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Forward flow and creative thought: Assessing associative cognition and its role in divergent thinking

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ABSTRACT

Creative thinking is thought to be supported by both spontaneous associative and controlled executive processes. Recently, a new measure of associative cognition has been developed—forward flow—which uses computational semantic models (e.g., latent semantic analysis; LSA) to capture "how far" people travel in semantic space during a chained free association task. The present research aims to extend the psychometrics of forward flow by 1) leveraging multiple computational semantic models for forward flow computation (reliability) and 2) testing how this metric of associative ability relates to divergent creative thinking (validity). In addition, using structural equation modeling, we test dual-process theories of creative cognition by examining the relative contribution of associative and executive abilities to divergent thinking. Study 1 (n = 151) finds moderately improved reliability of forward flow using the new multi-model approach (compared to LSA only), as well as positive effects of both forward flow (β = .48) and general intelligence (β = .36) on divergent thinking (human creativity ratings) in the same structural regression model. This pattern of results was replicated in Study 2 (n = 150), which showed large effects of forward flow (β = .42) and general intelligence (β = .46) on divergent thinking. The results expand the psychometrics of forward flow and provide new evidence for dual process models of creative cognition.

1. Introduction

Creativity has long been linked to free association—the mind's ability to spontaneously connect concepts to form ideas. Yet the measurement of associative cognition has been challenging, preventing progress in understanding its role in creativity. Recently, however, a new method has been introduced—*forward flow*—which quantifies associative cognition using computational semantic models, capturing "how far" a person travels in semantic space when they freely associate (Gray et al., 2019). Forward flow is based on a "chained free association" task: people start with a cue word and produce the first word that comes to mind, continuing to produce linked words in this chained fashion. The forward flow measure is computed as the average distance between all pairs of associative responses, based on text-based corpus analysis, denoting the breadth and depth of one's ability to search memory and generate chained associates. Gray and colleagues provided preliminary evidence for the reliability and validity of forward flow as an index of associative

Data and input files are available at Open Science Framework: https://osf.io/7p5mt/.

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thought, reporting small but reliable correlations with creative thinking and achievement. The present research aims to build on the psychometrics of forward flow by employing a recently developed computational approach that samples a much broader range of semantic space than the original method. In two studies, we test this approach and examine the relative contributions of forward flow to divergent creative thinking—beyond intelligence, an index of cognitive control that has been previously related to divergent thinking—providing a novel test of dual-process models of creative thought.

According to the associative theory of creativity (Kenett, 2019; Kenett & Faust, 2019; Mednick, 1962), creative thinking involves making connections between remote concepts stored in semantic memory. The semantic system consists of acquired knowledge about the world, and it is thought to be organized as a network of inter-connected concepts, with related concepts represented "closer" than unrelated concepts (Collins & Loftus, 1975). The advent of network science methods in cognitive science has allowed the modeling of semantic memory, in turn permitting empirical tests of the associative theory of creativity. In semantic networks, words (concepts) are represented as nodes, and the relations between them are represented as edges. Using network science methods, Kenett and colleagues (Kenett et al., 2014; Kenett & Faust, 2019) have demonstrated that, compared to less-creative people, higher-creative people—those with more creative achievements and who do better on creative thinking tests—tend to show a more "flexible" semantic network structure, marked by high connectivity and short paths between concepts. This network structure is thought to be conducive to creative thought by allowing people to connect concepts more efficiently within their networks, particularly those that are seemingly unrelated and thus potentially creative.

To measure associative cognition, Gray et al. (2019) developed the forward flow task. In this task, people are presented with "seed" words (e.g., snow), asked to type the first word that comes to mind, then to repeat this process for consecutive words in a chained manner. Forward flow was designed to capture spontaneity in thought, or directed search processes that unfold over time within semantic memory. In a series of studies, Gray and colleagues found that more creative people "travel farther" in semantic space when completing forward flow tasks (even when not instructed to think creatively). Here, semantic distance is assessed computationally using latent semantic analysis—a natural language processing method that computes the co-occurrence of words in large text corpora. For example, the words "speak" and "listen" tend to co-occur frequently and would therefore be given a low semantic distance value. The forward flow method computes the semantic distance between the starting word and all subsequent pairs of words, yielding a quantitative assessment of how far a person "travels" in semantic space when freely associating words. Gray et al. reported initial evidence for the psychometric properties of the forward flow task, including small-to-medium correlations with divergent thinking and creative achievement.

In addition to associative processes, executive processes are increasingly implicated in studies of creative cognition. The controlled attention theory of creativity (Beaty et al., 2014; Benedek et al., 2012, 2014) posits that creative thought benefits from the ability to direct attention and cognition, allowing people to strategically search memory, execute complex search strategies, and inhibit common ideas that come to mind when attempting to think of new ideas. Several studies have reported associations between creative cognition (e.g., divergent thinking) and cognitive abilities related to executive control, including fluid intelligence (Frith et al., 2021; Karwowski et al., 2016; Nusbaum & Silvia, 2011; Silvia, 2015; Silvia & Beaty, 2012; Sligh et al., 2005), broad retrieval ability (Lee & Therriault, 2013; Silvia et al., 2013), working memory (Beaty & Silvia, 2012; de Dreu et al., 2012; Gilhooly et al., 2007), and inhibition (Benedek et al., 2012, 2014). The idea that both controlled executive and spontaneous associative processes support creative thought is consistent with dual processes models of creativity, such as the classic Geneplore model of creative cognition, which suggests that thinking creatively involves an iterative processes of spontaneous generation and controlled evaluation (Finke et al., 1992).

Despite the popularity of dual processes models in the creativity literature, only a handful of studies have considered both associative and executive processes in the same study (Beaty et al., 2014; Benedek et al., 2017). For example, Beaty et al. (2014) found that both abilities predicted divergent thinking (creativity ratings) in a structural regression model, indicating that their contributions to creative cognition are unique. However, a key limitation of this study was the assessment of associative and executive abilities from the same cognitive task (i.e., verbal fluency). Here, participants completed two category verbal fluency tasks, which are commonly administered to assess executive control over memory retrieval (the total number of items retrieved is a common index of executive control). To assess associative ability, the authors computed semantic distance between the category prompt words (e.g., synonyms for the word "good") and participants' responses, reasoning that this metric reflects underlying network structure and the associative processes operating over it. However, because the task involves goal-directed memory retrieval—people have an explicit goal in mind that guides and constrains search processes (e.g., "find synonyms for the word good")—it is unclear if this purported associative metric actually captures network structure/spontaneous retrieval. Therefore, whether and to what extent associative and executive processes support creative cognition remains unclear.

2. The Present Research

Forward flow is a promising new measure of associative cognition, opening doors to test theories on the role of associative thought in creativity. In the present research, we aim to build on this method and further examine its psychometric properties. We do so by 1) expanding and enhancing its underlying computational method and 2) examining its contribution to divergent creative thinking.

In their initial work, Gray et al. (2019) assessed forward flow with LSA, a "count model" that counts the number of co-occurrences of word pairs in text corpora. Importantly, the choice of semantic model (e.g., LSA) and text corpora (e.g., textbooks, encyclopedia entries) can impact the generalizability of corresponding semantic metrics (Kenett, 2019). For example, the Touchstone Applied Science Associates (TASA) corpus—currently used to calculate forward flow—includes many textbooks (some from decades ago), which may not provide the best approximation of most people's mental lexicon. To better capture natural language, new text corpora have been developed, such as those based on subtitles from thousands of movies. New computational models have also been developed that use machine learning to predict word co-occurrences from surrounding context words (i.e., predict models; e.g., word2vec), providing a powerful extension of count models such as LSA.

