Higher emotional awareness is associated with greater domain-general reflective tendencies

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Funding: RS is supported by the William K. Warren Foundation, the Stewart G. Wolf scholarship, and the National Institute of General Medical Sciences (P20GM121312). The study was supported by funding from the U.S. Army Medical Research and Development Command (W81XWH-16-1-0062) to WDSK.

Conflict of Interest: None of the authors have any conflicts of interest to disclose.

Informed consent: Informed consent was obtained from all individual participants included in the study.

Abstract

The tendency to reflect on the emotions of self and others is a key aspect of emotional awareness (EA) – a trait widely recognized as relevant to mental health. However, the degree to which EA draws on general reflective cognition vs. specialized socio-emotional mechanisms remains unclear. Based on a synthesis of work in neuroscience and psychology, we recently proposed that EA is best understood as a learned application of domain-general cognitive processes to socio-emotional information. In this paper, we report a study in which we tested this hypothesis in 448 (125 male) individuals who completed measures of EA and both general reflective cognition and socio-emotional performance. As predicted, we observed a significant relationship between EA measures and both general reflectiveness and socio-emotional measures, with the strongest contribution from measures of the general tendency to engage in effortful, reflective cognition. This is consistent with the hypothesis that EA corresponds to the application of general reflective cognitive processes to socio-emotional signals.

Keywords: Emotional Awareness; Domain-General Cognition; Cognitive Reflection; Emotion Recognition; Social Cognition

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Trait differences in emotional awareness (EA) have been the topic of a growing body of empirical work in psychology and psychiatry. Individuals with high EA report granular emotional experiences and perceive similar experiences in others – often promoting more adaptive social and emotional functioning (for a review, see (Smith et al., 2018)). Current theoretical models posit that the tendency to consciously reflect on the emotions of self and others is a key aspect of EA (Smith et al., 2018), as well as of related constructs such as emotional intelligence (Petrides et al., 2016) and alexithymia (Bagby et al., 1994). One important unanswered question pertains to the degree to which the tendency to reflect on emotion in EA depends on domain-general reflective cognitive processes vs. specialized socio-emotional mechanisms. Some models make strong distinctions between emotional and cognitive processes (e.g., (Panksepp & Biven, 2012)); and some neuroscientific studies also suggest the presence of brain regions selectively engaged by social cognition (e.g., (Fernandez et al., 2018)). In contrast, other cognitive and neural models suggest less separability between socio-emotional and cognitive process (Barrett, 2017). In a recent review (Smith et al., 2020), we drew on work within evolutionary, developmental, and cognitive neuroscience to argue that EA may have an important dependence on domain-general cognitive processes. Specifically, EA appears to require holding emotional information in mind, integrating it with other available information in perception and memory, and using this information to reflectively plan adaptive courses of action (especially in social situations). While these abilities may be constrained by cognitive capacity (e.g., working memory span, IQ; (Smith et al., 2017)), trait differences in EA may further depend on the habitual tendency to engage these reflective processes, independent of whether latent cognitive capacity is high or low. In this view, EA involves the application of effortful/reflective

cognitive processes to both intra- and interpersonal socio-emotional signals. The domain-general processes under discussion are ‘reflective’ in the sense that they operate on mental contents in an integrative, slow, and deliberate manner – often reducing the chances of responding maladaptively in emotionally charged situations. However, the degree to which EA depends on these processes requires further empirical testing.

In this report, we describe a study testing the relationship between EA and measures of both general reflective tendencies and emotion-specific skills. We predicted that higher EA would be associated with both sets of measures, as opposed to only the emotion-specific measures. If confirmed, this would support our previously proposed hypothesis regarding how EA emerges through the interaction between affective signals and general reflective cognitive processes.

Methods

Participants

A convenience sample of students at the University of Arizona as well as individuals from the surrounding community (mean age = 23.71, SD = 5.58 years), 125 male and 323 female, was recruited from Tucson, AZ. Participants gave informed consent and were paid for their participation. This study was approved by the University of Arizona Institutional Review Board (Protocol #1607696724) and the Human Research and Protection Office of the U.S. Army Medical Research and Development Command (Protocol #A-19136.a and A-19136.b).

Measures

For each measure below, we here include a brief description; more details and example items are

provided in the **Supplementary Methods**.

Levels of emotional awareness scale (LEAS).

The 10-item LEAS (Barchard et al., 2010; Lane et al., 1990) asks participants to describe what they believe they and another individual would feel in each of 10 hypothetical scenarios. Freely written responses (typed into a web-based interface; <http://eleastest.net/>) are scored based solely on the words chosen to describe feelings (scoring is done automatically by computer software). Each item is given a score of 0-5 based on the level of granularity and complexity of the combination of words used in each description, as well as based on the degree of differentiation between descriptions for self vs. other. Item scores are then summed. Subscale scores can also be calculated for self- and other-focused descriptions separately.

