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Feeling low, thinking slow? Associations between situational cues, mood and cognitive function

Article (Accepted version)
(Refereed)

Original citation:
von Stumm, Sophie (2018) *Feeling low, thinking slow? Associations between situational cues, mood and cognitive function*. Cognition and Emotion. ISSN 0269-9931
DOI: 10.1080/02699931.2017.1420632

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Abstract

Within-person changes in mood, which are triggered by situational cues, for example someone's location or company, are thought to affect contemporaneous cognitive function. To test this hypothesis, data were collected over 6 months with the smartphone application (app) *moo-Q* that prompted users at random times to rate their mood and complete 3 short cognitive tests. From 24,313 people across 154 countries, who downloaded the app, 770 participants submitted 10 or more valid *moo-Q* responses (mean = 23; SD = 18; range 10 to 207). Confirming previous research, consistent patterns of association emerged for 6 different situation cues with mood and cognitive function: For example, being alone rather than with others when completing the app resulted in worse mood but better cognitive task performance. Notwithstanding, changes in mood and cognitive function were not coupled. The advantages and challenges of using smartphone technology for studying mood and cognitive function are discussed.

147 words.

Keywords: mood; cognitive function; memory; smartphone; ecological momentary assessment; within-person differences;

Mood refers to temporary mental and emotional states that usually have positive or negative valence, as in good or bad mood. Changes between good and bad mood that people typically experience in their day-to-day lives are thought to occur primarily as a result of situational cues, for example a person's location and company (e.g. Sandstrom, Lathia, Mascolo, & Rentfrow, 2016). Furthermore, within-person mood changes are believed to affect a wide range of other psychological faculties, including most notably cognitive function (von Stumm, 2016), which encompass several mental processes, such as reasoning, memory, attention, and language, that lead to the attainment of knowledge and affect all important life outcomes (Deary, 2012).

The majority of evidence for the effects of mood on cognitive function comes from mood induction paradigms (e.g. Isen, Daubmann, & Nowiki, 1987; Mitchell & Phillips, 2007; Storbeck, 2016) and clinical studies (e.g. Joorman, 2008). Both research designs are inadequate for testing coupling effects between changes in mood and contemporaneous changes in cognitive function for two reasons. First, they observe drastic, extreme and mostly negative mood states (i.e. mood disorder depression) that people do not typically experience in their day-to-day lives. Second, mood induction paradigms and clinical studies typically assess between-person differences in mood and cognitive function, for example by comparing participants in neutral and sad mood conditions or by matching clinical cases to typical ones. However, coupling effects refer to within-person differences, which differ substantially from between-person differences (Brose, Schmiedek, Loevden, Molenaar, & Lindenberger, 2010).

To test for coupling effects between typical changes in mood and cognitive function that occur in everyday life, studies are most appropriate that assess non-clinical samples repeatedly at short time intervals (e.g. minutes, hours or days) in natural settings (i.e. ecological momentary assessments). Indeed, ecological momentary assessment studies capture inter- and intra-individual differences in the experience of situations as they occur in real time and life, which reduces biases that hamper traditional, retrospective survey or lab-based data (Wrzus & Mehl, 2015).

The advent of mobile and smart-phones as people's omnipresent companions has paved the way for ecological momentary assessment studies in all areas of psychology (Harari, Lane, Wang, Crosier, Campbell, & Gosling, 2016), including mood and cognition. Indeed, two previous studies used mobile phone technology to collect ecological momentary assessments and to investigate if changes in mood were associated with contemporaneous changes in cognitive function (i.e. coupling effects; details below). However to the best of our knowledge, no previous ecological momentary assessment study has explored the effect of situational cues on cognitive function. The current study addresses this gap, because we report here for the first time data collected with a smartphone application (app) that assessed users repeatedly on cognitive function and situational cues, as well as on mood.

In the following, we first review the findings from two previous phone-based ecological momentary assessment studies that investigated coupling effects between changes in mood and cognitive function. We then describe the three recent ecological assessment studies that tested the effect of situational cues on mood, before introducing app *moo-Q* that was developed for the current study.

Coupling effects between changes in mood and in cognitive function

The dual-task perspective argues that cognitive resources are limited and can either be allocated to performing a given task or to affective experiences and other task-unrelated cognitive processes (Ellis & Ashbrook, 1988; Goschke & Bolte, 2014). Accordingly, emotion regulation, especially that of extreme negative emotions, has been shown to be cognitively costly and to impair short- and long-term cognitive performance (Goschke & Bolte, 2014; Joormann, 2008). For example, adults, who experienced negative moods after recalling negative, neutral or positive life events while listening to condition-matched music during a mood induction, performed worse in short-term memory and processing speed tasks than adults who experienced positive moods (Stanley & Isaacowitz, 2011).

To date, five independent studies have been reported in the psychological literature that repeatedly assessed mood and cognitive function to test coupling effects between the respective within-person variances (von Stumm, 2016). Three of these were lab-based, which affects mood and cognitive function in ways that do not occur in everyday life, compared to ecological momentary assessments that allow capturing mood and cognition 'on-the-go' and independent of lab-related influences (von Stumm, 2016).

In the first of the remaining two studies that employed ecological momentary assessments, 271 American adults were recruited and received specifically programmed pilot palm devices that prompted them at pseudo-random times to rate their mood and to complete six cognitive tests (Salthouse & Berish, 2005). Across 30 assessments over the course of 5 days, no coupling effects were observed between the within-person differences in mood and the within-person differences in the six cognitive abilities (Salthouse & Berish, 2005). The second study equipped 371

German adults with pre-set mobile phones that alerted participants overall 54 times over the course of 9 days to rate their mood and complete working memory tasks (Riediger, Wrzus, Schmiedek, Wagner, & Lindenberger, 2011). The authors reported that working memory performance was impaired when participants experienced greater negative affect, suggesting that within-person changes in mood and in cognitive function are coupled (Riediger et al., 2011). Their findings confirmed that bad mood is cognitively costly (e.g. Ellis & Ashbrook, 1988) but failed to corroborate the benefits of positive mood for cognitive task performance (cf. Goschke & Bolte, 2014; Isen et al., 1987; Storbeck, 2016). Because both previous ecological momentary assessment studies (a) were adequately powered, (b) employed reliable measures for cognition and mood, and (c) differed only minimally in analytical strategy, it is difficult to explain their discrepancy in findings (von Stumm, 2016).

Ecological momentary assessment studies of mood and situational cues

Situational cues broadly describe a person's environment, including "(a) persons and interactions (who?); (b) objects, events, and activities (what?); and (c) spatial location (where?)" (p. 679, Rauthmann et al., 2014). We identified three previous studies that collected ecological momentary assessments of different situational cues and mood from typical samples (i.e. not clinical). The first asked 517 adolescent 8th to 10th graders to use an 'ecological momentary assessment device' for reporting their mood and contemporaneous activities 5 to 7 times per day over the course of a week (Weinstein & Mermelstein, 2007). Adolescents reported the highest positive and lowest negative affect when engaged in activities related to 'party', while doing schoolwork was linked to the lowest positive and highest negative affect

(Weinstein & Mermelstein, 2007), suggesting that adolescents experienced better mood during leisure time compared to study-related activities.