Here we aim to improve the generalizability of forward flow by leveraging multiple semantic models and text corpora. To this end, we use a new computational approach employed in recent work on semantic distance and verbal creativity assessment (Beaty & Johnson, 2020). In five studies, Beaty and Johnson showed that combining five semantic models—applied to different verbal creativity tests, such as novel word associations—provided a reliable and valid alternate to LSA alone, yielding robust associations with human creativity ratings and other creativity measures. Moreover, to optimize semantic distance calculation, the authors used factor analysis to extract a latent variable from the five semantic models, thus capturing common measurement variance beyond what can be achieved with simply averaging the five model scores. The present research applies this approach to the assessment of forward flow, with the broader goal of improving the measurement of associative cognition.

A second goal of the present research was to test dual process theories of creative cognition, asking to what extent associative and executive processes are relevant for divergent thinking. We thus extend the previous study of Beaty et al. (2014), who explored the contributions of associative and executive processes in divergent thinking, with the limitation of using the same task to measure both constructs. To assess associative ability, we use the forward flow task; to assess executive ability, we use several measures of intelligence, which are considered proxy measures of one's ability to control attention and cognition.

3. Study 1

Our first study assessed the reliability and validity of the multi-model approach to forward flow assessment. We administered three forward flow tasks and used six semantic models to calculate forward flow, allowing us to compare the relative reliabilities of each semantic model. Given related work showing reliable prediction of divergent thinking when combining all semantic models, we expected that this multi-model method would provide a reliable approach to forward flow computation (compared to single models). After establishing the optimal forward flow model, we tested a dual-process theory of creativity by examining the extent to which forward flow and general intelligence jointly predict divergent thinking.

4. Method

4.1. Participants

The study sample included 151 adults from Penn State University (PSU; 94 females; mean age = 19.26, SD = 2.04). Participants received credit toward a research option in their psychology course for their participation. The study was approved by the Institutional Review Board (IRB) at PSU.

4.2. Measures

4.2.1. Forward Flow

We administered the forward flow task from Gray et al. (2019). Participants completed three trials, using the same starting words from Gray and colleagues: table, bear, and candle. For each trial, participants were shown one of the starting words and asked to "write down (type) the next word that follows in your mind from the previous word." They were instructed to only type single words, and not to type proper nouns (such as names, brands, etc.), which are not commonly included in text corpora used to compute semantic distance (cf., Olson et al., 2020). Each trial presented a starting word followed by 19 text boxes, where participants typed their chained free association responses. To compute forward flow scores, we compared the approach described in Gray et al. with the multi-model approach (see *Forward Flow Computation and Semantic Spaces*).

4.2.2. Intelligence Assessment

Participants completed a battery of intelligence tasks commonly used in past work on intelligence and creativity (Beaty & Silvia, 2012; Frith et al., 2021; Kenett et al., 2016). The tasks assessed three lower-order facets of general intelligence: fluid intelligence (*Gf*), crystallized intelligence (*Gc*), and broad retrieval ability (*Gr*). *Gf* tasks included: 1) a number series task (15 items, 5 minutes), which presents sequences of numbers that change based on a rule and asks participants to select the next sequence (Thurstone, 1938) and 2) a series completion task from the Culture Fair Intelligence Test (13 items, 3 minutes), which presents sequences of three changing images (small line drawings) and asks participants to select the next image that fits the rule governing their change (Cattell & Cattell, 1961/2008). *Gc* tasks included: 1) the advanced vocabulary test (18 items) and 2) the extended range vocabulary test (Ekstrom et al., 1976). Both tasks require selecting a synonym of a target word from a list (8 minutes total). *Gr* tasks included two category fluency tasks: listing animals and listing fruits/vegetables (2 minutes each).

4.2.3. Divergent Thinking

To assess creative cognition, participants completed three trials of the alternate uses task (AUT; Guilford, 1967): box, rope, and pen (2 min each; randomized order). For each trial, they were presented with one of the objects and asked to think of novel and unusual uses for it, typing their ideas into text boxes on the screen. Consistent with best practices in divergent thinking assessment (Acar et al., 2020; Said-Metwaly et al., 2020), participants were explicitly instructed to "think creatively," and to come up with ideas that "strike people as clever, unusual, interesting, uncommon, humorous, innovative, or different" (Nusbaum et al., 2014). AUT responses were scored by four trained raters using the subjective scoring method (Silvia et al., 2008). Raters were blind to the participant and order of responses (the rater response sheet was alphabetized by response and stripped of participant ID numbers). Raters rated each response using a 1 (*not at all creative*) to 5 (*very creative*) scale, achieving good inter-rater agreement across the three AUT items: box (α = .89) rope (α = .75) and pen (α = .91).

4.3. Forward Flow Computation and Semantic Spaces

We extend the original study of forward flow in two ways: 1) computing forward flow using multiple computational semantic spaces (not just LSA) and 2) combining these models into a latent factor score (instead of averaging). This approach allowed us to test whether leveraging multiple semantic models via latent variables—which model measurement variance separately from error variance—can improve the reliability and validity of forward flow (compared to LSA only).

To compute forward flow, we employed a multi-model approach described in Beaty and Johnson (2020). We used seven semantic spaces that met the following criteria: 1) variation in the computational model (e.g., LSA), 2) variation in the text corpora (e.g., textbooks, subtitles), and 3) validity evidence with human relatedness judgments. Our analysis included four continuous bag of words (CBOW) predict models and three count models. CBOW/predict models were built using a neural network architecture that employs a sliding window to move through text corpora and aims to predict a central word from surrounding context words (e.g., word2vec); count models, in contrast to predict models, compute the co-occurrence of words within these large text corpora. The four CBOW models included (abbreviated names in parentheses): 1) a concatenation of the ukwac web crawling corpus (~ 2 billion words) and the subtitle corpus (~385 million words; window size = 12 words, 300 dimensions, most frequent 150,000 words; hereafter referred to as "rep"; Mandera et al., 2017); 2) the subtitle corpus only (window size 12 words, 300 dimensions, most frequent 150,000 words; "subs"; Mandera et al., 2017); 3) a concatenation of the British National Corpus (~2 billion words), ukwac corpus, and the 2009 Wikipedia dump (~ 800 million tokens; window size = 11 words, 400 dimensions, most frequent 300,000 words; "baroni"; Baroni et al., 2014); and 4) a smaller concatenation of the British National Corpus, ukwac corpus, and 2009 Wikipedia dump (~5 million words, 300 dimensions, most frequent 100,000 words; "en100k"; Günther et al., 2015) .

The three count models include: 1) an LSA model, TASA, which computes word co-occurrences within a text corpus (37,651 documents, middle and high school textbooks and literary words, 92,393 different words), followed by a singular value decomposition (SVD) on the resulting sparse matrix ("tasa"; Günther et al., 2015) 2) the T7 model of the TASA corpus, which includes different source corpora (textbooks, literature, fiction, and nonfiction works; includes stop words) than the first TASA space, but is also constructed with word co-occurrences (followed by a SVD; "tasa7"; Ştefănescu et al., 2014); and 3) the global vectors model, which is trained on ~6 billion tokens (300 dimensions, top 400,000 words) and uses weighted least squares to extract global information across a concatenation of the 2014 Wikipedia dump and the Gigaword corpus (news publications from 2009–2010; "glove"; Pennington et al., 2014). Calculations of all forward flow values for the seven semantic spaces were completed using the R package LSAfun (Günther et al., 2015). Finally, we computed a composite average of all seven semantic models ("mean") that was the focus of the present study (i.e., the multi-model method).

Following Gray et al., for each semantic space, semantic similarity between word pairs was computed by taking the cosine angle between word vectors; semantic distance was then computed by simply taking the inverse of these values. This process was repeated for each seed word/trial (e.g., bear) and all word pairs in the 20 × 20 matrix. Formally, we have the following equation:

$$\frac{\sum_{i=1}^{n-1} Dn,i}{n-1} \tag{1}$$

Where the instantaneous forward flow of the n^{th} response (word) in a stream is calculated as the average semantic distance (D) between that response and all (n - 1) preceding responses. The forward flow referred to in the present study, also called dynamic forward flow, is the average of equation 1 across all words in a thought sequence:

$$\frac{\left(\sum_{i=2}^{n}\frac{\sum_{j=1}^{i-1} Di,j}{i-1}\right)}{n-1} \tag{2}$$

4.4. Procedure

The study was completed in groups of 1 to 6. Participants were given consent forms and briefed on the purpose of the study. Following written informed consent, they completed a series of cognitive tasks on desktop computers running Qualtrics.

