

Real-World Exploration Increases Across Adolescence and Relates to Affect, Risk Taking, and Social Connectivity



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Abstract

Cross-species research suggests that exploratory behaviors increase during adolescence and relate to the social, affective, and risky behaviors characteristic of this developmental stage. However, how these typical adolescent behaviors manifest and relate in real-world settings remains unclear. Using geolocation tracking to quantify exploration—variability in daily movement patterns—over a 3-month period in 58 adolescents and adults (ages 13–27) in New York City, we investigated whether daily exploration varied with age and whether exploration related to social connectivity, risk taking, and momentary positive affect. In our cross-sectional sample, we found an association between daily exploration and age, with individuals near the transition to legal adulthood exhibiting the highest exploration levels. Days of higher exploration were associated with greater positive affect irrespective of age. Higher mean exploration was associated with greater social connectivity in all participants but was linked to higher risk taking selectively among adolescents. Our results highlight the interplay of exploration and socioemotional behaviors across development and suggest that societal norms may modulate their expression in naturalistic contexts.

Keywords

exploration, adolescence, risk taking, open data

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Exploration is a fundamental human behavior that promotes the acquisition of knowledge by bringing individuals into contact with novel experiences. The drive to explore has been proposed to arise, in part, from the intrinsically rewarding properties of novelty (Kakade & Dayan, 2002; Krebs et al., 2009; Wittmann et al., 2007, 2008). Novelty engages the brain's reward circuitry (Bardo et al., 1996; Bunzeck et al., 2012; Horvitz, 2000; Rebec et al., 1997) and reinforces associated actions (Houillon et al., 2013; Myers & Miller, 1954; Reed et al., 1996). Studies across species find that, relative to adults, adolescents exhibit heightened exploration of constructed laboratory environments (Adriani et al., 1998; Lynn & Brown, 2009; Philpot & Wecker, 2008; Spear, 2000a, 2000b; Stansfield & Kirstein, 2006) and choice options in computerized decision-making tasks (Christakou et al.,

2013; Jepma et al., 2020; Lloyd et al., 2021), suggesting that increased exploration may be a normative characteristic of adolescent development (Spear, 2000a, 2000b). Increased exploration may stem from heightened sensitivity to the reinforcing properties of novelty (Laviola et al., 1999; Philpot & Wecker, 2008; Stansfield & Kirstein, 2006), potentially reflecting reorganization of dopaminergic reward circuitry during adolescence (Crews et al., 2007; Doremus-Fitzwater et al., 2010; Galván, 2010; Spear, 2000a, 2011; Wahlstrom et al., 2010). Functionally, heightened exploration may facilitate the transition toward independence by allowing adolescents to learn about

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new situations and contexts and to establish social networks beyond their families.

To date, the study of adolescent exploration has been largely constrained to controlled laboratory experiments or ethological research. Few studies have examined exploratory behavior across human adolescence in naturalistic contexts. In a recent study (Heller et al., 2020), we investigated real-world exploration in adults, using geolocation tracking to derive a measure of daily exploration or *roaming entropy*—the unpredictability of one's location over time (Freund et al., 2013). Consistent with the proposition that novelty has subjectively rewarding properties (Bardo et al., 1989; Berlyne, 1970; Bevins & Bardo, 1999; Douglas et al., 2003), our results showed that adults reported greater positive affect on days in which they exhibited greater roaming entropy. However, it remains unclear whether there are normative developmental changes in naturalistic exploration across adolescence or whether the degree to which exploration is subjectively rewarding varies by age.

Social networks expand (Levitt et al., 1993; Wrzus et al., 2013) and change dynamically (Bowker, 2004; Brown, 2004; Poulin & Chan, 2010) across adolescence. It has been proposed that such social exploration facilitates adaptive transitions toward independence during adolescence (Blakemore & Mills, 2014; Spear, 2000a). Like exploration over physical space, social exploration may also arise from an individual's propensity to seek out novel and intrinsically rewarding experiences (Calcagnetti & Schechter, 1992; Dölen et al., 2013; Doremus-Fitzwater et al., 2010; El Rawas et al., 2012; Trezza et al., 2011; Walker et al., 2017). Thus, social connectivity may be positively associated with environmental exploration, and heightened sensitivity to novelty may render this coupling more pronounced during adolescence. However, links between naturalistic exploration and social connectivity across human adolescence have yet to be studied empirically.