The second study collected data through the app Mappiness for iOS, which asked users at random times of the day to (a) rate how awake, happy and relaxed they felt, (b) state the activities that they were currently engaged in and whom they were with, and (c) describe their location, which was also assessed through the phone's inbuilt Global Positioning System (GPS). Mappiness users reported being happier when they were outdoors in all green or natural habitats compared to being in urban environments (MacKerron & Mourato, 2013). Subsequent analyses showed that Mapiness users' happiness and relaxation was lower when engaged in paid work than when doing any of 39 other activities, with the exception of being sick in bed (Bryson & MacKerron, 2016). Overall, the Mappiness data suggested strong effects of situational cues on contemporaneous mood.

A second app is called EmotionSense for Android, which asks users twice a day to rate their mood on a two-dimensional affect grid and also assessed users' location through self-reports and GPS (Sandstroem et al., 2016). In subsamples of more than 12,000 EmotionSense users, social situations, which were defined as being either in a 'family/ friend's house' or in a 'restaurant/ café/ pub', were associated with experiencing a better mood than when people were at home (Sandstroem et al., 2016). Furthermore, EmotionSense users reported a more positive mood when they were at home than when they were at work, confirming the findings from Mappiness (Bryson & MacKerron, 2016; MacKerron & Moutaro, 2013) and thus, that mood varies as a function of situational cues.

The Current Study

Here, we report data from the freely available iOS smartphone application (app) *moo-Q* (https://itunes.apple.com/gb/app/moo-q/id1012982181?mt=8) that assessed cognitive function, mood, and situational cues. *moo-Q* prompts users at random times during the day to complete brief measures of good and bad mood, to perform three cognitive tests, including short-term memory, processing speed and working memory, and to describe several characteristics of their current situation (e.g. location).

With these data, we are able to (a) clarify if mood changes are coupled with contemporaneous changes in cognitive function, (b) confirm previously reported associations between specific situational cues and mood changes, and (c) explore the relationship between situational cues and cognitive function. With reference to (a), we sought here to produce new evidence to add to the existing, albeit contradictory body of empirical studies. With regard to (b), we wanted to replicate earlier findings (i.e. MacKerron & Moutaro, 2013; Sandstroem et al., 2016; Weinstein & Mermelstein, 2007), predicting that that people reported a better mood when they were at home compared to being at work, and also when they were with people they knew (i.e. social situation) than alone or with strangers. We also extended previous work in this area by adding to the list of assessed situational cues to include self-reported physiological states that inform well-being (e.g. Jackowska, Ronadlson, Brown, & Steptoe, 2016; Geiger & MacKerron, 2016). We predicted that sleeping and eating enough benefitted mood and also, that having experienced intoxication through alcohol or other substances enhanced mood (Geiger & MacKerron, 2016). With regard to (c), we predicted that being at home or work was unrelated cognitive function, because both places were assumed to offer similar degrees of distraction. By contrast, we expected that being with other people was associated with poorer cognitive task performance than when being alone. Finally, we hypothesised that having slept and eaten enough benefitted cognitive test performance, while having drunk alcohol or been elsewise intoxicated resulted in poorer cognitive function.

Insert Figure 1 Here

METHODS

Sample

Between its launch date on 24/08/2015 and the start of the current analysis on 24/01/2016, corresponding to a data collection phase of exactly 6 months, 24,313 people downloaded and registered for *moo-Q*, which was specifically developed for this study and continues to be freely available for download. Participants came from 154 countries around the world (Figure 1), and are herein referred to as registration sample. The registration sample included 16,615 (68%) men, 7,483 (31%) women, and 215 (<1%) people, who preferred not to state their gender. Self-reported age ranged from 18 to 118 years, with a mean of 31.44 (SD = 1.09).

Procedure

To encourage mass participation and create a crowd-sampling moment, *moo-Q* was extensively advertised in print, online and social media, via TV and radio, at scientific meetings, through research societies, and to undergraduate psychology programs in the UK and US. The download frequency and number of active users of *moo-Q* peaked after the application's launch in late August 2015 with a maximum of 5,670 new user registrations and 7,061 completed *moo-Q* responses. By January 2016, new registrations had notably declined, averaging about 5 per day. Likewise, the number of active users declined to an average of approximately 20 responses per day in January 2016. Thus, data for the current analyses were collected during the first five months following *moo-Q's* launch (i.e. all data obtained between 24/08/2015 to 24/01/2016). That said, *moo-Q* is still available at the Apple App Store and counts daily new registrations and active users.

Participants downloaded *moo-Q* for free from the Apple Store and consented to sharing their data, before indicating their demographic background and choosing alert settings that defined the frequency of alerts per day (1 to 4) within users' preferred time window (i.e. within 24 hours of the day). Participants completed *moo-Q* at times unique to themselves, but the order in which tests were presented was fixed to the assessment count. In other words, two participants who completed *moo-Q* for the third time were assessed on exactly the same items, even though the date and time of completion differed. *moo-Q* presented measures in the following fixed order: mood, short-term memory, processing speed, working memory, and information about users' surroundings (i.e. situation cues). Completing the app took on average 2 minutes. After completing *moo-Q* five times in response to alerts, users unlocked personalised feedback charts that plotted their mood and cognitive function across assessment occasions in time.

Measures

Cognitive function. The cognitive measures were specifically developed for *moo-Q* and previously validated in a lab-based study, which is described in detail in von Stumm (2016) and briefly summarized here. To reliably capture within-person and between-person differences in cognitive function across repeated assessments using a smartphone app, we adapted three cognitive from a previous study that sought to repeatedly assess short-term and working memory (Brose, Schmiedek, Loevden, & Lindenberger, 2012) and from the ETS testing kit (Ekstrom, French, Harman, & Dermen, 1976). Items needed to be comparable in difficulty and discrimination across assessment occasions to ensure the independence of within- and between-person differences and thus, all tests' items varied only in content (i.e. letters and numbers) rather than by structure or logic. The tests are illustrated in Figure 2. Prior to adaptation for moo-Q, 98 undergraduates completed the tests, together with two traditional cognitive ability measures of logical and spatial reasoning (i.e. lettersets and cube comparisons; Ekstroem et al., 1976) five times on consecutive days (von Stumm, 2016). 99% of the test scores' inter-correlations were positive with an average r = .27, suggesting that the three newly developed cognitive tests corresponded to the established measures' scores and thus, that between-person differences in cognitive function were reliably assessed. In addition, significant training effects across the five study days were observed in the three cognitive tests, suggesting that the scores also captured systematic within-person differences (i.e. gains, von Stumm, 2016).