5. Analysis Strategy

The goals of Study 1 were twofold: 1) to test the reliability of forward flow, using the multi-model approach combined with structural equation modeling and 2) to test the validity of forward flow in predicting divergent thinking ability. To address the first goal, we examined reliability and inter-item correlations between the three forward flow prompts for the six semantic spaces/models. To address the second goal, we used the top performing model(s) from the reliability analysis and tested associations with divergent thinking (human creativity ratings)—alongside general intelligence—thus assessing the relative contribution of associative and controlled processes to creative thought.

6. Results

Descriptive statistics for the seven semantic spaces, along with the average (for each of the three cue words), are presented in Table 1. Table 2 lists the descriptive statistics for intelligence and divergent thinking measures. Correlations between all observed variables are shown in Fig. 1 (all correlation matrices generated using sjPlot package in *R*; Lüdecke, 2021).

The reliabilities (Cronbach alphas) of the seven semantic models (and their combined average) are listed in Table 3, and the correlations between all spaces and items are listed in Supplementary Table 1. As seen in Table 3, the most reliable spaces across the three forward flow items were baroni, subs, and tasa, with all three showing a moderate level of reliability (i.e., above .6); the least reliable semantic model was glove (.43). Higher reliabilities of some spaces and lower reliabilities of others produced an average of the seven semantic spaces (i.e., the "mean" variable) in the middle range (.56). In light of this variability, and the expected variability across semantic models in Study 2, we analyzed the mean forward flow variable to assess relationships with intelligence and divergent thinking.

6.1. Forward Flow, Intelligence, and Divergent Thinking

How do associative (forward flow) and controlled (intelligence) cognition relate to divergent thinking? To address this question, we modeled forward flow as a latent variable and assessed its correlations with intelligence and divergent thinking. We thus specified a confirmatory factor analysis (CFA) with three correlated factors: forward flow (indicated by the aggregated semantic distance scores for the three tasks), intelligence (indicated by the six intelligence tasks; fluid, crystallized, and retrieval ability), and divergent thinking (a higher-order factor comprised of the box, rope, and pen AUT items, each indicated by four raters; see Fig. 2). This model fit the data well: χ^2 (183) = 236.760, p = .005; CFI .956; TLI .95 RMSEA .044; SRMR .076. All indicators loaded significantly onto their respective latent variables, with moderate to large loadings. Importantly, the three forward flow tasks showed comparable and moderately-large loadings onto the forward flow factor, further indicating that the forward flow tasks measure a coherent construct.

The forward flow factor showed a large latent correlation with divergent thinking: r = .43, $p < .001$. However, the forward flow factor showed a small, negative, and nonsignificant correlation with intelligence: r = -.14, p = .26. Consistent with past work, we found a significant positive correlation between divergent thinking and intelligence: r = .29, p = .01. The CFA thus replicates and extends recent work on the predictive and discriminant validity of forward flow using a multi-model approach combined with latent variable modelling.

We then tested the relative contribution of associative (forward flow) and controlled (g) factors in predicting creative thinking (DT). A structural regression model was specified, with forward flow and g predicting DT (the model fit is mathematically identical to the

Table 1
Descriptive statistic for all forward flow variables for Study 1

Task	*M*	*SD*	*R* (min-max)	*Skew*	*Kurtosis*
b_tasa	0.93	0.03	0.81–0.99	-0.88	1.12
b_tasa7	0.78	0.04	0.65–0.87	-0.40	0.09
b_rep	0.78	0.04	0.64–0.85	-0.61	0.79
b_subs	0.86	0.03	0.78–0.93	-0.35	-0.41
b_baroni	0.87	0.03	0.77–0.93	-0.69	0.99
b_en100k	0.59	0.05	0.42–0.72	-0.19	1.05
b_glove	0.81	0.04	0.69–0.92	-0.39	0.53
b_mean	0.80	0.03	0.72–0.88	-0.27	0.08
c_tasa	0.92	0.03	0.80–0.99	-0.44	0.18
c_tasa7	0.79	0.04	0.63–0.90	-0.46	1.07
c_rep	0.77	0.03	0.68–0.86	-0.21	-0.24
c_subs	0.85	0.03	0.74–0.91	-0.34	-0.15
c_baroni	0.85	0.02	0.76–0.90	-0.51	0.43
c_en100k	0.58	0.05	0.44–0.70	-0.17	-0.46
c_glove	0.81	0.04	0.71–0.92	0.06	-0.04
c_mean	0.80	0.03	0.68–0.88	-0.22	0.25
t_tasa	0.93	0.04	0.79–1.00	-0.84	0.70
t_tasa7	0.78	0.04	0.61–0.90	-0.31	1.16
t_rep	0.76	0.04	0.61–0.88	-0.26	1.00
t_subs	0.86	0.03	0.78–0.93	-0.27	0.00
t_baroni	0.87	0.02	0.80–0.92	-0.45	0.30
t_en100k	0.62	0.04	0.50–0.72	-0.19	-0.38
t_glove	0.80	0.04	0.68–0.92	-0.02	0.29
t_mean	0.80	0.03	0.73–0.90	0.02	0.37

Note. b = bear prompt word; c = candle prompt word; t = table prompt word; tasa = touchstone applied sciences corpus; tasa_7 = touchstone applied sciences corpus, T7; rep = ukwac web crawling and subtitle corpus; subs = subtitle corpus only; baroni = concatenation of British national corpus and the 2009 Wikipedia dump; en100k = English 100k corpus (subset of baroni); glove = concatenation of 2014 Wikipedia dump and the gigaword corpus; mean = average value of all semantic spaces.

Table 2
Descriptive statistics for intelligence measures and averaged AUT originality scores for Study 1

Task	*M*	*SD*	*R* (min-max)	*Skew*	*Kurtosis*
gf_cfiq	7.47	2.11	0.00–12.00	-1.06	1.62
gf_numb	9.85	2.66	2.00–14.00	-0.33	-0.42
gc_ext	10.64	3.19	1.00–21.00	0.29	0.57
gc_adv	8.30	2.16	1.00–17.00	0.08	1.46
gr	23.70	5.25	10.50–35.00	-0.37	-0.24
Box_mean	2.70	0.44	1.50–3.71	-0.29	-0.47
Rope_mean	2.32	0.36	1.58–3.46	0.17	-0.42
Pen_mean	2.51	0.55	1.00–3.50	-0.38	-0.50

Note. gf = fluid intelligence measure; gf_cfiq = culture fair intelligence test; gf_numb = number sequence test; gc = crystallized intelligence measure; gc_ext = extended vocabulary task; gc_adv = advanced vocabulary task; gr = animal fluency task; Box_mean, Rope_mean, Pen_mean = mean human originality ratings of divergent thinking for three alternate uses task prompts.

