates a shift in narrative from directional hypotheses regarding swift trust formation and development to one that incorporates quantifiable estimates regarding the magnitude of effects, something which is often absent among theoretical expositions within the psychological sciences (Edwards & Christian, 2014). Our meta-analytic finding of partial mediation from trust to collective performance via team processes also conflicts with the proposal that trust only affects performance directly (Dirks & Ferrin, 2001).

The direction of associations reported here is consistent with the broader team trust literature, yet the magnitude of effects differ regarding the team process or performance metric for comparison purposes. Regarding team processes, for example, our estimate that incorporates a broad range of indicators (β_c = .39) is smaller, similar, or larger in magnitude depending on the specific processes summarised in previous meta-analyses including knowledge sharing (r_c = .53), team learning (r_c = .55, Breuer et al., 2016), risk taking behaviours (r_c = .42), counterproductive behaviours (r_c = -.33), and citizenship behaviours (r_c = .27, Colquitt et al., 2007). In contrast to team processes, our statistical summary of team performance (β_c = .19) was smaller in magnitude than estimates of task (r_c = .27, Breuer et al., 2016; r_c = .33, Colquitt et al., 2007) and contextual performance (r_c = .27, Breuer et al., 2016) as well as team performance (r_c = .30, de Jong et al., 2016; r_c = .48, Morrissette & Kisamore, 2020) synthesised in previous meta-analyses. That trust evidenced a stronger association with team processes relative to team performance makes intuitive sense. Team processes reflect those interpersonal dynamics between two or more members that convert inputs (e.g., human capital resources) into outcomes such as collective performance (Marks et al., 2001). Trust is most salient in social contexts involving dependency between a trustor and trustee(s), vulnerability to potential losses in functioning due to this dependency, and uncertainty regarding potential risks of the dependency (Patent & Searle, 2019). The highly dependent nature of STATs who are formed with little to no knowledge of their teammates at inception likely exacerbates the importance of swift trust for interpersonal dynamics within early performance episodes, primarily action and interpersonal processes (Wildman et al., 2012). Theoretically, trust increases the likelihood that members will commit to shared values (including goals, behaviours, and policies that are un/important) and therefore invest the necessary actions required to maximise the likelihood that the objective is achieved (Morgan & Hunt, 1994). Thus, swift trust likely provides the motivational drive needed for members to accept some degree of interpersonal vulnerability and enact subsequent action processes.

Wildman and colleagues (2012) offered a compelling case for the salience of situationally-activated emotional reactions upon first interaction with teammates as an essential determinant of trust formation in STATs, yet we were unable to test this hypothesis meta-analytically, given the absence of empirical data in the published literature. Nevertheless, we were able to examine emotional reactions as an outcome of initial evaluations of swift team trust, specifically regarding one's satisfaction with the team. As one exemplar of affect-laden evaluations of job-related targets (Schleicher et al., 2011), team satisfaction reflects one's evaluative judgement of collaborative outcomes of the team with whom they work to achieve organisational or operational objectives (Standifer et al., 2015). Consistent with previous work from the broader teams literature (Breuer et al., 2016; Costa et al., 2001), we found that swift team trust perceptions were positively associated with one's satisfaction with their team or the outcome of their collaboration. Although we were unable to test this expectation directly, it is likely that swift trust perceptions influence one's satisfaction with their team via firsthand experiences executing team processes (Ilgen et al., 2005; LePine et al., 2008). If this expectation is supported in future work, there will be a need to expand conceptual expositions of trust formation and development to incorporate affective outcomes of collaborative experiences (e.g., satisfaction, commitment, viability) because they might inform updates to one's repertoire of imported information for future engagements with new STATs or reciprocal influences on subsequent performance episodes with their current STAT.

The idea that collective performance in one episode (outcomes) provides feedback (input) for subsequent trust cycles with the same or new STAT is consistent with the widely accepted IMOI model of team effectiveness (Ilgen et al., 2005). Wildman and colleagues (2012) proposed that this feedback loop occurs primarily via updates to imported information and trust-related schemas.