For moo-Q, all item contents (i.e. letters and numbers) for the different test versions were randomly generated. *Short-term memory*: Columns that consisted of 5 or 7 number pairs or of 5 number quartets were shown individually for 7 seconds. After each, participants were asked to recall the number pairs or quartets in order within 30 seconds. Overall, the test included 22 items. Items with shorter number pairs were shown first, so that items were arranged to increase in difficulty. *Processing speed*: 10 pairs of strings that each consisted of 13 letters and numbers were shown for 15 seconds. Participants had to mark the string pairs that were identical. When strings of a pair differed they differed by one letter or digit. *Working memory*: A column that consisted of single or double-digit numbers was presented for

5 seconds, followed by a second column of matched single or double-digit numbers with mathematical operators (+/-) presented for 5 seconds. Participants were asked to enter the correct sums in order on a third screen within 30 seconds. This test included 16 items. Again, items were arranged to increase in difficulty within each assessment occasion.

Insert Figure 2

Mood. Users rated their overall mood on six items using 1 to 5 scale sliders. Three items had positive valence (i.e. happy, relaxed, awake) and three had negative valence (nervous, distressed, irritable). These items were selected because they captured the greatest amount of variance in mood across assessment occasions in a previous lab-based study (von Stumm, 2016). Also, the items for good mood were previously implemented in Mappiness (MacKerron & Moutauro, 2013). Mood items were presented in a fixed alternate order, starting with a positive item.

Situation cues. Participants stated first if they were (a) alone or with strangers versus (b) with people that they knew. They then indicated if they were (a) work, (b) home, or (c) elsewhere; the latter was excluded from the current analyses. To assess physiological states, users reported if (a) they had slept enough, (b) eaten enough, (c) drunk alcohol, and (d) been otherwise intoxicated.

RESULTS

The analysis sample

Although users could complete *moo-Q* at any time that they wanted to, only completions that were in response to an alert were considered valid momentary assessments, because they precluded biases due to participants self-selecting the completion time. Likewise, *moo-Q* completions that occurred more than 1 hour after the alert were treated as invalid momentary assessments. Out of 76,860 recorded app completions, (a) 17,276 were given not in response to a *moo-Q* alert; (b) 25,670 were submitted more than 1 hour after the application alert; and (c) 59 were associated with negative response times (i.e. response prior to the alert), which occur when users travel and change time zone. All these app responses were excluded. Because reliable estimates of changes in mood and cognitive function require 10 but preferably more assessments (Wang & Grimm, 2012), our final analysis sample included 770 participants, who had produced 10 or more valid *moo-Q* responses (overall 17,735 valid *moo-Q* completions). The sample size and number of retained *moo-Q* responses correspond to 3.2% of the registration sample and 23.1% of all *moo-Q* responses (Figure 1).

Demographic differences between analysis and registration sample

The analysis sample included 525 men (68%), 242 women (31%), and 3 (<1%) participants who did not indicate their gender (Figure 1). This gender distribution was identical to the registration sample (i.e. 16,615 (68%) men, 7,483 (31%) women, and 215 (<1%) gender non-identified). Participants in the analysis sample came from overall 56 countries compared to 154 countries in the registration sample. In both samples, the majority of *moo-Q* users came from Australia, Iran, United Kingdom, and United States. Participants from these four countries accounted for 57% and 55% of all participants in the analysis and registration sample, respectively. Age in the analysis sample ranged from 18 to 75 years with a mean of

35.38 (SD = 1.29), which was significantly older than the registration sample by almost 4 years (mean = 31.44; SD = 1.09).

Insert Table 1

Psychological differences between analysis and registration sample

A logistic regression model tested for differences in mood and cognitive test performance between the analysis and the sample of people who completed *moo-Q* once (i.e. for the first time; $N = 15{,}262$). Note that comparing the analysis sample to the entire registration sample is not possible because only 60% of the registration sample completed at least once the assessments of mood and cognitive function. All variables were *z*-transformed and entered simultaneously to estimate the odds associated with one SD increase in each predictor of being in the analysis versus the registration sample (Table 1). Only two odds ratios were associated with Confidence Intervals of 95% that excluded 1, suggesting they differed significantly between the analysis and registration sample. For one, being one SD above the mean in feeling awake when first completing *moo-Q* was associated with a 22% increase in the odds of being in the analysis sample compared to the registration sample. Likewise, a SD increase in working memory when first completing *moo-Q* was associated with 30% higher odds for continuing with the app and being included in the analysis sample.

App completion rates in analysis and registration sample

In the registration sample, participants completed *moo-Q* on average 5 times (SD = 11.00) ranging from once to a maximum of 358 times (Figure 3). The completion rates did not differ between men (N = 10,071; mean = 5.01; SD = 11.28) and women (N = 5,170; mean = 5.00; SD = 1.55) but participants who preferred not to state their gender completed *moo-Q* fewer times (N = 108; mean 3.81; SD = 5.81). In the registration sample, age and completion rates correlated at .13. By comparison, participants in the analysis sample completed moo-Q on average 23 times (SD = 18.29) ranging from 10 to a maximum of 207 completions (Figure 3). Again, completion rates did not differ between men (N = 525; mean = 23.01; SD = 18.87) and women (N = 242; mean = 23.15; SD = 17.10), while participants who did not state their gender completed moo-Q fewer times (N = 3; mean = 18.00; SD = 1.39). In the analysis sample, age and completion rates correlated at .12.

Insert Figure 3 Here

Reliability

All reliability analyses were conducted in the analysis sample. For all cognitive tests, correct responses were coded as 1 and incorrect or missed answers were coded as 0. The mood ratings were scored from 0 to 1 with .25 increments.

Internal consistency of mood and cognitive function

Cronbach's alpha is known to be limited as measure of internal consistency (Sijtsma, 2009), although it continues to be the most frequently reported statistic for psychometric test evaluation. Here, we report Cronbach's alpha, which most readers will be familiar with, as well as the greater lower bound of the Guttman split-half reliability (glb; Guttman, 1945). glb estimates the communalities of the test items from a factor model, where the number of factors is the number with positive Eigenvalues (Revelle, 1979), and is a more adequate statistic for internal consistency than Cronbach's alpha, especially when analysing binary variables (Sijtsma, 2009). All reliability estimates were computed in R with the psych package (Revelle, 2016).

For these analyses, the first five test versions (i.e. first five *moo-Q* assessments that participants completed) were used, which we assume to be representative of all later assessments.

Table 2 shows the internal consistency values for the cognitive tests short-term memory, processing speed and working memory. Overall, the internal consistency values suggested that short-term memory and working memory were highly reliable tests with glb coefficients ranging between .78 and .92 and Cronbach's alpha values from .66 to .82. By comparison, internal consistency values for processing speed were markedly lower, ranging from .61 to .72 for glb and .41 to .51 for Cronbach's alpha. Cronbach's alpha coefficients for good mood, including relaxed, happy and awake, ranged from .56 to .71 (mean = .62) and the respective glb values ranged from .61 to .75 (mean = .73). For bad mood, including distressed, nervous, and irritable, Cronbach's alpha coefficients ranged from .75 to .82 (mean = .79) and the respective glb values ranged from .76 to .81 (mean = .79) Good and bad mood were negatively correlated ranging from -.44 to -.53 across five assessment times (mean = -.48). This correlation is substantially higher than in other studies (e.g. Watson, Clark, & Tellegen, 1988; von Stumm, 2016) and suggests that measures of good and bad mood captured overlapping, rather than independent constructs spaces (Russell & Barrett, 1999). Even so, good and bad mood remain sufficiently independent, because they share on average only 25% of variance with one another, to be treated as separate entities in the analyses. As the internal consistency coefficients for all measures were by and large satisfactory, unit-weighted composites were computed for short-term memory, processing speed, and working memory, as well as for good and bad mood, for the subsequent analyses.