General reflectiveness measures

We used three related measures to assess general reflective cognition: the cognitive reflection test (CRT-7; (Toplak et al., 2014a)), the actively open-minded thinking scale (AOMTS; (Toplak et al., 2014b)), and the 2-subscale version of the comprehensive assessment of rational thinking (CART; (Stanovich et al., 2016)). The CRT-7 asks seven short questions designed such that there is an immediately intuitive, but incorrect answer, and a correct answer that, while not difficult, requires the individual to devote effortful cognitive resources instead of immediately choosing the intuitively appealing response. It tests the tendency to “stop and think” before immediately trusting one’s intuition.

The AOMTS is a self-report scale which asks individuals to rate 30 statements, from 1 (strongly disagree) to 6 (strongly agree), which describe more or less reflective or “rational”

attitudes. Higher scores indicate more open-minded, reflective attitudes.

The CART assess vulnerability to various common reasoning biases that arise (in part) from insufficient engagement of reflective capacities. The 2-subscale version we used includes probabilistic/statistical and scientific reasoning problems. Higher scores indicate a greater tendency to engage effortful cognition and avoid common reasoning biases during problem-solving.

Participants were also asked to complete the 2-subscale Wechsler abbreviated scale of intelligence (WASI-II; (Wechsler, 2011)) to assess IQ. This was important to ensure that EA was not simply associated with cognitive ability (as found previously; (Smith et al., 2017)), but also associated with the habitual tendency to engage in effortful cognition after accounting for cognitive ability.

Socio-Emotional Measures

To assess emotion-specific processes, we used the Geneva emotion recognition test (GERT-S; (Schlegel & Scherer, 2016)), the brief situational test of emotion management (STEM-B; (Allen et al., 2015)), and the Mini-K (Manson et al., 2020). The GERT-S shows 42 short video clips with audio in which ten actors express 14 different emotions (duration 10 min). After each clip, participants are asked to choose which of the 14 emotions was expressed by the actor. The STEM-B has 18 items, where each item describes an emotional situation. In multiple-choice format (4 choices per item), individuals are asked to select the most effective response for managing both the emotions the person is feeling and the problems presented in each situation. Correct answers are based on norms that were established by a set of solicited subject matter experts. Specifically, they corresponded to the course of action on each item deemed most

effective by a group of academics, counselors, psychiatrists, & life coaches with backgrounds in psychology.

The Mini-K is a self-report measure of the amount of cognitive and behavioral resources an individual tends to allocate toward maintaining long-term relationships and future planning more generally – a trait referred to as life history strategy (LHS). It is hypothesized to depend on early learning based on the level of predictability in early childhood environments. For example, an early environment that is safe and includes warm, stable parental/social relationships would be associated with “slow” LHS (high Mini-K scores), where individuals invest heavily in long-term relationships and spend effort planning for the distant future, while a dangerous early environment (e.g., a low socio-economic status neighborhood with high crime rates) that includes inconsistent or absent parental/social relationships would be associated with a “fast” LHS (low Mini-K scores), where individuals do not tend to maintain long-term relationships and do not focus on distant future outcomes (engaging in more impulsive, risk-seeking behavior). Those with higher Mini-K scores might therefore expected to greater LEAS scores either to more experience in stable relationships and/or greater engage in effortful future-oriented cognition generally, both of which pertain to our hypothesis about the basis of emotional awareness.

As a supplementary measure, we also collected the Toronto Alexithymia Scale (TAS-20; (Bagby et al., 1994)), which is a self-report scale asking participants to provide ratings from 1 (completely disagree) to 5 (completely agree) on 20 items pertaining to difficulties with understanding and expressing emotions. It includes three subscales reflecting: difficulty identifying feelings, difficulty describing feelings, and externally-oriented thinking. As our focus is on emotional awareness, we only included the TAS-20 in supplementary analyses to examine whether self-reported emotional difficulties might also relate to our cognitive and emotional

measures in a similar manner to the LEAS (noting that the LEAS and TAS-20 show very weak negative associations in previous literature (Maroti et al., 2018)).

Analyses

To assess the relations between EA and each of the cognitive and emotional measures, we first ran JZS Bayes factor analyses (multiple regressions) with default prior scales in R (BayesFactor package: <https://cran.r-project.org/web/packages/BayesFactor/BayesFactor.pdf>; (Rouder et al., 2012)) comparing null (intercept only) models to the space of models that included all combinations of main effects of age, sex, IQ, and the predictor of interest on LEAS total scores. Because there were significant or marginal differences between males and females for all cognitive and emotional measures (see **Table 1**), Bayes factors (BFs) were also calculated in relation to models with possible interactions between sex and these other measures. A BF represents the ratio of the probability of the data under two competing models, indicating the relative evidence for those models (e.g., BF = 3 indicates that the data are three times as probable under one model relative to another; for more details on BFs and their statistical advantages, see **Supplementary Methods**). We adopt the guidelines described in Lee and Wagenmakers (2014) for interpreting the strength of evidence provided by different BF values: BF = 1-3, poor/anecdotal evidence; 3-10, moderate evidence; 10-30, strong evidence, 30-100, very strong evidence, >100, extremely strong evidence.