However, we were unable to test this expectation because of the absence of such data in the literature. What we were able to test and show for the first time are positive feedback loops from team processes and collective performance directly to one's subsequent perceptions of trust in their team in contexts where members experienced multiple performance episodes with the same team. The positive direct link between performance execution and outcomes with subsequent trust perceptions is likely most salient in situations where the same STAT engages in multiple performance cycles because trust estimations can be informed by firsthand experiences with the collective rather than indirectly via general experiences or third-party sources. These updates to subsequent trust perceptions from firsthand experiences are most likely optimised via collective reflections between performance episodes (Wildman et al., 2012), yet this expectation remains untested in the teams debrief literature (Keiser & Arthur, 2021; Lines et al., 2021). Nevertheless, our meta-analytic finding on this feedback loop provides an important starting point for knowledge of trust dynamics that need to be studied via temporally rich assessments of key factors as teams engage in independent yet related performance episodes.

Strengths, Limitations, and Future Directions

Key strengths of this study include a pre-registered study protocol, transparency regarding deviations from our registered protocol, accommodation of effect size dependency within our statistical model, open data and materials (Steel et al., 2021), and incorporation of data published in peer-reviewed outlets and research student theses. Nevertheless, the findings of this meta-analysis are best interpreted within the context of its limitations and those of the existing evidence base. First, we were unable to test Wildman and colleagues' (2012) conceptual model of swift trust formation and development in its entirety and several core propositions (e.g., mediating effects of trust-related schema and emotional reactions) because of the unavailability of essential data in the literature identified via our systematic search protocol. One potential way to address this concern in future research is to conduct several systematic reviews of the literature that focus on sub-components of the model to populate the correlation matrix (e.g., initial inputs to psychological mediators). Of course, this solution will be burdensome because there are 190 possible bivariate correlations that require at least one data point to test Wildman and colleagues' conceptual model in its entirety so may require a 'big team' approach among the scholarly community that pools together resources of individual labs or groups (Forscher et al., 2020). Second, the extent to which some of the findings reported here generalise is limited because of the low number of primary studies available to generate a statistical estimate of the associations. Relatedly, we excluded 14 of 67 eligible primary studies (~21%) identified via our systematic review of the literature because we were unable to access data from the paper or corresponding author and therefore hinders the likely representativeness of the swift trust literature. Third, as is the case with all systematic reviews of the literature and meta-analytic summaries of primary research, we applied several decisions along the way that might have affected our findings. For example, our liberal operationalisation of STATs means that the results presented here are best considered a first look at statistical estimates of factors considered salient for swift trust formation and development. Addressing the reliance on student samples rather than 'real teams' (3 of 53 studies) in primary research is essential for advancing knowledge in this area because it speaks to the essence of the target concept of Wildman and colleagues' (2012) conceptual model and the literature of swift trust, that is, teams with limited or no experience working together who are assembled rapidly to complete a collective objective within high-stakes settings. Relatedly, we implemented a sensitivity analysis approach to correcting effect sizes for measurement unreliability because of inconsistent reporting in primary studies and, where available, level-specific reliability estimates that were incongruent with the level at which they assess (i.e., individual reliability for team-level concepts). Scholars studying swift team trust are advised to calculate and report level-specific reliability estimates, which can be calculated within a multilevel framework (Geldhof et al., 2014). Fourth, MASEM is a relatively new methodology in which best practices are still being development (Cheung, 2018; Yu et al., 2018). Finally, conceptual and empirical expositions of swift trust prioritise mean-level assessments or the magnitude of key factors for trust formation and development, yet evidence indicates that variation in trust propensity (Ferguson & Peterson, 2015) and team trust (de Jong et al., 2021) among members also plays an important role in trust dynamics. Thus, there is a need to consider both the magnitude and dispersion of key factors in future research on swift trust (see also Costa et al., 2018). Relatedly, there also is a need to enhance the operationalisation of trust so that it accurately reflects the essence of the concept (i.e., willingness to accept vulnerability of someone else) rather than the cognitive or affective foundations (e.g., McAllister, 1995), as well as avoid tautological propositions (i.e., using the term trust to assess trust).

Conclusions

Our analysis of 199 effect sizes from 53 studies confirmed the importance of propensity to trust as a salient determinant of swift trust, and one's trust in their team as a facilitator of collective processes and team performance. We also shed new light on individual-level emotional reactions as a direct outcome of one's trust perceptions of their teammates, indirect effects of trust on collective performance via team processes, and feedback loops from team processes and performance after a collaboration episode to updates in one's trust in their team. Despite the importance of these findings, our systematic review of the literature also revealed several gaps in empirical estimates of key elements of conceptual perspectives of swift trust formation and development, as captured by Wildman and colleagues' (2012) multilevel conceptual model. Our hope is that this work encourages scholars to consider these gaps systematically in future research so the concept of swift trust can fulfill its potential in science and practice.