Beyond the marked socioemotional development that occurs during adolescence, epidemiological statistics identify a range of risky behaviors that peak in prevalence during this developmental stage (Duell et al., 2018; Mahalik et al., 2013; Romer, 2010). Although sometimes considered maladaptive, heightened risk taking may be a normative by-product of exploration as adolescents acquire autonomy (Casey, 2015; Crone & Dahl, 2012; Romer et al., 2017; Spear, 2000a, 2000b). Sampling novel contexts facilitates learning about the likely consequences of actions in uncertain—and potentially risky—situations. Indeed, novelty-seeking (Stansfield & Kirstein, 2006; Vidal-Infer et al., 2012; Wills et al., 1994, 1995), engagement with uncertainty (Rosenbaum & Hartley, 2019; Tymula et al., 2012; van den Bos & Hertwig, 2017),

Statement of Relevance

Environmental exploration allows us to discover novel and rewarding experiences and meet new people. Increases in exploration during adolescence are thought to be adaptive, enabling people to learn from new experiences, form social ties beyond their families, and gain greater independence. However, few studies have examined how human exploration in naturalistic settings changes over development, or how these behavioral patterns relate to well-being. Here, using GPS tracking to measure “real-world” exploration, we found that adolescents nearing the transition to adulthood explored more than younger adolescents. Individuals of all ages reported better moods when they explored more, linking exploration to well-being. Highly exploratory individuals reported larger social networks, and highly exploratory adolescents—but not adults—reported taking more risks in everyday life. These findings point to an important role for exploration in sustaining adolescent well-being and establishing social connectivity, and suggest that risk taking may similarly serve an adaptive function during adolescence.

and exploratory choice (Macrì et al., 2002; Somerville et al., 2017) in laboratory settings are all associated with adolescent risk taking. Moreover, because adolescents inherently have had fewer experiences than adults, they may more frequently encounter real-world contexts in which outcomes are uncertain (Romer, 2010). Thus, an adolescent's drive to explore may simultaneously promote engagement with the novel and uncertain contexts in which risk taking typically occurs (Dellu et al., 1996; Laviola et al., 1999; Romer et al., 2017; Spielberg et al., 2014).

In the present study, we set out to test whether real-world exploration differs by age and whether such variation relates to social-affiliative and risk-taking behaviors across adolescence. Leveraging the ecological measurement framework used by Heller et al. (2020), we acquired daily geolocation data and repeated affective-experience sampling data across 58 participants, ages 13 to 27, over a 3-month period. We hypothesized that, relative to adults, adolescents would exhibit greater levels of real-world exploration (i.e., roaming entropy) and would demonstrate greater positive coupling between exploration levels and positive affect. Further, we hypothesized that greater roaming entropy would correlate with social connectivity and self-reported risky behaviors, particularly in adolescents.

Method

Participants

We recruited 29 adolescents and 34 adults through a laboratory participant database of adolescents and adults residing in or near New York City. Four participants were excluded because of insufficient GPS data (fewer than 10 days of GPS data; 2 female, mean age = 20.40 years). One other participant was excluded for choosing the highest value on the positive-affect scale every day (male, age = 24.87 years). Our final sample consisted of 28 adolescents (15 females, age range = 13.04–17.70 years, mean age = 15.62) and 30 adults (16 females, age range = 18.35–27.65 years, mean age = 22.30). To avoid potential seasonal effects on affect and patterns of exploration, we recruited as many adolescents and adults as possible within a predefined 3-month window, between August 2017 and November 2017 (note that we also adjusted for daily weather patterns in our multilevel models; see the Control Variables section for a detailed description). Based on self-report, 50% of participants were Caucasian, 22% were Asian, 14% were mixed race, 12% were African American, and 2% were Native American. Twenty-six percent of the sample identified as Hispanic. Participants had no reported history of diagnosed psychiatric disorders and were not taking psychoactive medications. All participants were compensated for their time. Participants received bonus money in the form of Amazon gift cards if they maintained the GPS tracking application open for 80% of the days during the tracking period (assessed twice, once at the halfway point and once at the end of the tracking period) and if they responded to at least 90% of the affect text surveys. Participants received an additional Amazon gift card if they responded to the social network survey, which was completed in the middle of their 3-month tracking period. All recruitment, consent forms, and data collection were completed in accordance with the requirements of the New York University Institutional Review Board. All data collection took place prior to the COVID-19 pandemic and quarantine.