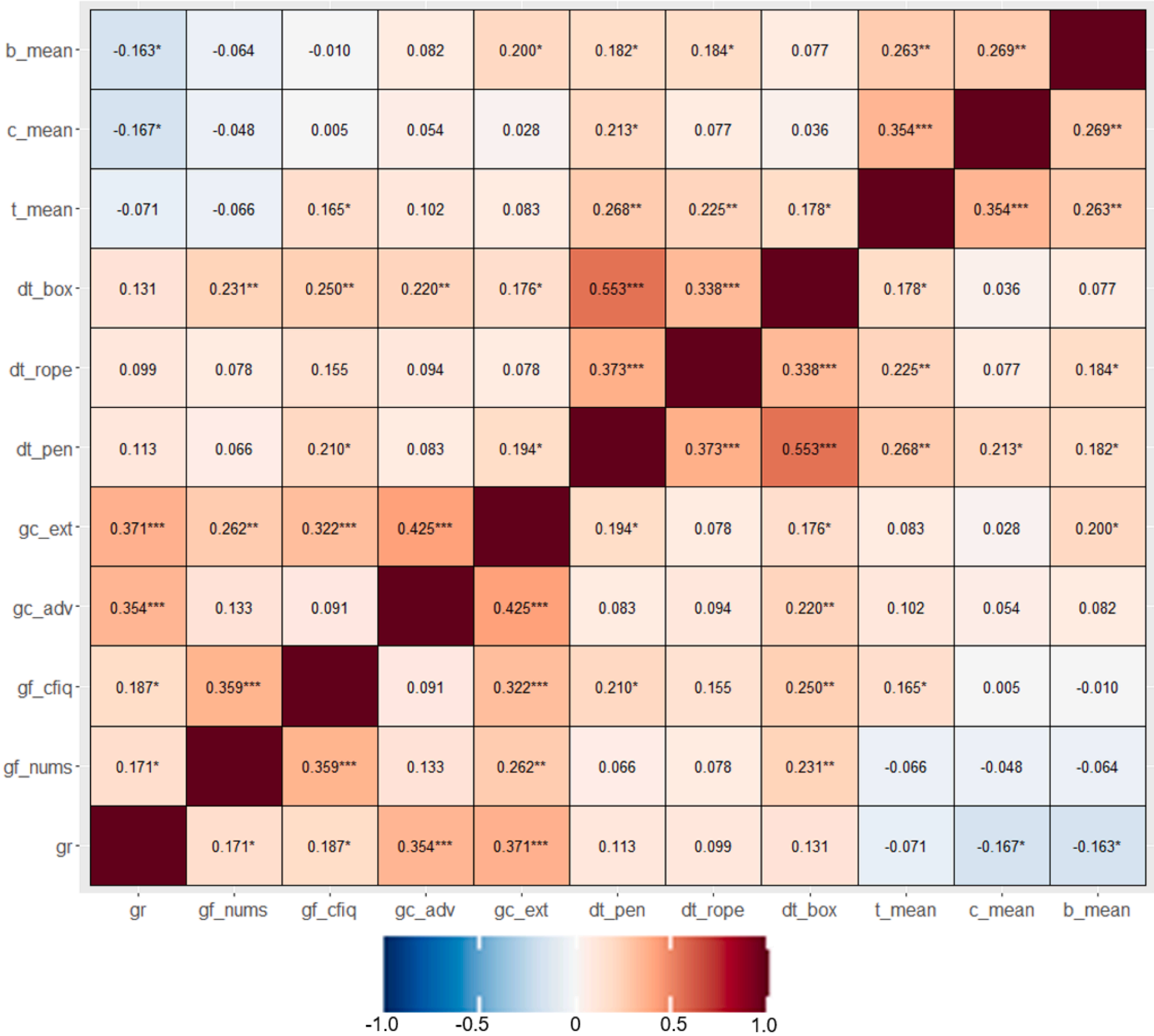

Fig. 1. Correlation matrix of individual forward flow, general intelligence, and divergent thinking tasks from Study 1. b_mean, c_mean, t_mean = mean forward flow scores across all spaces, separated by prompt; dt_box, dt_rope, dt_pen = mean human originality ratings of divergent thinking for three alternate uses task prompts; gc_ext = extended range vocabulary test; gc_adv = advanced vocabulary test; gf_cfiq = Cattell Series Completion; gf_nums = fluid intelligence, number series; gr = broad retrieval ability; N = 146 (max sample size), 123 (min sample size).

Table 3
Reliabilities of seven semantic spaces (and their combined average) for three Forward Flow items from Study 1 and 2

Space	α (Study 1)	α (Study 2)
baroni	0.63	0.49
en100k	0.52	0.47
glove	0.43	0.53
mean	0.56	0.48
rep	0.52	0.45
subs	0.63	0.46
tasa	0.62	0.46
tasa7	0.50	0.46

Note. rep = ukwac web crawling and subtitle corpus; subs = subtitle corpus only; baroni = concatenation of British national corpus and the 2009 Wikipedia dump; en100k = English 100k corpus (subset of baroni); glove = concatenation of 2014 Wikipedia dump and the gigaword corpus; mean = average value of all semantic spaces.

CFA). Results showed significant effects of both forward flow ($\beta = .48$, $p < .001$) and *g* ($\beta = .36$, $p = .002$) on DT (Fig. 3). Together, the model explained 31% of the variance in DT. Thus, forward flow and *g* showed unique contributions to DT, with forward flow showing a larger effect size than *g*.

7. Study 2

Study 1 sought to test a new approach to forward flow—combining multiple semantic models and latent variable analysis—and assess forward flow's contribution to divergent thinking, alongside general intelligence. Item analysis comparing the reliabilities of seven semantic models and their combined average showed a range of alpha values, from low (glove; .43) to moderate (subs; .63). Notably, the tasa model, which was used in the initial forward flow paper, showed a similarly moderate level of reliability (i.e., .62). This finding indicates that the choice of semantic model influences the reliability of forward flow. Regarding forward flow's relationship to divergent thinking, when modeled at the latent level, forward flow showed a large effect on DT in a structural regression model with intelligence (which also significantly predicted DT), adding to the construct validity evidence for forward flow and demonstrating its unique role in the prediction of DT beyond intelligence. In Study 2, we sought to replicate these findings in an independent sample of participants.

8. Method

8.1. Participants

The study sample included 150 adults from PSU (122 females; mean age = 19.16, SD = 1.4). Participants received optional course credit for their participation in the study. The study was approved by the PSU IRB.

8.2. Measures

8.2.1. Forward Flow

The forward flow items were the same as Study 1 (bear, candle, table). A notable difference, however, was the task administration. Whereas Study 1 presented a cue word (e.g., bear) and 19 textboxes below via Qualtrics, similar to Gray et al. (2019), Study 2 only showed the cue word at the beginning of the trial, and participants only saw their previous word as they generated subsequent words. The same multi-model approach from Study 1 was used to calculate forward flow.

8.2.2. Intelligence

A similar battery of *Gf, Gc*, and *Gr* tasks as Study 1 was administered. To assess *Gr*, participants completed the animal fluency task; to assess *Gc*, they completed the advanced vocabulary test (Ekstrom et al., 1976); to assess Gf, they completed the number series task (Thurstone, 1938), the series completion task (Cattell & Cattell, 1961/2008), and a letter sets task, which presented sequences of four-letter sets and required participants to select the set that did not fit the rule governing the other sets (16 trials, 4 min; Ekstrom et al., 1976).

8.2.3. Divergent Thinking

Participants completed two AUT trials from Study 1: box and rope (2 minutes each; randomized order). The task instructions and subjective scoring procedure were the same as Study 1. Inter-rater agreement was good for the two AUT items: box ($\alpha = .91$) and rope ($\alpha = .81$).