After identifying the model with the most evidence, we conducted post-hoc Pearson correlations and hierarchical clustering analyses to further characterize relationships between the LEAS and other measures (using the agglomerative complete linkage method within the ‘hclust’ function and ‘corrplot’ package in R; <https://cran.r->

project.org/web/packages/fastcluster/fastcluster.pdf). Although not the focus of our primary analyses, we also explored whether the TAS-20 might show a similar pattern of relationships to the LEAS. For directional consistency when performing clustering, TAS-20 scores were inverted such that higher scores indicated lower alexithymia (i.e., higher self-reported emotional awareness).

Results

The descriptive statistics for all variables are shown in **Table 1**. LEAS, GERT-S, and MINI-K scores were greater in females than in males, while CRT-7, AOMTS, and CART scores were greater in males than in females.

Table 1. Summary statistics (mean and SD) for study measures by sex

	Usable Data (N)*	Total	Female	Male	Effect of Sex**
Age	Female: 323 Male: 125 Total: 448	23.7 (5.58)	23.39 (5.49)	24.5 (5.74)	$t(446) = -1.9, p = 0.06, d = -0.18$; BF = 0.65
LEAS	Female: 292 Male: 113 Total: 405	38.54 (4.97)	39.44 (4.73)	36.19 (4.83)	$t(403) = 6.16, p < \mathbf{0.001}, d = 0.61$; BF > 100
IQ	Female: 320 Male: 125 Total: 445	108.57 (11.52)	107.97 (11.25)	110.11 (12.1)	$t(443) = -1.77, p = 0.08, d = -0.17$; BF = 0.52
CART	Female: 319 Male: 124 Total: 443	10.52 (2.47)	10.06 (2.26)	11.7 (2.58)	$t(441) = -6.57, p < \mathbf{0.001}, d = -0.63$; BF > 100
CRT-7	Female: 311 Male: 119 Total: 430	2.67 (2.09)	2.31 (1.93)	3.62 (2.19)	$t(428) = -6.1, p < \mathbf{0.001}, d = -0.59$; BF > 100
AOMTS	Female: 321 Male: 125 Total: 446	134.65 (13.41)	133.35 (13.05)	137.98 (13.78)	$t(444) = -3.31, p = \mathbf{0.001}, d = -0.31$; BF = 21.61
STEM-B	Female: 312 Male: 121 Total: 433	0.63 (0.08)	0.64 (0.08)	0.62 (0.09)	$t(431) = 1.7, p = 0.09, d = 0.16$; BF = 0.47

GERT-S	Female: 299 Male: 113 Total: 412	26.46 (4.12)	26.71 (4.11)	25.8 (4.1)	$t(410) = 2.01, p = \mathbf{0.04}, d = 0.2; BF = 0.84$
MINI-K	Female: 317 Male: 123 Total: 440	24.09 (12.46)	25.3 (12.5)	20.97 (11.85)	$t(438) = 3.31, p = \mathbf{0.001}, d = 0.32; BF = 21.46$
TAS-20	Female: 320 Male: 125 Total: 445	42.65 (10.91)	42.95 (11.29)	41.88 (9.85)	$t(443) = 0.93, p = 0.35, d = 0.09; BF = 0.18$

*Not all data were available from all participants. Outlier values greater than three standard deviations from the mean were also removed. We therefore report final available Ns for each measure. **Significant sex differences at $p < .05$ are bolded for clarity.

General Reflectiveness Measures

CART

Bayes factor analyses comparing models including possible combinations of age, sex, IQ, and CART total scores (and interactions between sex and both IQ and CART) revealed the most evidence for a model with sex, IQ, and CART total scores as predictors of LEAS total scores (Bayes factor [BF] > 100 relative to an intercept-only model; extremely strong evidence). This model had moderate evidence (BF = 3.50) relative to the 2nd-best model, which also included an interaction between sex and IQ. It also had very strong evidence (BF = 78.08) relative to a model with only sex and IQ. Posterior regression coefficients for the best model were: sex (female): $b = 1.96$, 95% credible interval [CI] = [1.44 2.48]; IQ: $b = 0.08$, CI = [.03 .12]; CART: $b = .41$, CI = [.19 .63]. A post-hoc Pearson correlation analysis showed the hypothesized positive relationship between CART total scores and LEAS total scores ($r = .20, p < .001, BF > 100$; see **Figure 1** for a scatterplot depiction). Due to the sex differences observed in both variables, we also examined these correlations separately in each sex (males: $r = .39, p < .001, BF > 100$; females: $r = .28, p < .001, BF > 100$). These correlations were not significantly different between males and females.

Figure 1. Scatterplots illustrating the relationship between LEAS total scores and three general reflective cognition measures (AOMTS, CART, CRT-7), as well as three socio-emotional cognition measures (GERT-S, STEM-B, Mini-K).