Geolocation tracking

At the beginning of the study, participants came into the lab at New York University. The smartphone application FollowMee (2020) was installed onto participants' phones, and participants were instructed to keep the application open and their phones on for the duration of the study. For 3 months, we recorded GPS location in 2-min intervals for each participant. Latitude and longitude values were rounded to four decimal degrees of GPS resolution, which corresponds to about one city

block (Heller et al., 2020). Because GPS data has an inherent level of noise (i.e., changes in location that are not due to veridical movement), we postprocessed the data using a custom-built algorithm that filtered the geolocation data to reduce extraneous noise (github.com/nsaragosaharris/GPS_Study/blob/master/filter_entropy_calculator.R). The algorithm removed a point as extraneous if two conditions held: (a) The distance between the point and its subsequent point was less than 0.5 kilometers, and (b) the point created an angle between its previous and subsequent point that was less than 0.4 radians or 22.918 degrees.

Calculation of roaming entropy

We operationalized exploration as the roaming entropy over daily geolocation latitude and longitude (Freund et al., 2013):

$$\text{Roaming entropy}_i = -\sum_{j=1}^n (p_{ij} \times \log(p_{ij})) / \log(n).$$

In this equation, p_{ij} is the within-day historical probability that location j was visited by participant i —quantified as the proportion of the day spent in location j (number of minutes in that location divided by the 1,440 minutes in a day)—and n is the total number of unique locations on Earth at four decimal degrees of GPS resolution. Thus, visiting a greater number of locations and distributing one's time equally across those locations would result in higher roaming entropy, whereas spending all day in one or very few locations would result in lower roaming entropy.

Assessment of location-based novelty

Previous work demonstrates that roaming entropy is highly related to the number of novel locations visited in a day (Heller et al., 2020). To verify the relation between days of higher roaming entropy and location novelty, we computed the number of novel locations visited each day. For each day of GPS data collection, we coded every coordinate location as novel if it had not been previously visited by the participant during the tracking period. For this measure, we counted the number of novel locations visited on each day for every participant. Because this measure of novelty by definition relies on data solely acquired during the tracking period, we cannot determine with certainty that novel locations truly reflected first encounters. To avoid arbitrary inflation of this novelty estimate early in the recording period, we held the first 10 days of data out from this analysis (Heller et al., 2020).