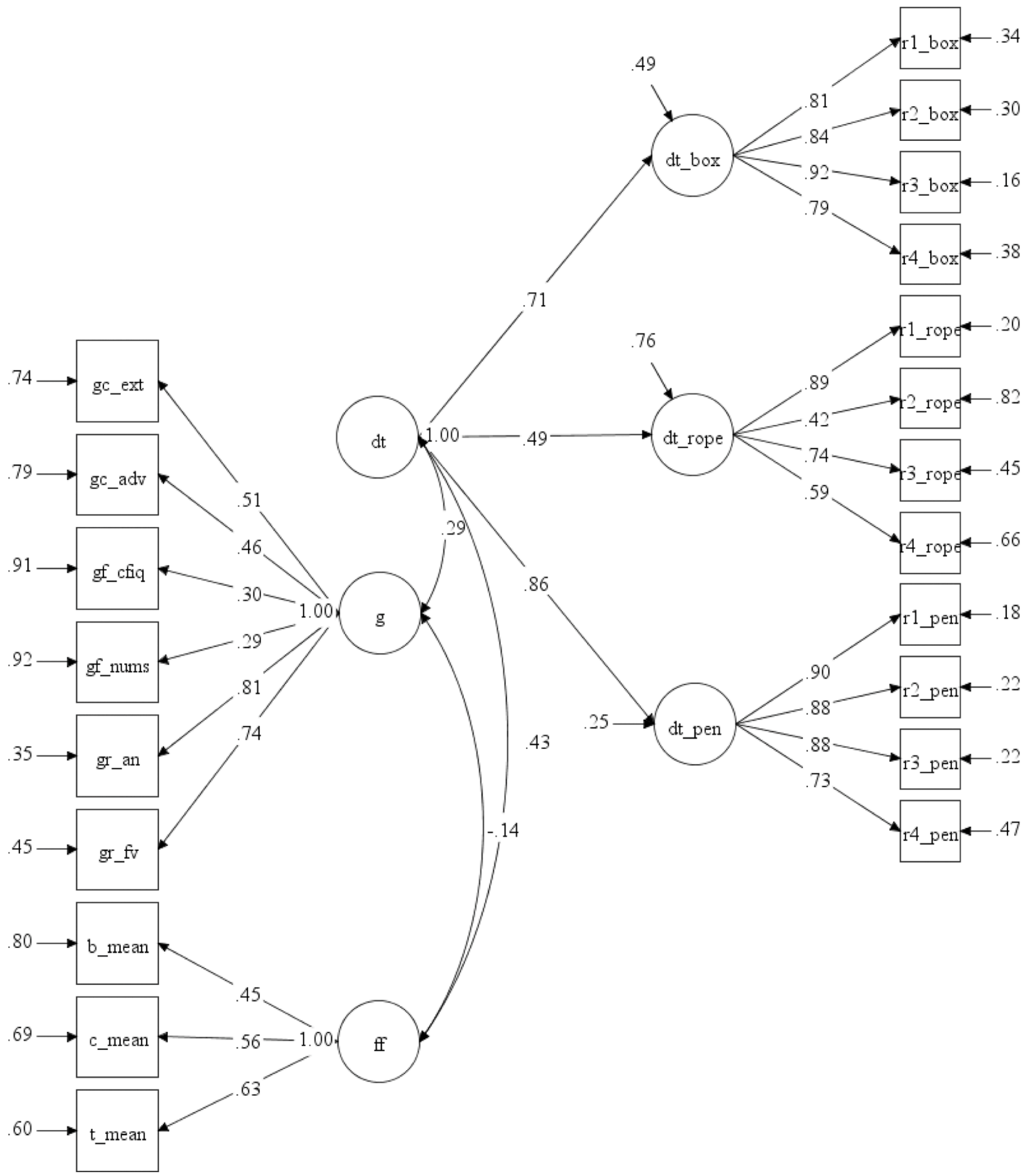

Fig. 2. Confirmatory factor analysis of forward flow, general intelligence, and divergent thinking from Study 1. dt = divergent thinking; dt_box = divergent thinking, box prompt; dt_rope = divergent thinking, rope prompt; dt_pen = divergent thinking, pen prompt; r1-r4 = rater 1-rater4; gc = crystallized intelligence; gc_adv = advanced vocabulary test; gc_ext = extended range vocabulary test; ff = forward flow; b_mean = forward flow, bear seed/mean; c_mean = forward flow, candle seed/mean; t_mean = forward flow, table seed/mean; gf = fluid intelligence; gf_cfiq = Cattell Series Completion; gf_nums = fluid intelligence, number series; gr = broad retrieval ability; gr_an = verbal fluency, animal category; gr_fv = verbal fluency, fruits and vegetable category; N = 151.

8.3. Procedure

The study followed a similar procedure as Study 1. Following written informed consent, participants completed a series of cognitive tasks on desktop computers running PsychoPy.

9. Results

The descriptive statistics for the seven semantic spaces, along with the average (for each of the three prompt words), are presented in Table 4. Table 5 lists the descriptive statistics for intelligence and divergent thinking measures.

Reliabilities of the semantic models are listed in Table 3, and the correlations between all models/items are listed in Supplementary

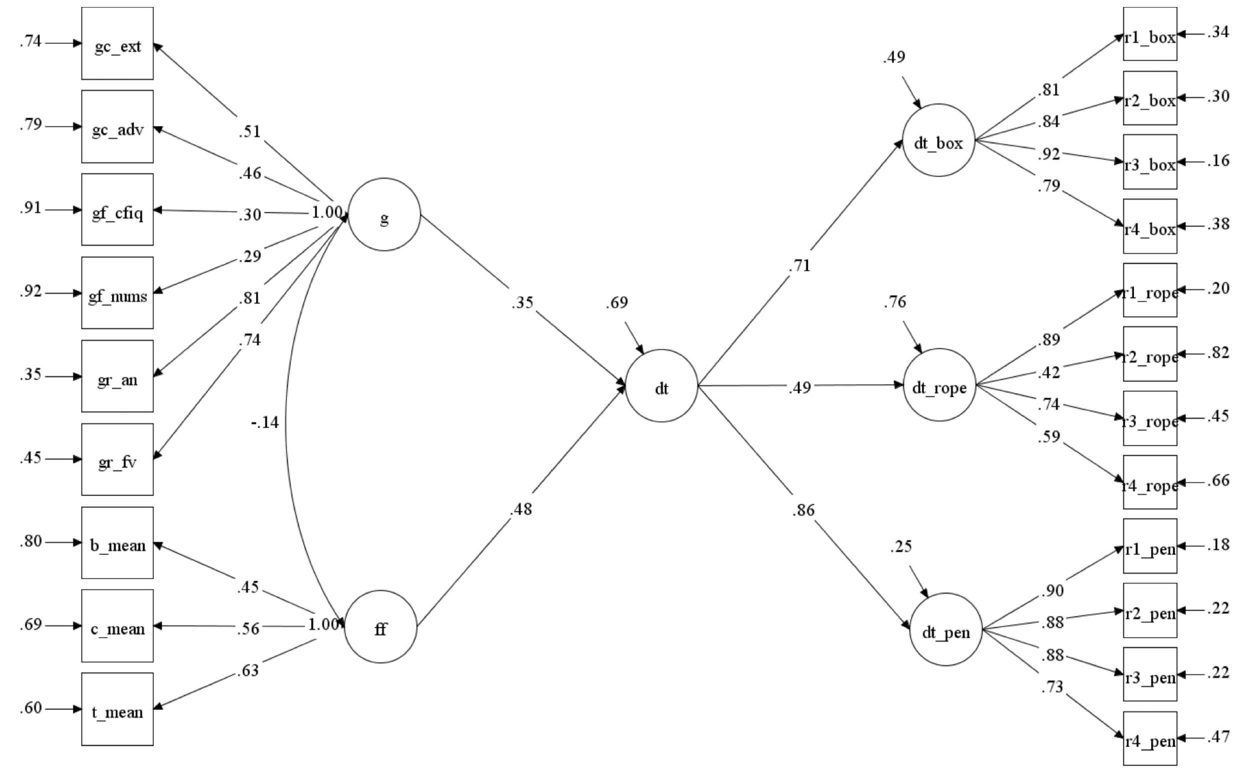

Fig. 3. Structural equation model with forward flow and general intelligence predicting divergent thinking from Study 1. dt = divergent thinking; dt_box = divergent thinking, box prompt; dt_rope = divergent thinking, rope prompt; dt_pen = divergent thinking, pen prompt; r1-r4 = rater 1-rater4; gc = crystallized intelligence; gc_adv = advanced vocabulary test; gc_ext = extended range vocabulary test; ff = forward flow; b_mean = forward flow, bear seed/mean; c_mean = forward flow, candle seed/mean; t_mean = forward flow, table seed/mean; gf = fluid intelligence; gf_cfiq = Cattell Series Completion; gf_nums = fluid intelligence, number series; gr = broad retrieval ability; gr_an = verbal fluency, animal category; gr_fv = verbal fluency, fruits and vegetable category; N = 151.