AOMTS

Bayes factor analyses comparing models including possible combinations of age, sex, IQ, and AOMTS total scores (and interactions between sex and both IQ and AOMTS) revealed the most evidence for a model with sex, IQ, and AOMTS total scores ($BF > 100$ relative to an intercept-only model; extremely strong evidence). However, this model had poor evidence ($BF = 1.06$) relative to the 2nd-best model, which removed AOMTS. Posterior regression coefficients for the best model were: sex (female): $b = 1.74$, 95% credible interval $[CI] = [1.24 \ 2.25]$; IQ: $b = 0.11$, $CI = [.07 \ .15]$; AOMTS: $b = .04$, $CI = [.002 \ .07]$. A post-hoc Pearson correlation analysis showed the hypothesized positive relationship between AOMTS total scores and LEAS total scores ($r = .14$, $p = .001$, $BF = 6.6$; see **Figure 1**). Due to the sex differences observed in both variables, we also examined these correlations separately in each sex (males: $r = .16$, $p = .09$, BF

= .84; females: $r = .20$, $p < .001$, $BF = 46.2$). These correlations were not significantly different between males and females.

CRT-7

Bayes factor analyses comparing models including possible combinations of age, sex, IQ, and CRT-7 total scores (and interactions between sex and both IQ and CRT-7) revealed the most evidence for a model with sex and IQ as predictors of LEAS total scores ($BF > 100$ relative to an intercept-only model; extremely strong evidence). This model had moderate evidence ($BF = 5.04$) relative to a model that added CRT-7. Posterior regression coefficients for the model including CRT-7 were: sex (female): $b = 1.66$, 95% credible interval $[CI] = [1.31\ 2.16]$; IQ: $b = 0.11$, $CI = [.07\ .16]$; CRT-7: $b = .11$, $CI = [-.14\ .38]$. A post-hoc Pearson correlation analysis showed a positive relationship between CRT-7 scores and LEAS total scores ($r = .11$, $p = .03$, $BF = 1.11$; see **Figure 1**). Due to the sex differences observed in both variables, we also examined these correlations separately in each sex (males: $r = .21$, $p = .03$, $BF = 1.91$; females: $r = .19$, $p < .001$, $BF = 27.00$). Thus, hypothesized relationships were present, but may be accounted for by differences in IQ. The correlations were not significantly different between males and females.

Socio-Emotional Measures

GERT-S

Bayes factor analyses comparing models including possible combinations of age, sex, IQ, and GERT-S scores (and interactions between sex and both IQ and GERT-S) revealed the most evidence for a model with sex, IQ, and GERT-S scores as predictors of LEAS total scores ($BF >$

100 relative to an intercept-only model; extremely strong evidence). This model had moderate evidence ($BF = 3.26$) relative to the 2nd-best model, which removed GERT-S. Posterior regression coefficients for the best model were: sex (female): $b = 1.54$, 95% credible interval $[CI] = [1.02 \ 2.04]$; IQ: $b = 0.11$, $CI = [.06 \ .15]$; GERT-S: $b = .15$, $CI = [.04 \ .27]$. A post-hoc Pearson correlation analysis showed the hypothesized positive relationship between GERT-S scores and LEAS total scores ($r = .24$, $p < .001$, $BF > 100$; see **Figure 1**). Due to the sex differences observed in both variables, we also examined these correlations separately in each sex (males: $r = .21$, $p = .04$, $BF = 1.75$; females: $r = .23$, $p < .001$, $BF > 100$). The correlations were not significantly different between males and females.

STEM-B

Bayes factor analyses comparing models including possible combinations of age, sex, IQ, and STEM-B scores (and interactions between sex and both IQ and STEM-B) revealed the most evidence for a model with sex, IQ, and STEM-B total scores as predictors of LEAS total scores ($BF > 100$ relative to an intercept-only model; extremely strong evidence). This model had moderate evidence ($BF = 3.75$) relative to the 2nd-best model, which also included an interaction between IQ and STEM-B, and strong evidence ($BF = 43.19$) relative to a model with only sex and IQ (i.e., removing STEM-B). Posterior regression coefficients for the best model were: sex (female): $b = 1.53$, 95% credible interval $[CI] = [1.05 \ 2.01]$; IQ: $b = 0.10$, $CI = [.06 \ .14]$; STEM-B: $b = 9.93$, $CI = [4.43 \ 15.66]$. A post-hoc Pearson correlation analysis showed the hypothesized positive relationship between STEM-B scores and LEAS total scores ($r = .27$, $p < .001$, $BF > 100$; see **Figure 1**). Due to the sex differences observed in both variables, we also examined these correlations separately in each sex (males: $r = .19$, $p = .05$, $BF = 1.49$; females: $r = .29$, $p < .001$, $BF > 100$). The correlations were not significantly different between males and females.