Insert Table 2 & 3

Temporal stability of mood and cognitive function

To examine the stability of moo-Q's cognitive measures across time, the cognitive scores' inter-correlations across five assessment occasions were first computed[1]. In a next step, intra-class correlations were estimated for mood and cognitive function across all assessment occasions, using the R package ICC (Wolak, 2015).

Table 3 shows the cognitive scores' inter-correlations across five assessment occasions after pairwise omission. Within-test correlations ranged from .36 to .59 for short-term memory (mean = .50), and from .48 to .66 for working memory (mean = .58). For processing speed, the correlations were notably lower, ranging from -.16 to .29 with an average of .12. Short-term and working memory scores correlated on average .37 across the five assessment occasions, while processing speed scores correlated on average .08 and .11 with short-term and working memory scores, respectively. Overall, these coefficients suggest that short-term and working memory scores had adequate test-retest reliability across assessment occasions. Also, they were consistently positively inter-correlated, as expected by the positive manifold of g (Carroll, 1993). By contrast, the processing speed scores differed mainly within rather than between individuals and accordingly, did not correlate with the other two

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[1] We excluded the first assessment in this analysis, because the sample size at this time was very low (N =51). Instead, we conducted the analysis using data from the assessment occasions 2 through 6. The reason for comparatively small N at time 1 is that most moo-Q users completed *moo-Q* for the first time not in response to an alert and thus, their *moo-Q* response was invalid and excluded (see above).

cognitive tests. Thus, the processing speed task appeared to be an unreliable measure of cognitive function.

The intra-class coefficients for all measures are shown in Figure 4. For all variables, except processing speed, participants differed as much within themselves as between each other. That is, about half of the variance in good and bad mood and working and short-term memory was intra-individual and the other half was inter-individual. For processing speed, the majority (91%) of the variance was within individuals, in line with the low test-retest values reported above. Because processing speed was repeatedly found to lack the psychometric qualities of a good test in the current analysis, the processing speed scores were excluded from all further analyses.

Insert Figure 4 here

Situation cues, mood and cognitive function

To test the relationship between situation cues and mood, mixed level linear effects modelling was applied using the lme4 package in R (Bates, Maechler, & Bolker, 2012). Mood and cognitive function were predicted by dummy codes (i.e. 0 versus 1) for people (i.e. with familiar people versus alone), location (home versus work[2]), and four physiological characteristics (i.e. not versus (a) slept enough, (b) eaten enough, (c) drunk alcohol, (d) otherwise intoxicated), which were at level 1 and grouped within participants (level 2). Fixed effects were specified for linear time trends (e.g. training gains in cognitive test performance) and the situation characteristics, while random effects were specified for situation characteristics by assessment occasion and participant. Models were fitted separately for each outcome

[2] The category 'elsewhere' was omitted from the current analyses.

(i.e. short-term and working memory, and good and bad mood) and predictors (i.e. people, location and four physiological states). Accordingly, the *p*-value for coefficients was adjusted to .002 (i.e. conventional *p*-value of .05 divided by 24 models). All models were rerun adjusting for gender, age and country of download, which did not alter the results.

Being alone versus with people you know

Out of 17,735 total *moo-Q* responses in the analysis sample, 57% were completed alone or when only surrounded by strangers and 43% while participants were with people they knew. Confirming Sandstroem et al.'s (2016) findings, being alone rather than with familiar people was negatively associated with good mood (β = -.05, SE = .01, t = -5.43, $p < .001$) and positively with bad mood (β = .03, SE = .01, t = 2.86, $p = .004$; non-significant after Bonferroni correction). Furthermore, being alone rather than with familiar people was positively associated with short-term memory (β = .46, SE = .05, t = 9.32) and with working memory performance (β = .38, SE = .04, t = 9.25; $p < .001$ in both cases). In short, participants reported worse mood but better cognitive performance when they were alone than when they were with people they knew.

Being at home versus at work

Overall 55% of the responses where provided when people were at home, and 29% were completed when they were at work (the remaining 16% were completed 'elsewhere'). Confirming Sandstroem et al.'s (2016) findings, being at work rather than home was negatively associated with good mood (β = -.06, SE = .01, t = -4.90, $p <$ .001) and also positively associated with bad mood (β = .12, SE = .01, t = 9.49, p <

.001), suggesting that people experienced worse mood at work and better mood at home. For cognitive performance, being at work versus home benefitted short-term memory performance (β = .17, SE = .05, t = 3.27, p < .002) but the positive association with working memory was not significant (β = .09, SE = .05, t = 2.07, *p* = .039), suggesting that location effects on cognitive performance were somewhat inconsistent.

Having slept and eaten enough

Overall, 75% and 61% of *moo-Q* responses were provided when participants had slept and eaten enough, respectively. Having slept enough was positively associated with good mood (β = .25, SE = .01, t = 21.67) and negatively with bad mood (β = -.12, SE = .01, t = -1.92, *p* < .001 in both cases). Likewise, having slept enough benefitted short-term memory (β = .18, SE = .05, t = 3.68) and working memory (β = .20, SE = .04, t = 4.89, *p* < .001 in both cases). Having eaten enough was positively associated with good mood (β = .12, SE = .01, t = 12.09) and negatively with bad mood (β = -.09, SE = .01, t = -7.86, *p* < .001 in both cases). Having eaten enough benefitted working memory (β = .20, SE = .04, t = 4.40, *p* < .001) but was not significantly associated with short-term memory performance (β = .07, SE = .05, t = 1.46, *p* = .144). Overall, having slept and eaten enough were reliably associated with better mood, and also with cognitive performance, except that there was no relationship between having eaten enough and short-term memory.

Alcohol and other intoxication

Around 6% and 4% of the responses were completed when participants had drunk alcohol or been elsewise intoxicated. Having drunk alcohol or been intoxicated was not significantly associated with good mood (alcohol: β = .03, SE = .02, t = 1.80, p = .072; intoxicated: β = -.10, SE = .03, t = -3.05, p = .002). However, having drunk alcohol related negatively to bad mood (β = -.13, SE = .02, t = -6.20, p < .001), while having been intoxicated was not significantly associated (β = .10, SE = .04, t = 2.42, p = .015). Having drunk alcohol was negatively associated with short-term memory (β = -.51, SE = .09, t = -5.57, p < .001) and with working memory (β = -.46, SE = .09, t = -5.88, p < .001). By contrast, having been intoxicated was neither significantly associated with short-term memory (β = -.28, SE = .13, t = -2.18, p = .029) nor with working memory (β = -.37, SE = .14, t = -2.54, p = .011). We caution that these results are based on a comparatively small number of *moo-Q* responses from a fractional proportion of participants in the analysis sample (N = 337 for alcohol, and N = 159 for elsewise intoxicated). That said, alcohol appeared to be linked with reduced bad mood and impaired cognitive test performance, while having been intoxicated was neither related to mood nor to cognitive performance.