Table 2. Notably, the reliabilities for all semantic models were lower than was found in Study 1, with the exception of glove (.53), which, interestingly, showed the lowest reliability in Study 1. Consistent with the overall lower reliabilities across models, the reliability of their composite average was .48, replicating the general pattern of modest reliability reported in Study 1.

9.2. Forward Flow, Intelligence, and Divergent Thinking

We sought to replicate the SEM results from Study 1 regarding relationships between forward flow, general intelligence, and divergent thinking. A CFA with three factors—forward flow, *g*, and DT—showed good fit: χ^2 (100) = 122.543, p = .063; CFI .974; TLI .969; RMSEA .039; SRMR .058. Consistent with Study 1, all indicators showed moderate to large loadings onto their respective latent variables, with comparable and moderately-large loadings onto the forward flow factor (Fig. 5). Replicating Study 1, we found a large latent correlation between forward flow and DT: $r = .49$, $p = .007$. We also found a large correlation between G and DT, $r = .52$, $p <$ .001, and a small, nonsignificant correlation between *g* and forward flow, $r = .15$, $p = .313$, replicating latent correlations reported in Study 1.

Finally, we specified a structural regression model to test relative effects of G and forward flow on DT (Fig. 6). Both forward flow (β = .42, p = .017) and *g* (β = .46, p < .001) significantly predicted DT, thus replicating the findings of Study 1 and indicating that associative (assessed via forward flow) and controlled processes (assessed via *g*) jointly predict creative cognition.

10. Discussion

Creativity theories have long emphasized the role of associative cognition in creativity, but reliably quantifying associative thought has proven challenging. The present research extends a promising new quantitative measure of associative cognition (i.e., forward flow), employing a computational approach to improve its generalizability. We also assessed the roles of forward flow and general intelligence in divergent thinking, thereby testing a dual process model of creative cognition. In two studies, we find that a multi-model approach to computing forward flow moderately improves its reliability and validity (compared to the single-corpus approach), and that forward flow and general intelligence show unique contributions to divergent thinking in the same structural regression models. Taken together, our findings build on the assessment of associative thought and provide empirical support for dual process models of

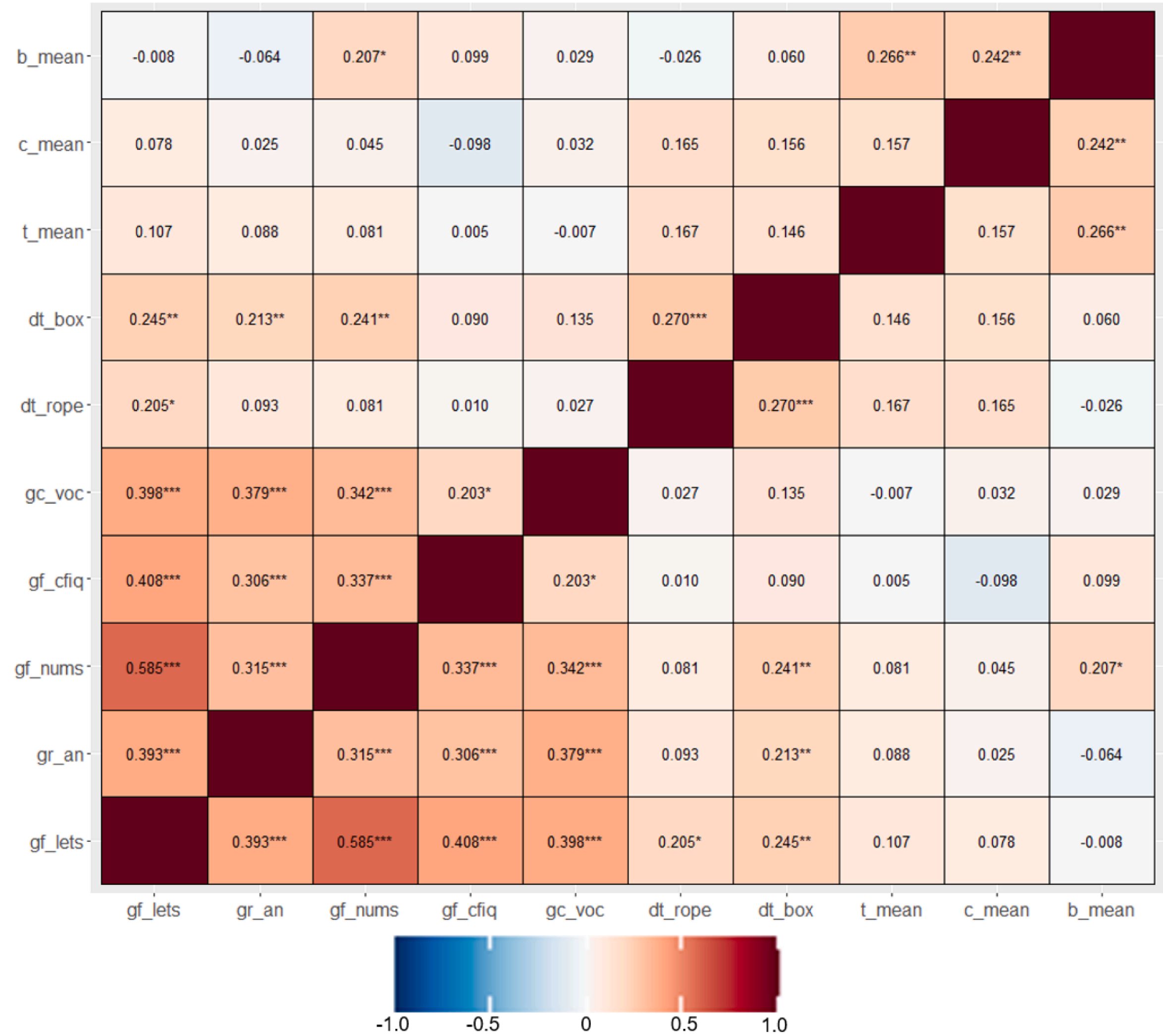

Fig. 4. Correlation matrix of individual forward flow, general intelligence, and divergent thinking tasks from Study 2. b_mean, c_mean, t_mean = mean forward flow scores across all spaces, separated by prompt; dt_box, dt_rope = mean human originality ratings of divergent thinking for three alternate uses task prompts; gc_voc = extended range and advance vocabulary test; gf_cfiq = Cattell Series Completion; gf_nums = fluid intelligence, number series; gr_an = verbal fluency, animal category; gf_lets = fluid intelligence, letter sets; N = 138 (max), 113 (min)

creative cognition.

In their original work, Gray et al. (2019) provided preliminary evidence for the reliability and validity of forward flow. The authors used LSA to compute forward flow, reporting small-to-medium effects of forward flow on creativity measures, including divergent thinking and creative achievement. Notably, a commentary on Gray and colleagues' paper (Rossiter, 2020) raised questions about the relative importance of forward flow in predicting creativity, including the modest effect sizes reported in the paper. Here, using structural equation models—instead of using single items, as was done in Gray et al.—we report much larger effects of forward flow on divergent thinking across two studies. It is common to see larger effects in SEM, to the extent any relationship exists between observed variables, because latent variables capture the common variance across observed variables, modeling error variance separately from true measurement variance. Here we demonstrate robust associations with divergent thinking, providing additional validity evidence for forward flow that should mitigate concerns about its use in creativity research.