Mini-K

Bayes factor analyses comparing models including possible combinations of age, sex, IQ, and Mini-K scores (and interactions between sex and both IQ and Mini-K) revealed the most evidence for a model with sex, IQ, and Mini-K scores as predictors of LEAS total scores ($BF > 100$ relative to an intercept-only model; extremely strong evidence). However, this model had poor evidence ($BF = 2.04$) relative to the 2nd-best model, which removed the Mini-K. Posterior regression coefficients for the best model were: sex (female): $b = 1.60$, 95% credible interval $[CI] = [1.09\ 2.11]$; IQ: $b = 0.12$, $CI = [.08\ .16]$; Mini-K: $b = .04$, $CI = [.006\ .08]$. A post-hoc Pearson correlation analysis showed the hypothesized positive relationship between Mini-K scores and LEAS total scores ($r = .15$, $p < .001$; see **Figure 1**). Due to the sex differences observed in both variables, we also examined these correlations separately in each sex, showing a numerically stronger relationship in females (males: $r = .06$, $p = .56$, $BF = .26$; females: $r = .13$, $p = .003$, $BF = 1.49$). The correlations were not significantly different between males and females.

Joint Model

Having found evidence in separate models for the contribution of both general reflectiveness and socio-emotional measures, we then included all contributing measures in a single model to assess the relative importance of each measure. Here we only included main effects found in the winning models above, due to the very large set of models generated if including all possible main effects and interactions. This revealed the most evidence for a model with sex, CART, GERT-S, and STEM-B scores as predictors of LEAS total scores ($BF > 100$ relative to an intercept-only model; extremely strong evidence). However, this model had poor

evidence relative to the 2nd- to 12th-best models (BFs = 1.37 to 2.69). All of these models included sex, CART, and STEM-B, but variably added IQ, CRT-7, and/or Mini-K, or removed GERT-S. To assess the importance of each predictor in the winning model, we compared it to models in which each term was removed. This revealed that all variables but GERT-S made an important contribution. In descending order, the winning model had BFs > 100 compared to models where sex or CART were removed, BF = 85.89 when STEM-B was removed, and BF = 1.4 when GERT-S was removed. Posterior regression coefficients for the winning model were: sex (female): $b = 1.74$, 95% credible interval [CI] = [1.21 2.27]; CART: $b = 0.46$, CI = [.27 .67]; GERT-S: $b = .12$, CI = [.01 .23]; STEM-B: $b = 10.53$, CI = [4.67 16.46].

Post-hoc correlations and associations with alexithymia

After completing our primary analyses, we ran a series of post-hoc correlations to provide a more complete characterization of relationships between all variables. Although performed primarily to characterize previously identified results, for the interested reader we note uncorrected p-value thresholds and BFs for associated Bayesian correlation analyses. As a further exploratory analysis, we also examined correlations between these measures and TAS-20 scores to assess whether self-reported difficulties associated with emotional awareness (i.e., alexithymia) might show a similar pattern as found for the LEAS (which is not based on self-perceived traits). Although post-hoc, we note that a sensitivity analysis, performed using G*Power3 (Faul et al., 2007), indicated that our sample of 447 participants was able to detect a small effect size of $\rho = .13$ for correlations between our variables of interest, assuming a power of .80 and $\alpha = .05$ (two-sided).

The left panel of **Figure 2** shows the resulting post-hoc correlation matrices. The right

panel of **Figure 2** also shows results of a hierarchical clustering analysis on this correlation matrix. Notably, the STEM-B and GERT-S were both positively correlated with the general reflectiveness measures, and all performance-based measures clustered (all positive correlations) separately from self-report measures – where AOMTS and Mini-K were negatively correlated with TAS-20 (i.e., higher alexithymia was associated with less self-reported reflectiveness and faster LHS). TAS-20 was not correlated with LEAS.

Figure 2. Left: Post hoc Pearson correlations between all variables. Although carried out post-hoc to further characterize results of prior planned analyses, for the interested reader we note their uncorrected significance levels (* = $p < .05$, ** $p < .01$, *** $p < .001$) and provide Bayes factors (BFs) from JZS Bayesian correlation analyses with default prior scales in R (see main text) indicating the level of evidence for each relationship. Right: Results of hierarchical clustering analyses. The LEAS, IQ, two performance-based general reflectiveness measures (CART, CRT-7), and two performance-based socio-emotional variables (STEM-B, GERT-S) clustered together with significant positive correlations; finer-grained clustering grouped the LEAS with STEM-B and GERT-S. The Mini-K clustered with a self-report reflectiveness measure (AOMTS) and a self-report measure of alexithymia (TAS-20) with negative correlations; finer-grained clustering separated the Mini-K from these other two variables. Note that clustering analyses were performed after making TAS-20 scores negative so that higher scores indicated higher levels of emotional awareness.

For further interpretation, **Supplementary Figure 1** also shows relationships between all measures and the subscales for the LEAS, CART, and TAS-20 (see **Supplementary Table S1** for descriptive statistics). As seen there, the pattern of relationships with LEAS subscale scores and CART subscale scores was similar to that observed for total scores. Notably, the TAS-20 externally oriented thinking subscale showed negative associations with the LEAS and multiple cognitive and socio-emotional measures.