Coupling effects between changes in mood and cognitive function

As before, mixed level modelling with the lme4 package was applied (Bates et al., 2012). Fixed effects on cognitive function were specified for a time trend (i.e. cognitive training gains) and for mood, which was the main effect and independent of changes in mood that occurred within a participant across assessment occasions. Random effects were specified for participants' mood that deviated from the population and that was not associated with systematic mood changes (i.e. random error). Random effects were also specified for the systematic within-person changes in mood, which are here of primary interest because they describe reliable changes in mood. While p-values from t-statistics can be reported for fixed effects, the explanatory power of random effects can only be inferred from comparing the fits of baseline models without the random effects for reliable changes in mood to that of models including random effects for mood changes (Bates et al., 2012). The *p*-value for model comparisons was adjusted to .013, because models were fitted separately for good and bad mood and short-term and working memory (i.e. conventional p-value of .05 by 4).

The fixed effects of good mood were neither significantly associated with short-term memory (β = .10, SE = .05, t = 2.09 *p* = .037) nor with working memory (β = 07, SE = .04, t = 1.87, *p* = .061). Likewise, the fixed effects of bad mood were not significantly associated with short-term memory (β = -.09, SE = .05, t = -1.89, *p* = .059). However, they were negatively related to working memory (β = -.10, SE = .04, t = -2.66, *p* = .007). The comparisons of the models including random effects for mood (i.e. reliable within-person changes in mood) suggested that changes in good and bad mood were not coupled with changes in short-term and working memory. Corresponding χ^2 differences (df 2) ranged from .21 to 2.72 with the associated *p*-values exceeding .05. The results did not change, when men and women were analyzed separately. Overall, these findings suggested that participants who scored higher on good or bad mood relative to the rest of sample did not perform systematically better or worse in the cognitive tests. Furthermore, the fluctuations in mood that a person experienced within themselves over time were not associated with contemporaneous changes in their cognitive performance (i.e. intra-individual variance). The failure to detect coupling effects cannot be explained by a lack of variance in mood or cognitive function, which both fluctuated substantially and to a similar extent across assessments. In summary, cognitive test performance was neither improved nor impaired when participants reported contemporaneously better or worse mood.

DISCUSSION

In the current study, approximately half of the differences in mood and in cognitive function occurred between people and half within people, in line with previous reports (von Stumm, 2016; Zheng, Plomin & von Stumm, 2016). This finding underscores the principal importance of studying within-person differences in behavioural science.

In the following, we will first discuss our findings on the relationship between situation cues and mood, which partly replicates pervious work (e.g. MacKerron & Moutauro, 2013; Sandstroem et al., 2016; Weinstein & Mermelstein, 2007), before addressing associations between situation cues and cognitive function, which are here reported for the first time. Subsequently, we will address our findings about the coupling (or lack thereof) between changes in mood and in cognitive function. Finally, the utility of smartphone-based ecological momentary assessments for the study of emotional and cognitive states will be discussed.

Situational cues and mood

Confirming previous results, (MacKerron & Moutauro, 2013; Sandstroem et al., 2016), *moo-Q* users reported generally better mood -- that is, more good mood and less bad mood -- when they were at home than when they were at work. Also akin to previous research (MacKerron & Moutauro, 2013; Sandstroem et al., 2016; Weinstein & Mermelstein, 2007), *moo-Q* users reported higher levels of good mood when they were with people they knew compared to when they were alone or surrounded by strangers.

Extending previous studies, we found that *moo-Q* users experienced a generally better mood at times when they had slept and eaten enough. Furthermore having drunk alcohol was not associated with elevated good mood but with reduced bad mood. By comparison, having been intoxicated otherwise was not significantly associated either mood or cognitive function, which may be due to the small number of 'intoxicated responses' observed here (4%), as well as to not differentiating various kinds of intoxication in the current study (i.e. stimulants versus depressants). Overall and perhaps unsurprisingly, people experienced better mood when they were engaged in leisure activities, and when their core physiological needs had been met.

Situational cues and cognitive function

Confirming our hypothesis, people performed better in short-term and working memory tasks when they were alone compared to when they were with people they knew. Partly confirming our hypothesis, working memory performance did not differ when *moo-Q* was completed at work versus at home, but short-term memory was improved during at-work-completions. A plausible explanation for the improved cognitive performance when alone or at work is that the latter help focusing one's attention, while being at home or with familiar people distracts from the focus on the cognitive tests. Here, we would assume that being at home or with familiar people does not truly dampen people's cognitive ability, in the sense that being at home does not lower cognitive ability per se. Instead, our findings are likely to be a result of differences in situational demands. However under this view, we might have to also question the interpretation of the relationship between situation characteristics and mood: Does being with familiar people really produce positive emotional experiences or merely distract from completing the mood assessment with focus? Future research will have to investigate to what extent within-person changes in psychological function can be attributed to differences in situation-dependent demands on engaging with smartphone-based ecological momentary assessments.

As expected, having slept enough was associated with improved cognitive function, while having eaten enough was less consistently linked to cognitive task performance. Thus, the effects of having eaten enough on cognitive performance appear to be less pervasive than those of enjoying sufficient amounts of sleep, in line with other studies that highlighted the importance of sleep for functioning and well-being (Jackowska et al., 2016). Having drunk alcohol was associated with impaired cognitive function, but experiencing other types of intoxication was not. The negative effect of drinking on cognitive performance is well-established and underlies many policies (e.g. legal drinking limits for driving) and thus, the findings are in line with the scientific literature and legal practice. Overall, situational cues appeared to influence cognitive function in comparable ways and to similar degrees as they affect mood.

Coupling effects in mood and cognitive function

Typical changes in mood -- as they happen in everyday life -- were not coupled with contemporaneous changes in cognitive performance in the current study. The failure to detect coupling effects cannot be explained by a lack of variance in mood or cognitive function, which both fluctuated substantially to similar extents across assessments within our participants. This "null" finding is in line with one previous study that analysed ecological momentary assessments of mood and cognitive performance (Salthouse & Berish, 2005) but contradicts another (Riediger et al., 2011). Although the cause for the discrepancy in results across the three studies is unclear, it is worth noting here that our sample was larger than the combined sample sizes of the two previous studies (Salthouse & Berish, 2005; Riediger et al., 2011). Also, our measures for mood and cognition were reliable and our participants completed a sufficient number of *moo-Q* responses (on average 23). Furthermore, our results regarding the relationship between situation characteristics and mood were consistent with earlier findings, confirming that our measures were valid, too. Overall, our study was well powered to detect associations between typical changes in mood and contemporaneous changes in cognitive function.

Although it may be sobering at first that typical changes in mood have little bearing on people's cognitive function, this finding ultimately conveys a positive message about the resilience of cognitive function against typical mood fluctuations. Of course, this result does not preclude that cognitive function will be affected by extreme mood changes that are more cognitively costly to regulate (Ellis & Ashbrook, 1988; Jormann, 2008). These are, however,, unlikely to be captured in a smartphone-based ecological momentary assessment study.