Another contribution of the present study is the multi-model approach to computing forward flow. Whereas Gray and colleagues used only LSA, we leveraged seven semantic models and text corpora, providing a broader and more diverse sampling of semantic space. Kenett (2019) and others (Beaty & Johnson, 2020) have highlighted limitations of relying on a single semantic model and text corpus, namely the potential lack of generalizability beyond that specific model/corpus. TASA, for example, was built on textbooks and other literary works. We capitalize on the availability of new text corpora, such as the subtitles corpus, which may offer a better approximation of natural language (e.g., conversations between characters in movies) compared to LSA/textbooks. We also use a range of semantic models: whereas LSA is a count model (it counts word occurrences), we use both count and predict models (which use

Table 4
Descriptive statistics for all forward flow variables from Study 2

Task	*M*	*SD*	*R* (min-max)	*Skew*	*Kurtosis*
b_tasa	0.94	0.03	0.82–0.99	-1.24	1.67
b_tasa7	0.80	0.05	0.67–0.91	-0.15	0.08
b_rep	0.78	0.04	0.68–0.87	-0.05	0.01
b_subs	0.87	0.03	0.74–0.93	-1.16	1.95
b_baroni	0.87	0.03	0.76–0.92	-0.98	1.46
b_en100k	0.59	0.06	0.40–0.72	-0.49	0.77
b_glove	0.82	0.05	0.71–0.93	-0.32	-0.24
b_mean	0.81	0.03	0.70–0.88	-0.47	0.53
c_tasa	0.93	0.03	0.80–1.00	-0.82	1.88
c_tasa7	0.80	0.04	0.67–0.91	-0.22	0.12
c_rep	0.77	0.04	0.66–0.88	-0.08	0.37
c_subs	0.86	0.03	0.75–0.94	-0.53	0.68
c_baroni	0.86	0.03	0.75–0.92	-1.05	2.47
c_en100k	0.59	0.06	0.42–0.73	-0.23	0.07
c_glove	0.82	0.04	0.69–0.94	0.11	1.03
c_mean	0.80	0.03	0.69–0.90	-0.39	1.16
t_tasa	0.93	0.04	0.79–1.00	-0.84	0.70
t_tasa7	0.78	0.04	0.61–0.90	-0.31	1.16
t_rep	0.76	0.04	0.61–0.88	-0.26	1.00
t_subs	0.86	0.03	0.78–0.93	-0.27	0.00
t_baroni	0.87	0.02	0.80–0.92	-0.45	0.30
t_en100k	0.62	0.04	0.50–.72	-0.19	-0.38
t_glove	0.80	0.04	0.68–0.92	-0.02	0.29
t_mean	0.80	0.03	0.73–0.90	0.02	0.37

Note. b = bear prompt word; c = candle prompt word; t = table prompt word; tasa = touchstone applied sciences corpus; tasa_7 = touchstone applied sciences corpus, T7; rep = ukwac web crawling and subtitle corpus; subs = subtitle corpus only; baroni = concatenation of British national corpus and the 2009 Wikipedia dump; en100k = English 100k corpus (subset of baroni); glove = concatenation of 2014 Wikipedia dump and the gigaword corpus; mean = average value of all semantic spaces.

Table 5
Descriptive statistics for intelligence measures and averaged AUT originality scores for Study 2

Task	*M*	*SD*	*R* (min-max)	*Skew*	*Kurtosis*
gf_cfiq	7.25	2.11	0.00–11.00	-1.23	2.10
gf_numb	7.63	3.55	0.00–14.00	-0.28	-0.66
gf_letter	7.01	2.07	0.00–14.00	-0.07	-0.64
gc_voc	16.44	6.60	0.00–34.00	-0.24	0.37
gr	50.69	15.50	8.00–108.00	0.29	0.80
Box_mean	2.32	0.42	1.12–3.38	0.00	0.04
Rope_mean	2.09	0.36	1.25–-3.12	0.07	0.12

Note. gf = fluid intelligence measure; gf_cfiq = culture fair intelligence test; gf_numb = number sequence test; gf_letter = letter sets task; gc = crystallized intelligence measure; gc_voc = vocabulary task (advanced and extended); gr = animal fluency task; Box_mean, Rope_mean = mean human originality ratings of divergent thinking for two alternate uses task prompts.

neural networks to predict missing words from surrounding context words). This multi-model approach—combined with latent variable modeling—was also used in our recent study that validated semantic distance for verbal creativity assessment (Beaty & Johnson, 2020); here, we found very large latent correlations between semantic distance and human creativity ratings on a range of verbal creativity tasks (AUT, novel word association), consistent with prior single-corpus work (Dumas et al., 2020; Prabhakaran et al., 2014) indicating that semantic distance provides a valid automated instrument for creativity assessment.

Interestingly, we found wide variability in the reliability of semantic models across our two studies. For example, although glove showed the lowest reliability in Study 1, it showed the highest reliability in Study 2. Likewise, tasa was among the more reliable models in Study 1, but like the other semantic models in Study 2, it showed reduced reliability. We suspect that such variability reflects the inherent noise in assessing associative thought, which is unconstrained and thus prone to highly variable responses. Another possibility is the difference in task administration across the two studies: Study 1 presented the cue word and 19 textboxes on the screen (continuously; like Gray et al.) whereas Study 2 only presented the previously typed word on the screen (other previous responses disappeared as they were entered). Future work could explore other potential sources of variance in forward flow data, such as item characteristics (cue words) and the number of items administered. The inclusion of more items to assess forward flow should bolster its reliability, as with any construct; here, we only used the three cue words from Gray et al. (2019). It is possible that adding cue words—or using different cue words, controlled for stimulus properties (e.g., word frequency, imageability)—would further improve the psychometric properties of forward flow. Although we generally recommend the multi-model approach to computing semantic distance for forward flow (and other word generation tasks; e.g., AUT), our results indicate that this method only moderately improves reliability, and that the TASA-only approach (i.e., the method employed in the original work by Gray and colleagues) can provide