Discussion

Based on a theoretical model we recently proposed (Smith et al., 2020), we tested the prediction that higher EA would be associated with the general tendency to engage in effortful/reflective cognition. We also tested relationships with other socio-emotional measures more traditionally expected to be associated with EA. In support of our predictions, positive associations were observed between EA (LEAS) and all measures of both reflective cognition and socio-emotional skills – with Bayesian analyses finding the strongest evidence for models that included sex, IQ, one measure of reflective cognition (CART) and two socio-emotional measures (GERT-S, STEM-B). When comparing models including all combinations of measures, the evidence suggested that, after sex, the CART was of highest importance, followed by a strong additional contribution of STEM-B. These results are consistent with our previous proposal (Smith et al., 2020) that EA draws on domain-general reflective cognitive capacities to a significant degree, as opposed to depending primarily on specialized socio-emotional mechanisms.

While EA was positively correlated with IQ, the effect of the CART remained present after accounting for this relationship. This means that the association between reflectiveness

measures and EA is not explained by differences in general cognitive ability. Instead, it corresponds to the general habit or tendency to *engage* those cognitive capacities when making decisions. Post-hoc correlations showed that the other socio-emotional measures were also associated with the general cognitive measures, suggesting an important contribution of domain-general cognition to socio-emotional processes more broadly.

Despite the sex differences in EA (higher in females) and in general effortful cognition (higher in males) – both of which replicate previous findings (Stanovich et al., 2016; Wright et al., 2017) – relationships between these measures were largely similar in both males and females. This suggests these relationships may be quite general, and not driven by overlap in a circumscribed set of narrower sub-processes. One exception was the Mini-K, where results suggested the relationship with EA was driven more by females. This is consistent with a previous study finding relationships between EA and another more comprehensive measure of life history strategy (the K-SF-42; (Smith et al., 2021)).

Finally, we performed supplementary analyses examining whether a self-report measure of alexithymia (TAS-20), which is conceptually similar to the construct of emotional awareness, would show a similar pattern of relationships to that observed for the LEAS. Consistent with previous literature (Maroti et al., 2018), LEAS and TAS-20 scores showed very weak negative associations; and the TAS-20 showed a unique pattern of relationships with other measures – primarily a negative relationship with self-report measures of reflective cognition (AOMTS) and life history strategy (Mini-K). Overall these findings are theoretically consistent with our prediction about the relationships between emotional awareness and reflective cognition, but also highlight the way that experimental operationalizations of alexithymia and emotional awareness can produce distinct patterns of results.

It is important to consider the strengths and limitations of this study. Major strengths include a sufficiently powered sample size to detect small effect sizes, the use of multiple convergent measures, and incorporation of Bayesian analyses facilitating model selection. One weakness is that there were fewer men than women, affording less confidence in observed relationships when examining men separately. Another weakness is that the study design only affords correlational analyses. It can therefore not provide a strong test of hypotheses about the way in which general reflective cognition interacts with specialized socio-emotional signal processing mechanisms to allow for high EA. Future research will be needed to address these questions further. Another limitation is that we did not incorporate other measures related to emotional awareness, such as measures of emotional granularity (Kashdan et al., 2015) or emotional intelligence (Petrides et al., 2016). A final limitation is that this is the first study to look at the relationships between measures of EA and reflective cognition, and our participants had a restricted age range and were sampled from a single geographic region. Thus, replication and extension to a broader range of demographics will be necessary to confirm the existence and generalizability of our findings.

In summary, the combination of findings in this study are consistent with the idea that acquiring high EA depends on developing general tendencies to engage in effortful, reflective cognitive processes. They also suggest a significant association between general cognitive capacities and socio-emotional capacities more broadly. This adds to a growing body of work, both in neuroscience and psychology, suggesting a strong overlap in the mechanisms underlying cognitive and emotional processes.

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Supplemental Materials:

Supplementary Methods

Measures

Levels of emotional awareness scale (LEAS).

The 10-item LEAS (Barchard et al., 2010; Lane et al., 1990) asks participants to describe what they believe they and another individual would feel in each of 10 hypothetical scenarios. Freely written responses (typed into a web-based interface; <http://eleastest.net/>) are scored based solely on the words chosen to describe feelings (scoring is done automatically by computer software). For each scenario, a score of 0 is given to non-emotional words (e.g., confused); a score of 1 is given to words related to bodily sensations (e.g., “exhausted”); a score of 2 is given to words describing emotional actions (e.g., “hitting”) or simple valence distinctions (e.g., “pleasant”, “unpleasant”) that entail approach/avoidance; a score of 3 is given to single emotion concept terms (e.g., “happy,” “afraid”); and a score of 4 is given when at least 2 emotion concept terms are used in a single scenario. For each scenario, the self- and other-related responses are scored separately (i.e., values of 0-4). A “total” score is then given for each scenario, which reflects the higher of the self- and other-related scores. However, if a score of 4 is given for both self and other, a total score of 5 is given for that scenario, as long as the self- and other-related responses are differentiable (for more details see (Lane et al., 1990)).