Smartphones for mood and cognition research

Smartphone applications offer vast possibilities for psychological and behavioural science, because they enable repeatedly assessing very large samples on complex trait variables on-the-go -- that is, in natural settings and environments. Indeed, *moo-Q* reached an extremely large sample that was diverse in age, gender and nationality. Although our sample was opportunistic, as is the case in all studies that are based freely available smartphone apps (MacKerron & Moutauro, 2013;

Sandstroem et al., 2016), it is not necessarily less representative of the general population than samples in traditional ecological momentary assessment studies (Riediger et al., 2011; Salthouse & Berish, 2005) or in psychological research in general (Stewart et al., 2015). That said, our registration sample differed markedly from other samples that have been described in the psychological literature (Buhrmester, Kwang, & Gosling, 2011), including a substantially higher proportion of male participants (68%), and a higher average age (about 31 years) than typical in web-based and lab-based psychology studies (around 25% males and average age of 25 years; Gosling, Vazire, Srivastava, & John, 2004).

While our registration sample was extremely large with more than 24,000 participants, the analysis sample was considerably smaller with 770 participants. Data loss was due to (a) invalid app completions (56%) and (b) too few app completions (i.e. less than 10 or more assessments; 21%), amounting 77% of app responses that were excluded. Despite the dramatic reduction in sample size, the analysis sample remained representative of the registration sample with regards to the gender and nationality; both were also psychologically remarkably similar. However, the samples differed in age by about 4 years, with older people being more likely to complete *moo-Q* 10 times or more and thus, to be included in the analysis sample. Future research must investigate how to reduce data loss in smartphone-based ecological momentary assessment studies, for example by successfully incentivizing participants to continuously respond to the app's alerts, for example through the gamification of measures or personalised feedback.

To the best of our knowledge, *moo-Q* is the first app to repeatedly assess cognitive function. Our reliability analyses showed satisfactory internal consistency and temporal stability for two out of three cognitive tests. While these tests are clearly not suited to mark a person's full-scale intelligence, they adequately captured within- and between-person differences in the performance of simple cognitive tasks. Therefore, our study demonstrates that reliable momentary assessments of cognitive function are possible and as a consequence, we hope it will encourage future ecological momentary assessment studies of cognition.

Conclusions

The current study demonstrated that mood and cognitive function vary as a function of situational cues. Specifically, people experienced better mood in situations that are associated with leisure (e.g. at home, with friends), and they showed enhanced cognitive function, when they were in situations that allow focusing attention (e.g. alone, at home and sober). Furthermore, changes in mood were found to be unrelated to contemporaneous changes in cognitive function, suggesting that within-person differences in both domains are not coupled. We therefore conclude that the experience of positive and negative mood states that ensue in every day life does not interfere with people's thinking capacity.

References

Bates, D. M., Maechler, M., & Bolker, B. (2012). lme4: Linear mixed-effects models using S4 classes. R package version .999999.

Brose, A., Schmiedek, F., Lövdén, M., Molenaar, P. C. M., & Lindenberger, U. (2010). Adult age differences in covariation of motivation and working memory performance: Contrasting between-person and within-person findings. *Research in Human Development, 7,* 61-78.

Brose, A., Schmiedek, F., Lövdén, M. & Lindenberger, U. (2012). Daily variability in working memory is coupled with negative affect: The role of attention and motivation. *Emotion, 12,* 605-617.

Bryson, A., & MacKerron, G. (2016). Are you happy while you work? *The Economic Journal*: doi:1.1111/ecoj.12269.

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science*, *6*, 3–5.

Carroll, J. B. (1993). *Human cognitive abilities: A survey of factor-analytic studies.* Cambridge University Press, New York: USA.

Deary, I. (2012). Intelligence. *Annual Review of Psychology, 63*, 453-82.

Ekstrom, R. B., French, J. W., Harman, H. H. & Dermen, D. (1976). *Manual for kit of factor- referenced cognitive tests*. Princeton, NJ: Educational Testing Service.

Ellis, H. C., & Ashbrook, P. W. (1988). Resource allocation model of the effects of depressed mood states on memory. In K. Fiedler & J. Forgas (Eds.), *Affect, cognition, and social behavior* (pp. 35–42). Göttingen: Hogrefe.

Geiger, B. B., & MacKerron, G. (2016). Can alcohol make you happy? A subjective well-being approach. *Social Science & Medicine. 156*, 184-191.

Goschke, T., & Bolte, A. (2014). Emotional modulation of control dilemmas: the role of positive affect, reward, and dopamine in cognitive stability and flexibility. *Neuropsychologia, 62*, 403-423.

Gosling, S. D., Srivastava, S., & John, O. P. (2004). Should we trust web-based studies? *American Psychologist, 59,* 93-104.

Guttman, L. (1945). A basis for analyzing test-retest reliability. *Psychometrika, 10*, 255-282.

Harari, G. M., Lane, N., Wang, R., Crosier, B., Campbell, A. T., & Gosling, S. D. (2016). Using Smartphones to Collect Behavioral Data in Psychological Science: Opportunities, Practical Considerations, and Challenges. *Perspectives on Psychological Science, in press*.

Isen, A.M., Daubman, K.A., & Nowicki, G. P. (1987). Positive affect facilitates creative problem solving. *Journal of Personality and Social Psychology, 52,* 1122-1131.

Jackowska, M., Ronaldson, A., Brown, J. & Steptoe, A. (2016). Biological and psychological correlates of self-reported and objective sleep measures. *Journal of Psychosomatic Research, 84,* 52-55.

MacKerron, G., & Moutauro, S. (2013). Happiness is greater in natural environments. *Global Environmental Change, 23*, 992-100.

Joormann, J. (2008). Cognitive aspects of depression. In I.H. Gotlib & C. Hammen (Eds.), *Handbook of depression, pp. 298-321*. New York, NY: Guilford Press.

Mitchell, R. L., & Phillips, L. H. (2007). The psychological, neurochemical and functional neuroanatomical mediators of the effects of positive and negative mood on executive functions. *Neuropsychologia, 45,* 617-629.

Rauthmann, J. F., Gallardo-Pujol, D., Guillaume, E. M., Todd, E., Nave, C. S., Sherman, R. A., Ziegler, M., Bell Jones, A. & Funder, D. C. (2014). The Situational Eight DIAMONDS: A taxonomy of major dimensions of situation characteristics. *Journal of Personality and Social Psychology*, *107*(4), 677.

Russell, J. A., & Barrett, L. F. (1999). Core affect, prototypical emotional episodes, and other things called emotion: Dissecting the elephant. *Journal of Personality and Social Psychology. 76,* 805–819.

Revelle, W. (1979). Hierarchical cluster-analysis and the internal structure of tests. *Multivariate Behavioral Research*, *14*, 57-74.

Revelle, W. (2016). psych: Procedures for psychological, psychometric, and personality research. R package version 1.6.6.