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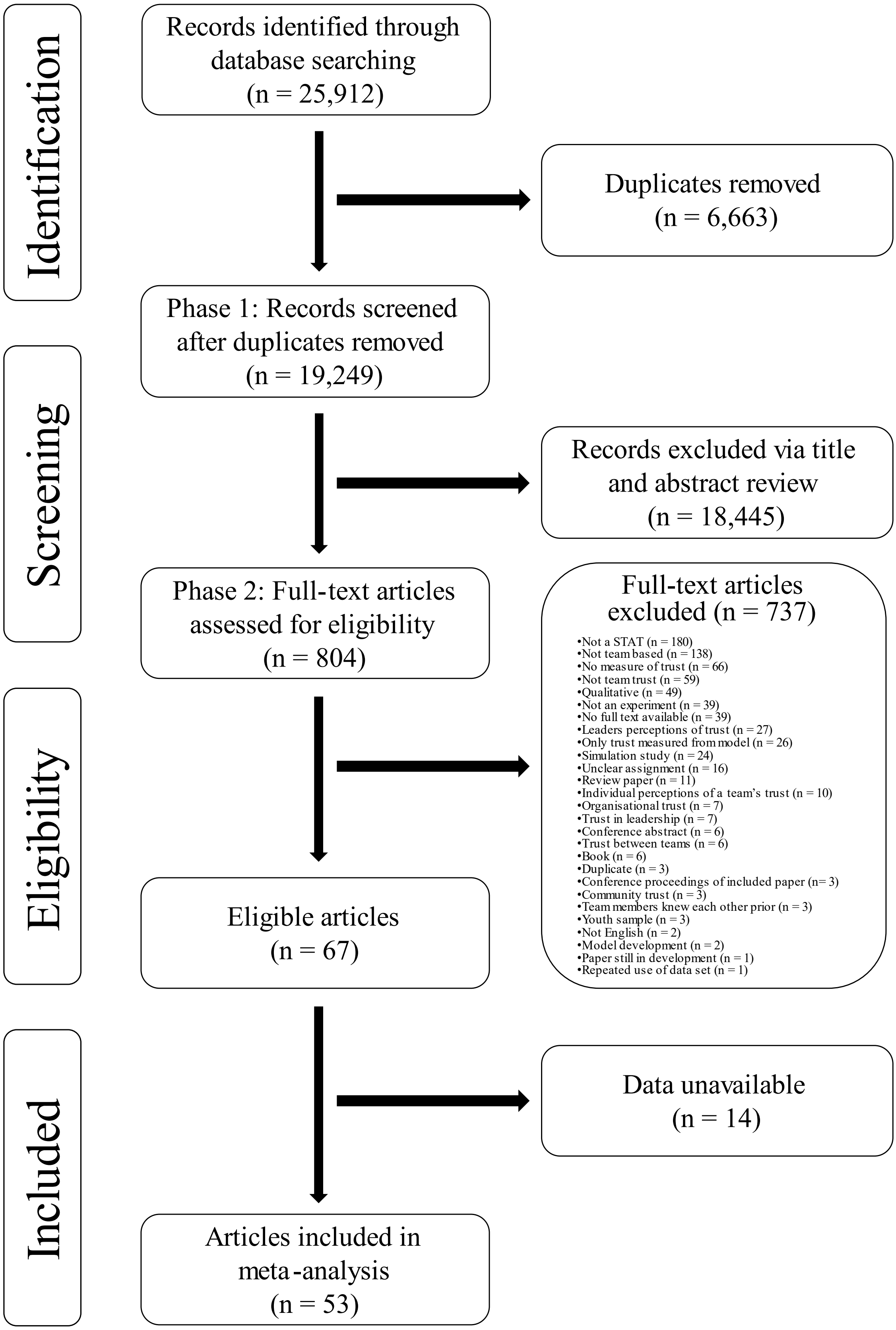