General reflectiveness measures

We used three related measures to assess general reflective cognition: the cognitive

reflection test (CRT-7; (Toplak et al., 2014a)), the actively open-minded thinking scale (AOMTS; (Toplak et al., 2014b)), and the 2-subscale version of the comprehensive assessment of rational thinking (CART; (Stanovich et al., 2016)). The CRT-7 asks seven short questions designed such that there is an immediately intuitive, but incorrect answer, and a correct answer that, while not difficult, requires the individual to devote effortful cognitive resources instead of immediately choosing the intuitively appealing response. Example item:

“If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?” (intuitive answer: 100 minutes; correct answer: 5 minutes)

It tests the tendency to “stop and think” before immediately trusting one’s intuition.

The AOMTS is a self-report scale which asks individuals to rate 30 statements, from 1 (strongly disagree) to 6 (strongly agree), which describe more or less reflective or “rational” attitudes. Example item:

“I like to gather many different types of evidence before I decide what to do.”

Higher scores indicate more open-minded, reflective attitudes.

The CART assess vulnerability to various common reasoning biases that arise (in part) from insufficient engagement of reflective capacities. The 2-subscale version we used includes probabilistic/statistical and scientific reasoning problems. Example item:

“Dice game: Even numbers win and odd numbers lose on a die throw. The fair die has six sides, with three even and three odd numbers. Jan has thrown seven odd numbers in a

row. What are her chances of throwing an even number on her next throw?” (correct answer: 3/6).

Higher scores indicate a greater tendency to engage effortful cognition and avoid common reasoning biases during problem-solving.

When assessing differences on these reflective cognition measures, it is important to first account for individual differences in general intelligence. While it is expected that EA will be correlated with IQ (e.g., see (Smith et al., 2017)), our primary interest is in whether EA is associated with the tendency to automatically engage reflective cognitive processes – independent of differences in latent cognitive capacity. As such, we also asked participants to complete the 2-subscale Wechsler abbreviated scale of intelligence (WASI-II; (Wechsler, 2011)), a common measure of IQ.

Socio-Emotional Measures

To assess emotion-specific processes, we used the Geneva emotion recognition test (GERT-S; (Schlegel & Scherer, 2016)), the brief situational test of emotion management (STEM-B; (Allen et al., 2015)), and the Mini-K (Manson et al., 2020). The GERT-S shows 42 short video clips with audio in which ten actors express 14 different emotions (duration 10 min). After each clip, participants are asked to choose which of the 14 emotions was expressed by the actor. The STEM-B has 18 items, where each item describes an emotional situation. In multiple-choice format (4 choices per item), individuals are asked to select the most effective response for managing both the emotions the person is feeling and the problems presented in each situation. Correct answers are based on norms that were established by a set of solicited subject matter experts. Specifically, they corresponded to the course of action on each item deemed most

effective by a group of academics, counselors, psychiatrists, & life coaches with backgrounds in psychology.

The Mini-K is a self-report measure of the amount of cognitive and behavioral resources an individual tends to allocate toward maintaining long-term relationships and future planning more generally – a trait referred to as life history strategy (LHS). It is hypothesized to depend on early learning based on the level of predictability in early childhood environments. For example, an early environment that is safe and includes warm, stable parental/social relationships would be associated with “slow” LHS (high Mini-K scores), where individuals invest heavily in long-term relationships and spend effort planning for the distant future, while a dangerous early environment (e.g., a low socio-economic status neighborhood with high crime rates) that includes inconsistent or absent parental/social relationships would be associated with a “fast” LHS (low Mini-K scores), where individuals do not tend to maintain long-term relationships and do not focus on distant future outcomes (engaging in more impulsive, risk-seeking behavior). Those with higher Mini-K scores might therefore be expected to have greater LEAS scores either to more experience in stable relationships and/or greater engagement in effortful future-oriented cognition generally, both of which pertain to our hypothesis about the basis of emotional awareness.

As a supplementary measure, we also collected the Toronto Alexithymia Scale (TAS-20; (Bagby et al., 1994)), which is a self-report scale asking participants to provide ratings from 1 (completely disagree) to 5 (completely agree) on 20 items pertaining to difficulties with understanding and expressing emotions. An example item is “I am often confused about what emotion I am feeling”. It includes three subscales reflecting: difficulty identifying feelings, difficulty describing feelings, and externally-oriented thinking. While high alexithymia is conceptually similar to low emotional awareness, a recent meta-analysis found that the TAS-20

and LEAS have a very weak negative relationship with one another ($r = -.12$; (Maroti et al., 2018)) – which may reflect differences in measurement approach (i.e., the LEAS does not ask individuals to self-report their emotional awareness), differences in content, and/or that some individuals may not be aware of their limited emotional capacities (see (Lane et al., 2020)). As our focus is on emotional awareness, we only include the TAS-20 in supplementary analyses to examine whether it is also related to our cognitive and emotional measures in a similar manner to the LEAS.