Riediger, M., Wrzus, C., Schmiedek, F., Wagner, G. G., & Lindenberger, U. (2011). Is seeking bad mood cognitively demanding? Contra-hedonic orientation and working- memory capacity in everyday life. *Emotion*, *11*, 656–665.

Salthouse, T. A., & Berish, D. E. (2005). Correlates of within-person (across-occasion) variability in reaction time. *Neuropsychology*, *19,* 77-87.

Sandstrom, G. M., Lathia, N., Mascolo, C., Rentfrow, J. (2016). Putting mood in context: Using smartphones to examine how people feel in different locations. *Journal of Research in Personality, in press.*

Stanley, J. T., & Isaacowitz, D. M. (2011). Age-related differences in profiles of mood-change trajectories. *Developmental Psychology, 47,* 318-330.

Stewart, N., Ungemach, C., Harris, A. J. L. X., Bartels, D. M., Newell, B. R., Paolacci, G., & Chandler, J. (2015). The average laboratory samples a population of 7,300 Amazon Mechanical Turk workers. *Judgment & Decision Making*, *10*, 479–491.

Sijtsma, K. (2009). On the use, the misuse, and the very limited usefulness of Cronbach's Alpha. *Psychometrika*, *74*, 107–12.

Storbeck, J. (2016). Is happiness a cure-all for mental fatigue? Mood interacts with situational requirements in predicting performance. *Motivation and Emotion*, *40*, 489–49.

von Stumm, S. (2016). Is day-to-day variability in cognitive function coupled with day-to-day variability in affect? *Intelligence*, 55, 1 -6.

Wang, L., & Grimm, K. (2012). Investigating reliabilities of intraindividual variability indicators. *Multivariate Behavioral Research*, *47,* 771–802.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54,* 1063-107.

Wolak, M (2015). *ICC: Facilitating estimation of the intraclass correlation.* R package version 2.3..

Wrzus, C. & Mehl, M. R. (2015). Lab and/or Field? Measuring personality processes and their social consequences. *European Journal of Personality, 29*, 250-271.

Weinstein, S. M., & Mermelstein, R. J. (2007). Relations between daily activities and adolescent mood: The role of autonomy. *Journal of Clinical Child and Adolescent Psychology*, 36, 1 – 13.

Zheng, Y., Plomin, R., von Stumm, S. (2016). Heritability of intra-individual mean and variability of positive and negative affect: Genetic analysis of daily affect ratings over a month. *Psychological Science, 27, 1611–1619.*

Table 1

Means, SDs, and Odds Ratios (OR) for moo-Q's measures across the analysis sample and the sample of people, who completed moo-Q once (i.e. for the first time)

	Once completed		**Analysis sample**		**OR**	**CI (95%)**	
	Mean	**SD**	**Mean**	**SD**		**Low**	**High**
Nervous	.32	.28	.29	.28	.98	.90	1.08
Happy	.49	.23	.50	.21	.93	.85	1.01
Awake	.52	.26	.57	.27	**1.22**	**1.13**	**1.31**
Distressed	.37	.28	.34	.28	.93	.85	1.02
Relaxed	.50	.25	.52	.26	1.01	.92	1.11
Irritable	.39	.28	.35	.29	.94	.86	1.03
Short-term memory	6.93	3.60	7.29	3.30	.98	.90	1.06
Processing Speed	6.27	1.02	6.35	.95	1.04	.96	1.12
Working memory	3.66	2.97	4.50	3.07	**1.30**	**1.21**	**1.41**

Note. Means and SDs are based on raw estimates. OR are based on z-transformed values. OR with CI(95%) excluding 1 are marked in bold.

Table 2

Internal consistency coefficients for *moo-Q's* cognitive tests across the first five test versions

		Short-term memory (n = 22)		**Processing speed (n = 10)**		**Working memory (n = 16)**	
Test version	**N**	**α**	**glb**	**α**	**glb**	**α**	**glb**
1	51	.78	.92*	.41	.61*	.82	.92*
2	353	.71	.83	.43	.53*	.77	.82
3	425	.69	.83	.51	.72	.77	.82
4	450	.66	.78	.49	.65	.73	.82
5	454	.71	.8	.43	.62*	.79	.86

*One or more items showed 0 variance. These were excluded when computing glb. A refers to Cronbach's alpha.

Table 3

Correlations between moo-Q's cognitive tests across the first five assessments

	SM1	SM2	SM3	SM4	SM5	WM1	WM2	WM3	WM4	WM5	PS1	PS2	PS3	PS4
SM1	-													
SM2	.48	-												
SM3	.51	.51	-											
SM4	.36	.47	.45	-										
SM5	.57	.53	.59	.55	-									
WM1	.42	.30	.32	.25	.28	-								
WM2	.36	.38	.37	.28	.33	.61	-							
WM3	.33	.37	.44	.38	.37	.58	.60	-						
WM4	.35	.36	.47	.45	.39	.50	.66	.60	-					
WM5	.36	.41	.43	.40	.45	.48	.63	.61	.55	-				
PS1	.04	.05	-.01	.05	-.02	.09	.03	.05	.10	.07	-			
PS2	.18	.10	.02	.14	.06	.20	.14	.09	.19	.16	.03	-		
PS3	-.04	-.07	.03	.10	-.02	.05	-.03	.05	.09	-.02	.29	-.16	-	
PS4	.01	.21	.18	.14	.13	.22	.14	.11	.18	.14	.15	.17	.26	-
PS5	.13	.09	.16	.16	.15	.17	.10	.16	.07	.17	.24	.24	-.06	.07

Note. SM is short-term memory; WM is working memory; PS is processing speed. Correlations are computed after pairwise omission.