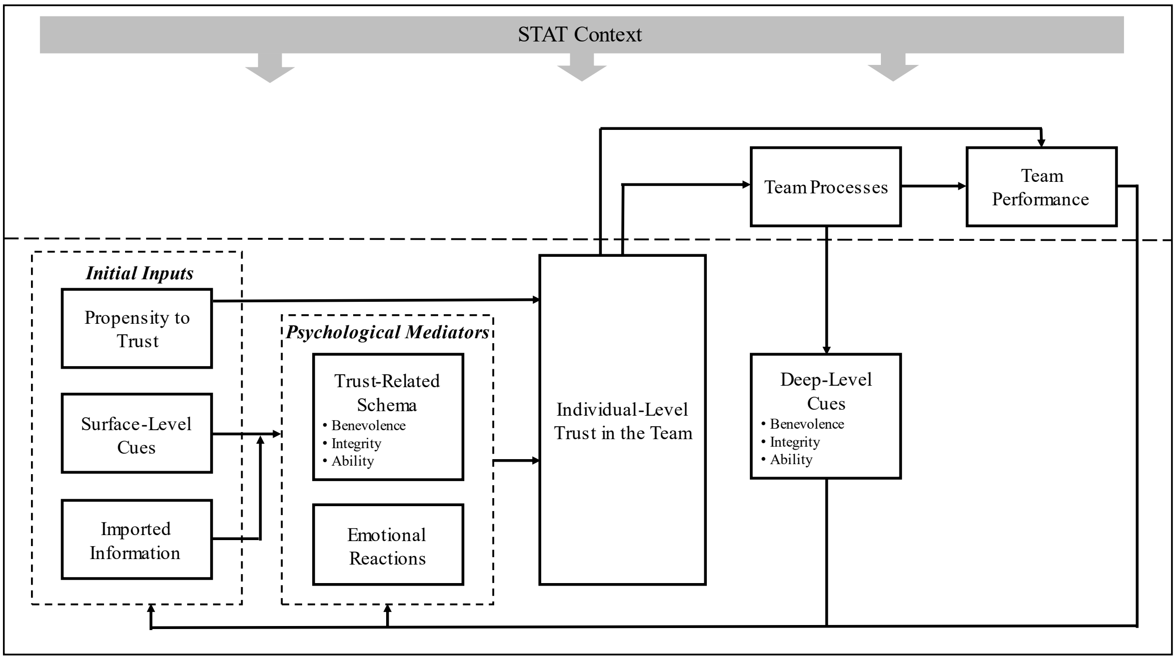
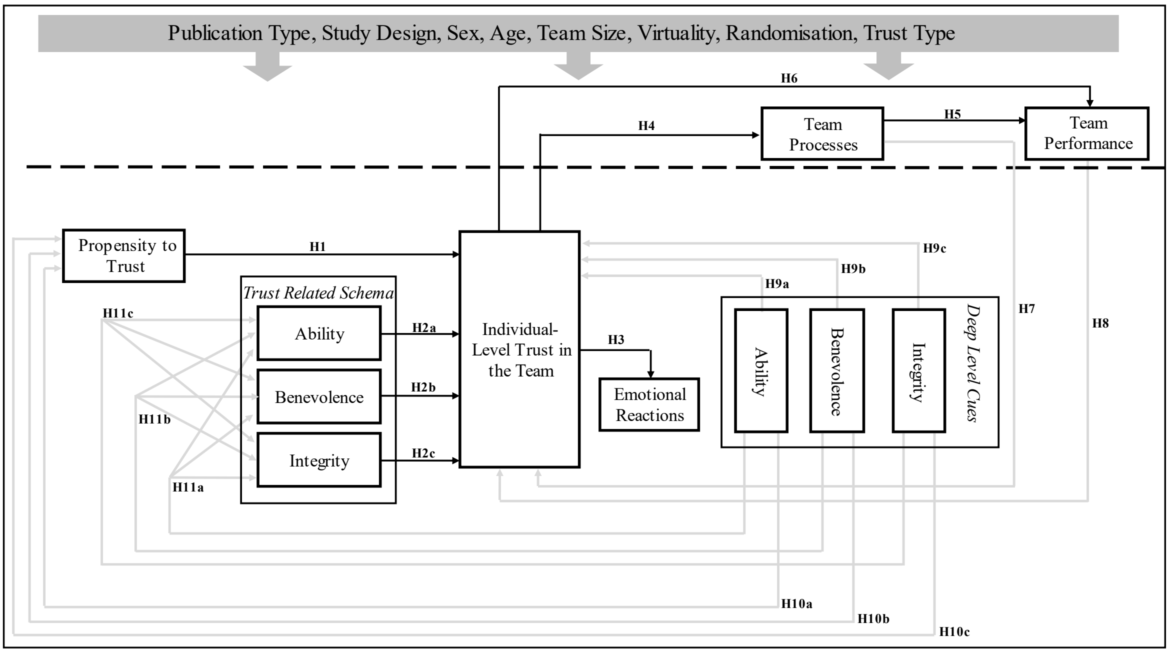