Analyses

To assess the relations between EA and each of the cognitive and emotional measures, we first ran JZS Bayes factor analyses (multiple regressions) with default prior scales in R (BayesFactor package (Morey & Rouder, 2015; Rouder et al., 2012)) comparing null (intercept only) models to the space of models that included all combinations of main effects of age, sex, IQ, and the predictor of interest on LEAS total scores. Because there were significant or marginal differences between males and females for all cognitive and emotional measures (see **Table 1**), Bayes factors (BFs) were also calculated in relation to models with possible interactions between sex and these other measures. A BF represents the ratio of the probability of the data under one model vs. another, indicating the relative evidence for different models. If H_0 indicates the null hypothesis, H_1 indicates the alternative hypothesis, and d indicates the data, then:

$$BF = \frac{p(d|H_1)}{p(d|H_0)}$$

Higher BF values indicate greater evidence for the alternative hypotheses; e.g., $BF = 3$ indicates

three times as much evidence for the alternative hypothesis than for the null hypothesis (i.e., the data are three times as probable under the alternative hypothesis). We adopt the guidelines described in Lee and Wagenmakers (2014) for interpreting the strength of evidence provided by different BF values: $BF = 1-3$, poor/anecdotal evidence; $3-10$, moderate evidence; $10-30$, strong evidence, $30-100$, very strong evidence, >100 , extremely strong evidence. Here we focus on Bayesian analyses because they have important statistical advantages. Namely, BFs provide a straightforward means of model comparison, their values do not require correction for multiple comparisons, and they are able to assess evidence for the null model as well as alternative models (Dienes, 2008, 2011, 2014).

After identifying the model with the most evidence, we conducted post-hoc Pearson correlations to assess the strength of relationships between each predictor variable and LEAS total scores. After confirming the hypothesized relationships, we then performed secondary correlational and hierarchical clustering analyses to further characterize relationships between our domain-general and socio-emotional measures (using the agglomerative complete linkage method within the ‘hclust’ function and ‘corrplot’ package in R; <https://cran.r-project.org/web/packages/fastcluster/fastcluster.pdf>). These secondary analyses were performed to best interpret the specific nature of the relationships supported by our initial results. Although not the focus of our primary analyses, we also explored whether the TAS-20 might show a similar pattern of relationships to the LEAS. For directional consistency when performing clustering, TAS-20 scores were inverted such that higher scores indicated lower alexithymia (i.e., higher self-reported emotional awareness).

Supplementary Results

Table S1. Summary statistics (mean and SD) for subscales

Measures	Usable Data (N)	Total 448	Female 323	Male 125	Effect of Sex
LEAS Self	Female: 292 Male: 113 Total: 405	32.57 (4.52)	33.45 (4.06)	30.3 (4.87)	$t(403) = 6.62, p < 0.001, d = 0.66; BF > 100$
LEAS Other	Female: 292 Male: 113 Total: 405	31.27 (4.32)	31.83 (4.08)	29.82 (4.6)	$t(403) = 4.28, p < 0.001, d = 0.43; BF > 100$
CART Prob. Stat. Reasoning	Female: 320 Male: 125 Total: 445	9.06 (2.63)	8.58 (2.43)	10.28 (2.72)	$t(443) = -6.41, p < 0.001, d = -0.61; BF > 100$
CART Sci. Reasoning	Female: 319 Male: 125 Total: 444	11.95 (3.05)	11.54 (2.87)	13 (3.25)	$t(442) = -4.64, p < 0.001, d = -0.44; BF > 100$
TAS-20 DIF	Female: 320 Male: 125 Total: 445	13.42 (5.31)	13.7 (5.4)	12.72 (5.02)	$t(443) = 1.75, p = 0.08, d = 0.17; BF = .51$
TAS-20 DDF	Female: 320 Male: 125 Total: 445	11.68 (4.68)	11.74 (4.92)	11.54 (4)	$t(443) = 0.41, p = 0.68, d = 0.04; BF = .13$
TAS-20 EOT	Female: 320 Male: 125 Total: 445	17.55 (3.77)	17.52 (3.79)	17.62 (3.71)	$t(443) = -0.27, p = 0.79, d = -0.03; BF = .12$

Figure S1. Post hoc Pearson correlations between all the LEAS, CART, and TAS-20 subscales and all other measures. Although carried out post-hoc to further characterize results of prior planned analyses, for the interested reader we note their uncorrected significance levels (* = $p < .05$, ** $p < .01$, *** $p < .001$) and provide Bayes factors (BFs) from JZS Bayesian correlation analyses with default prior scales in R (see main text) indicating the level of evidence for each relationship. Relationships were largely similar as with the total scores for these scales. Notably, however, the TAS-20 externally oriented thinking (EOT) subscale showed significant negative correlations with LEAS and multiple cognitive and socio-emotional measures. DIF = difficulty identifying feelings; DDF = difficulty describing feelings.