Figure Captions

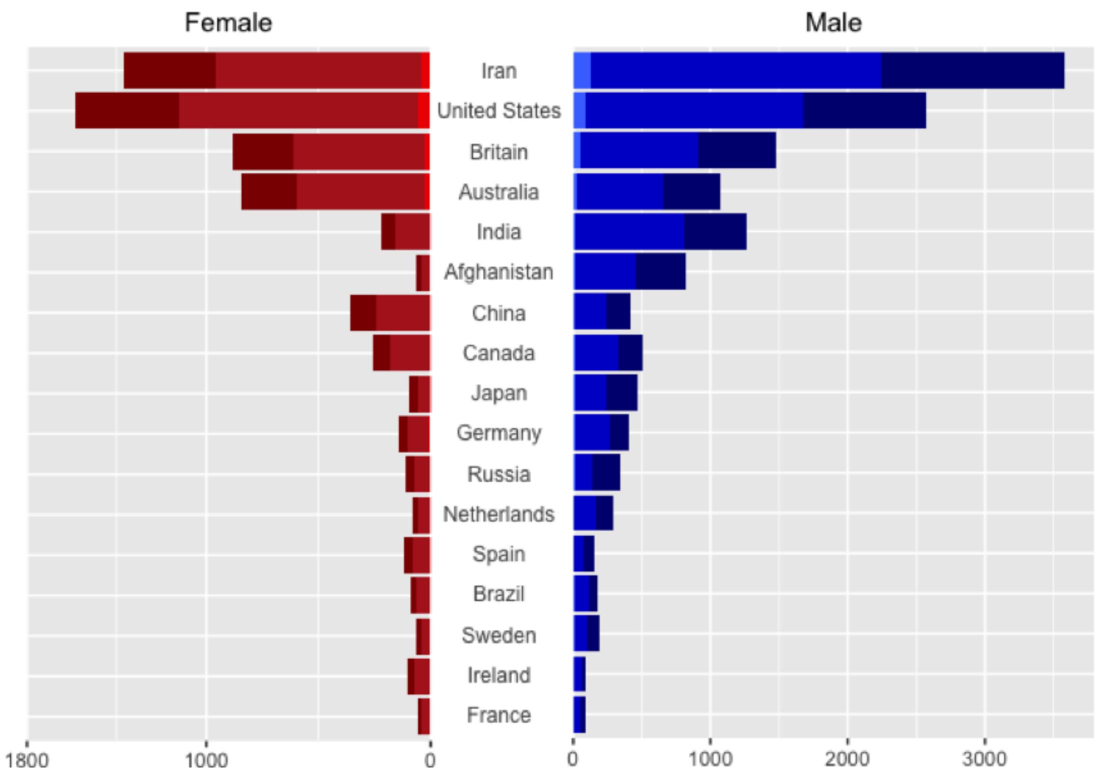

Figure 1: Numbers of *moo-Q* registrations and *moo-Q* completion rates across countries.

Note. Countries with more than 150 downloads and registrations are shown. The darkest bars represent number of registered *moo-Q* downloads (red for women, blue for men; users who did not indicate gender are not shown). The next lighter bars reflect users who completed *moo-Q* at least once, including alerted and self-triggered responses, while the lightest bars represent the number of users retained the analysis sample. Downloads and user numbers vary as a function of national media coverage; for example, *moo-Q* was heavily featured by the Persian media, resulting in a very high number of registrations in Iran.

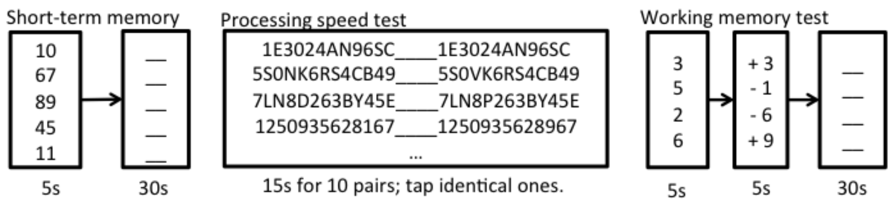

Figure 2: Cognitive tasks implemented in moo-Q.

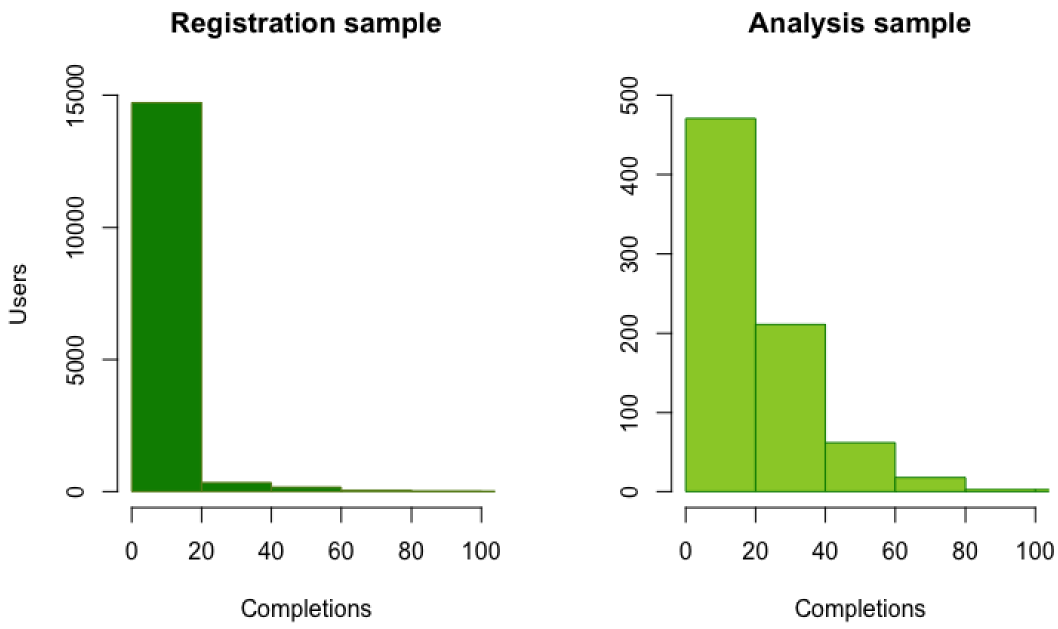

Figure 3: Moo-Q completion rates in registration and analysis sample.

Note. Completion rates from 0 to 100 are shown to maintain graphical clarity. In the registration sample, 34 participants completed moo-Q more than 100 times, and 6 did so in the analysis sample (i.e. < 1% in both cases).

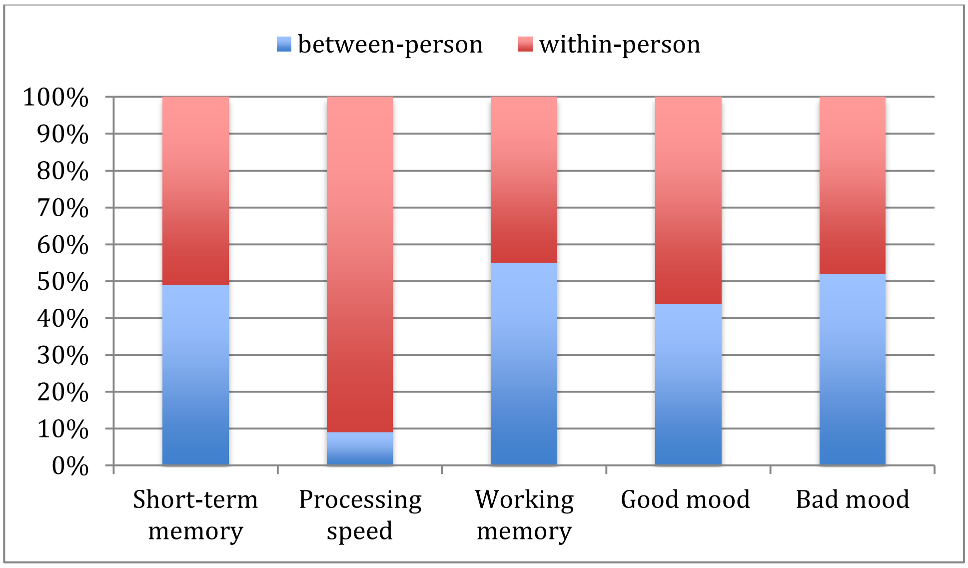

Figure 4: Intra-class correlations for study variables based on 17,735 observations from 770 moo-Q app users

Note. Correlation values are shown as percentages of within- and between-person variances.