Figure 1. PRISMA flow diagram.



Original model proposed by Wildman and colleagues (2012)



Adapted model for which we had data available to test

Figure 2. Visual depiction of hypothesised theoretical sequence: top image is the original model from Wildman et al. (2012), whereas bottom image is the model for which we had available data.

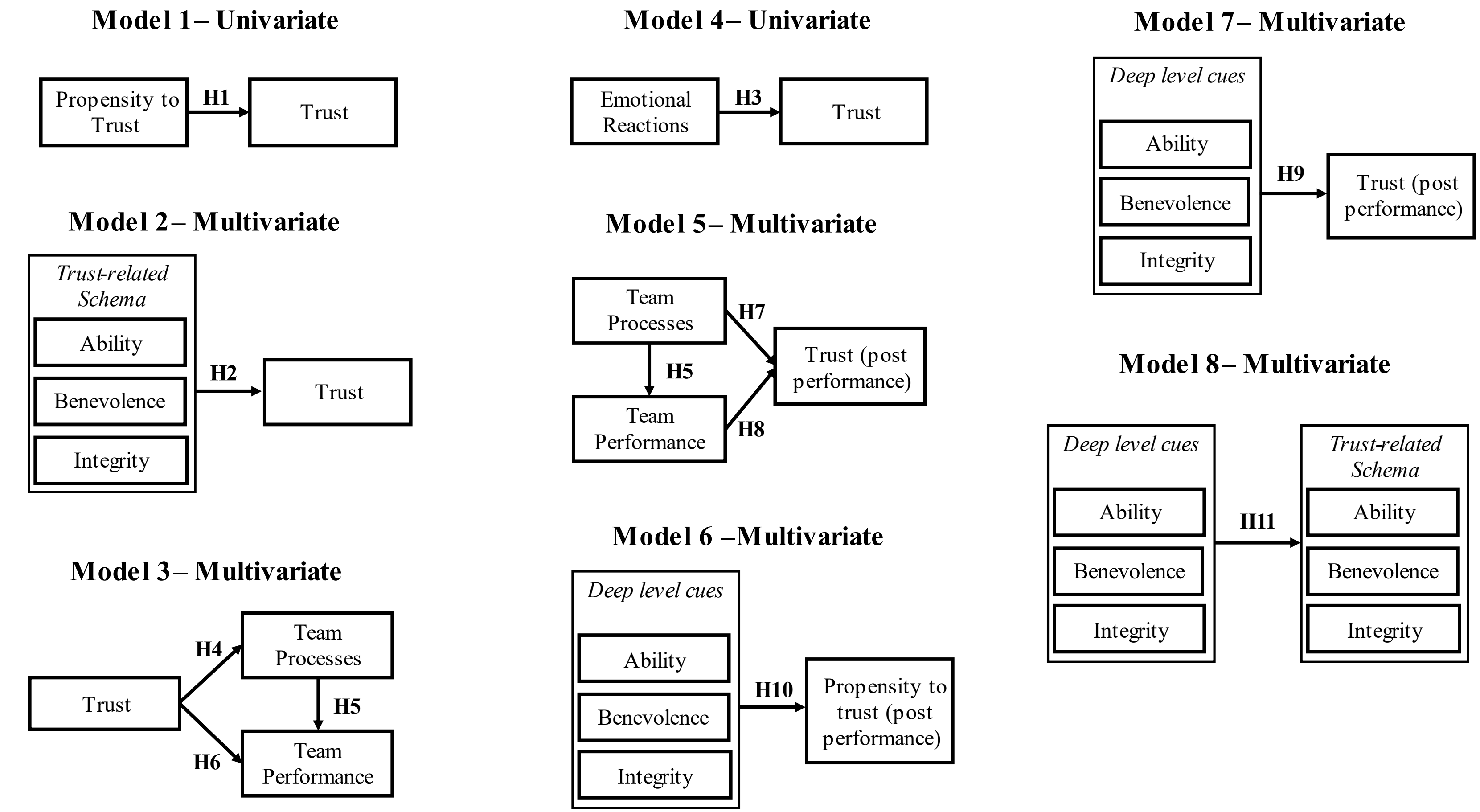


Figure 3. Visual depiction of the compartmentalised approach to testing the hypothesised theoretical sequence of trust development.