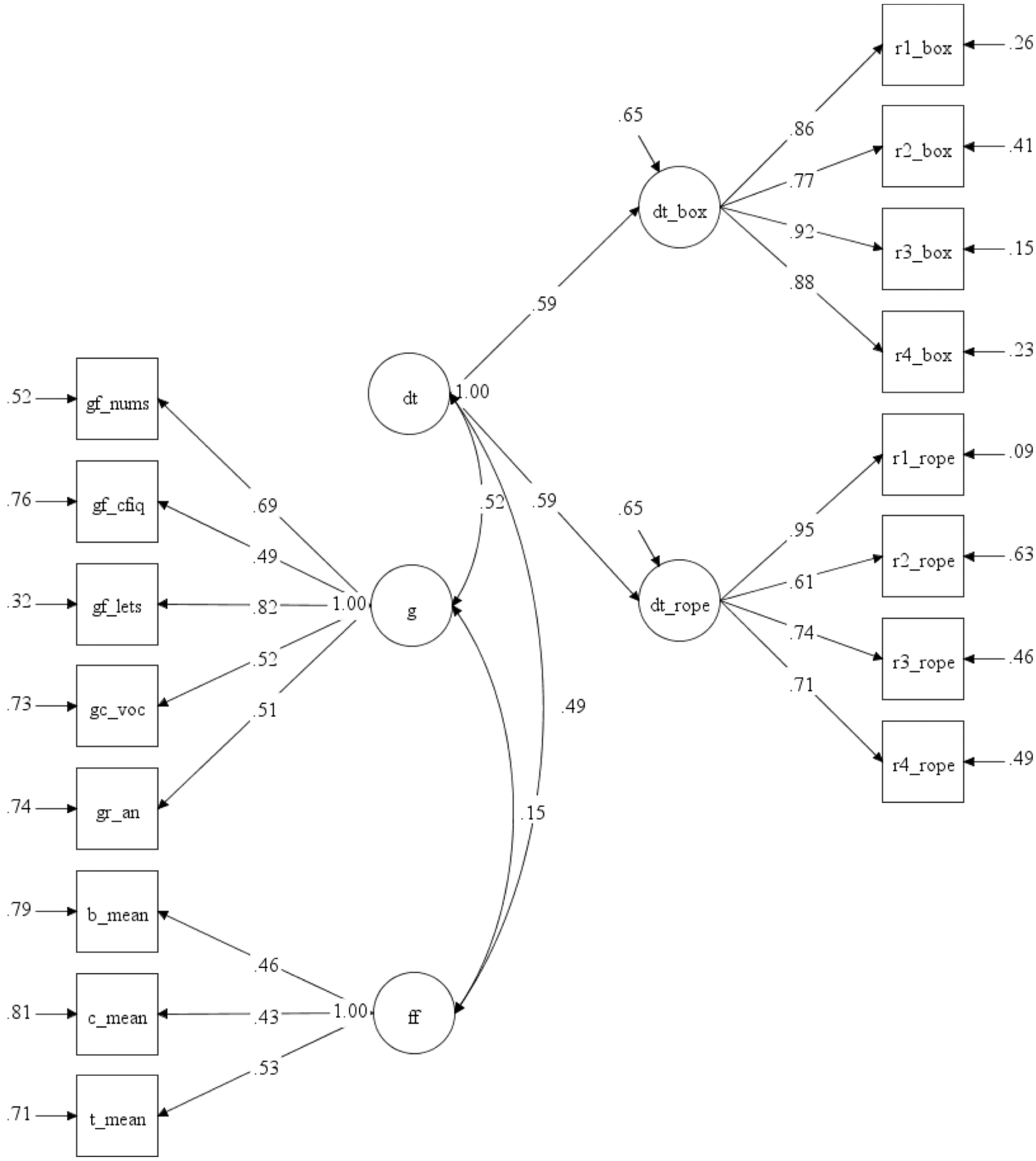

Fig. 5. Confirmatory factor analysis of forward flow, general intelligence, and divergent thinking from Study 2. dt = divergent thinking; dt_box = divergent thinking, box prompt; dt_rope = divergent thinking, rope prompt; r1-r4 = rater 1-rater4; gc = crystallized intelligence; gc_voc = advanced vocabulary test; ff = forward flow; b_mean = forward flow, bear seed/mean; c_mean = forward flow, candle seed/mean; t_mean = forward flow, table seed/mean; gf = fluid intelligence; gf_cfiq = Cattell Series Completion; gf_lets = fluid intelligence, letter sets; gf_nums = fluid intelligence, number series; gr = broad retrieval ability; gr_an = verbal fluency, animal category; N = 150.

acceptable reliability, given the computational demands of computing forward flow across six semantic models. Notably, however, the reliability of all semantic models included in the current study was relatively low (the highest was .62); more work is needed to determine the optimal number of items/trial duration to maximize the reliability and validity of forward flow.

The present study also provided support for dual process models of creative cognition (Allen & Thomas, 2011; Finke et al., 1992). Such models have theorized about the roles of associative and controlled cognition in creativity, but empirical support has been lacking. In two studies, we find reliable effects of both associative and controlled cognition for divergent thinking. Critically, both abilities showed large effects in the same structural regression model, pointing to their unique and substantial contributions. Our findings add to the growing literature on the role of cognitive control and intelligence in divergent thinking (Benedek & Fink, 2019; Jauk et al., 2013; Silvia, 2015) which emphasizes the importance of controlled attention in guiding the creative thought process. Recently, Frith et al. (2021) assessed the effects of controlled attention and fluid intelligence in divergent thinking performance (i.e., creativity ratings). Using bifactor modeling, the authors found that the relationship between fluid intelligence and divergent thinking was driven by a common “executive attention” factor (comprised of attention control and fluid intelligence tasks)—consistent with

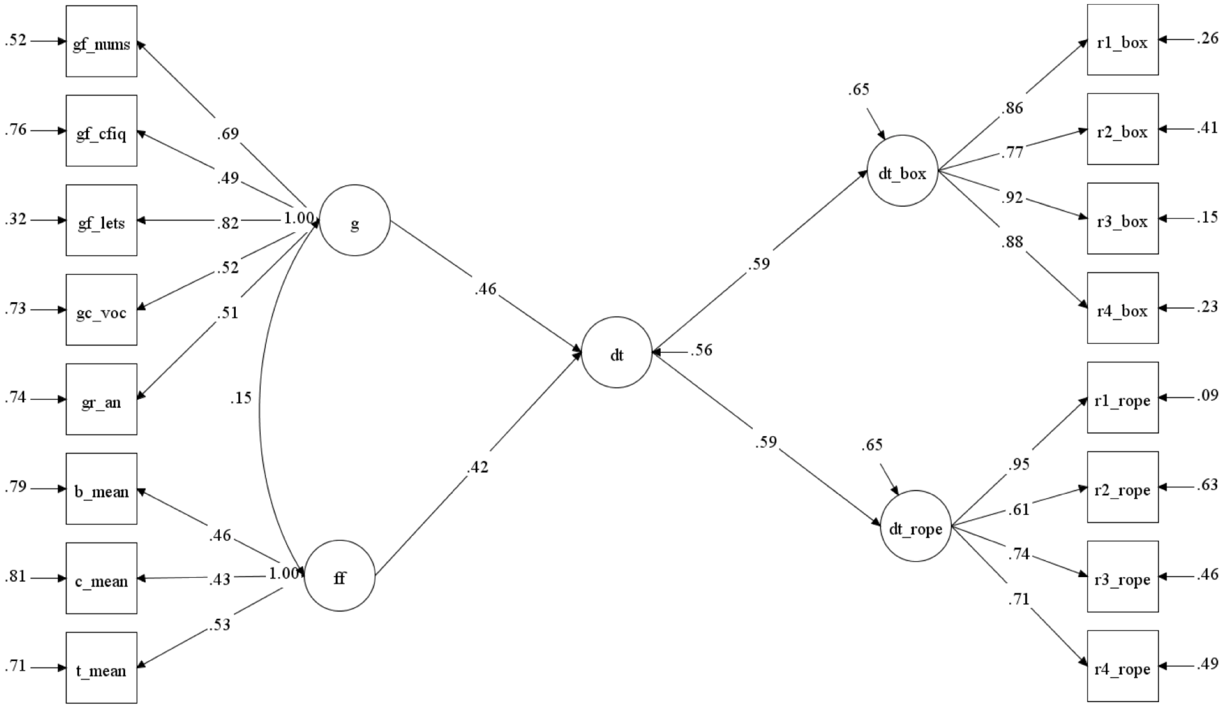

Fig. 6. Structural equation model with forward flow and general intelligence predicting divergent thinking from Study 2. dt = divergent thinking; dt_box = divergent thinking, box prompt; dt_rope = divergent thinking, rope prompt; r1-r4 = rater 1-rater4; gc = crystallized intelligence; gc_voc = advanced vocabulary test; ff = forward flow; b_mean = forward flow, bear seed/mean; c_mean = forward flow, candle seed/mean; t_mean = forward flow, table seed/mean; gf = fluid intelligence; gf_cfiq = Cattell Series Completion; gf_lets = fluid intelligence, letter sets; gf_nums = fluid intelligence, number series; gr = broad retrieval ability; gr_an = verbal fluency, animal category; N = 150.

prior work indicating that the association between intelligence and executive functions (e.g., working memory) is accounted for by a common executive attention factor. Given the strong correspondence between intelligence and executive control (cf. Kane et al., 2004, 2005; Kane & Engle, 2002), and the recent work of Frith et al. on intelligence and creative cognition, we interpret the intelligence effects here as reflecting a general ability to control attention and cognition. Nevertheless, we encourage future research to directly examine how attention control relates to divergent thinking—alongside associative cognition (e.g., forward flow)—to further clarify the role of executive and associative processes in creative cognition.

11. Conclusion

The present study extends and generalizes the recently developed forward flow task to quantitatively assess associative cognition. Building on Gray et al. (2019), we find that a multi-model approach to computing forward flow, combined with latent variable modeling, moderately improves its reliability and validity. We also provide support for dual process theories of creative cognition, showing joint effects of associative (forward flow) and controlled (general intelligence) process in divergent thinking ability. Our findings thus contribute to the automated assessment of cognitive associative abilities relevant for creative thinking and suggest that the production of creative ideas benefits from an interaction of spontaneous and controlled cognition.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.tsc.2021.100859.

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