Table 1. *Parameter estimates for unadjusted and covariate-adjusted analyses.*

							Unadjusted			Covariate-adjusted		
Model	Hypothesis	Path in Theoretical Sequence	k	ES	N_{teams}	N_{ind}	estimate	95% ci.lb	95% ci.ub	estimate	95% ci.lb	95% ci.ub
1	1	Propensity to Trust → Trust	13	13	580	2326	.34	.23	.46	.38	.30	.46
2	2a	TRS.ability → Trust	3	3	98	279	.15	-.22	.52	.14	-.23	.51
2	2b	TRS.benevolence → Trust	3	3	98	279	.13	-.40	.66	.14	-.39	.66
2	2c	TRS.integrity → Trust	3	3	98	279	.40	-.15	.94	.39	-.15	.93
4	3	Trust → Emotional Reactions	13	13	387	1769	.45	.35	.55	.49	.39	.59
3	4	Trust → Team Processes	30	62	1250	5635	.39	.33	.46	.39	.33	.45
3	5	Team Processes → Team Performance	23	41	1026	4719	.10	.02	.18	.10	.01	.18
5	5	Team Processes → Team Performance	8	12	439	1798	.24	.11	.36	.24	.12	.35
3	6	Trust → Team Performance	40	52	1988	8940	.19	.12	.27	.19	.11	.26
5	7	Team Processes → Trust (post performance)	7	11	347	1309	.26	.13	.39	.20	.08	.33
5	8	Team Performance → Trust (post performance)	10	13	602	2429	.12	-.02	.25	.16	.03	.29
7	9a	DLC.ability → Trust (post performance)	3	3	98	279	-.02	-.39	.34	-.02	-.39	.34
7	9b	DLC.benevolence → Trust (post performance)	3	3	98	279	.05	-.45	.55	.05	-.45	.55
7	9c	DLC.integrity → Trust (post performance)	3	3	98	279	.44	-.09	.96	.44	-.08	.95
6	10a	DLC.ability → Propensity to Trust (post performance)	2	2	36	172	-.34	-.95	.27	-.35	-.94	.24
6	10b	DLC.benevolence → Propensity to Trust (post performance)	2	2	36	172	.55	-.27	1.36	.52	-.25	1.30
6	10c	DLC.integrity → Propensity to Trust (post performance)	2	2	36	172	.25	-.61	1.12	.24	-.60	1.08
8	11a	DLC.ability → TRS.ability	3	3	98	279	.46	.24	.69	.47	.26	.67
8	11a	DLC.ability → TRS.benevolence	3	3	98	279	.34	.12	.57	.35	.14	.55
8	11a	DLC.ability → TRS.integrity	3	3	98	279	-.06	-.52	.40	-.06	-.52	.40
8	11b	DLC.benevolence → TRS.ability	3	3	98	279	.36	.13	.59	.36	.15	.57
8	11b	DLC.benevolence → TRS.benevolence	3	3	98	279	.56	.33	.78	.56	.35	.76
8	11b	DLC.benevolence → TRS.integrity	3	3	98	279	-.01	-.66	.64	-.01	-.66	.65
8	11c	DLC.integrity → TRS.ability	3	3	98	279	.35	.13	.58	.36	.15	.56
8	11c	DLC.integrity → TRS.benevolence	3	3	98	279	.42	.19	.64	.42	.21	.62
8	11c	DLC.integrity → TRS.integrity	3	3	98	279	.24	-.31	.79	.24	-.31	.79

Note: TRS = trust-related schema; DLC = deep level cues; Models 1 and 4 = correlation coefficient; Models 2, 3, 5, 6, 7, and 8 = beta coefficient; ci.lb = lower bound of 95% confidence interval; ci.ub = upper bound of 95% confidence interval; grey shade = significant at $p < .05$. Effect size magnitudes can be interpreted qualitatively using the latest guidelines (Funder & Ozer, 2019): $r \sim 0.05$ = very small, $r \sim 0.10$ = small, $r \sim 0.20$ = medium, and $r \sim 0.30$ = large.