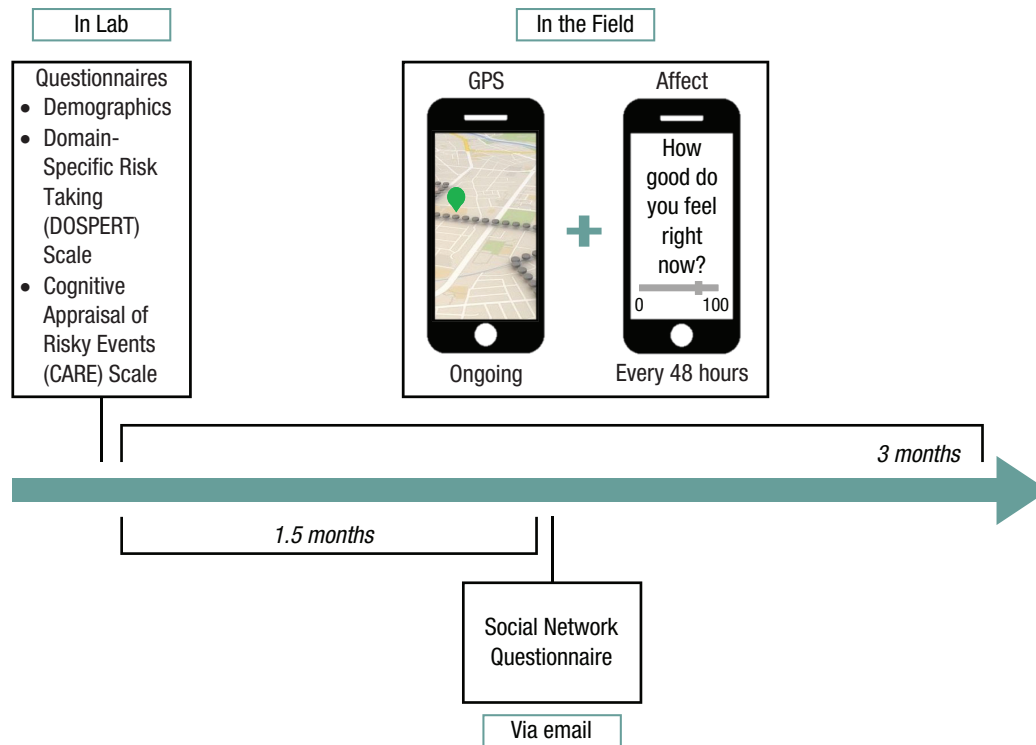


Fig. 1. Over a 3-month tracking period, we acquired ongoing geolocation data and surveyed affect approximately every 48 hr. We collected demographic and self-reported risk-taking data during the initial visit to the lab and administered a social network questionnaire via email about halfway through data collection.

Experience sampling

Approximately every 48 hours during the 3-month tracking period, participants received a text survey prompting them to report their current positive and negative affect, a method referred to as *ecological momentary assessment* (EMA). Text surveys were sent to participants at a random time between the hours of 10:00 a.m. and 8:00 p.m. Using a visual analog sliding scale, participants were asked to indicate, “How good do you feel right now?” and “How bad do you feel right now?” The scale for items ranged from 0 to 100, but participants could not see the number associated with the slider position (see Fig. 1). Positive- and negative-affect ratings had a mean within-subjects correlation of $-.73$ and a median correlation of $-.80$, indicating that participants likely used these ratings as opposite but complementary measures of their affective states. Because we had a priori hypotheses specific to positive affect based on prior work (Heller et al., 2020), and the negative-affect ratings did not appear to provide unique information, we analyzed only the positive-affect ratings (see the Supplemental Material available online for an additional analysis combining positive- and negative-affect ratings). To aid interpretation, we kept positive-affect ratings in their original scale (from 0–100),

and we report unstandardized coefficients for models involving positive-affect ratings.

Social network measure

Approximately halfway through their participation in the study (about 1.5 months after the in-lab session), participants were asked to complete an online self-report questionnaire to assess how many unique individuals they had interacted with via phone calls and direct-messaging platforms over the past month. We chose to assess phone-based interactions, rather than in-person interactions, in order to obtain a relatively objective measure of social network size. To this end, we explicitly instructed participants to refer to their phone history to determine the number of recent social interactions on a given platform. Although phone-based interactions are not qualitatively identical to in-person interactions, research suggests that adolescents and young adults use instant messaging and social media platforms primarily to keep in contact with their in-person social networks, and they demonstrate considerable overlap in their online and offline social groups (Subrahmanyam et al., 2008). The questionnaire prompted participants to refer to their phones and report how many unique individuals they had conversed with via phone calls, text messages,

GroupMe, Facebook Messenger, and similar messaging platforms in the past month. Social network size was computed as a sum of the number of unique people they conversed with via phone calls and messaging platforms. Because the questionnaire was not administered during the first session and was optional for participants to fill out online, only a subset of the final sample ($n = 46$; 21 adolescents) completed the social network questionnaire.

Risk-taking measures

To assess individual differences in risk taking, we asked participants to complete an abbreviated version of the Domain-Specific Risk-Taking Scale (DOSPERT; Blais & Weber, 2006; Weber et al., 2002) as well as the Cognitive Appraisal of Risky Events (CARE) questionnaire (Fromme et al., 1997; Katz et al., 2000). Participants completed both measures when they visited the lab at the beginning of the study. For each DOSPERT item, participants indicated how likely they would be to engage in the activity or behavior using a 7-point Likert scale (1 = *extremely unlikely*, 7 = *extremely likely*). Adolescents (ages 13–17) were administered the adolescent version of the DOSPERT, and adults (ages 18–27) were administered the adult version (Blais & Weber, 2006). The two versions use different wording to adjust the scenarios in an age-appropriate (minor vs. adult) manner (e.g., whereas one scenario in the adolescent questionnaire takes place at school, the same scenario in the adult questionnaire takes place at work), but both versions assess risk along five domains (ethical, financial, health/safety, social, and recreational). The adolescent version has 39 questions total and the adult version has 30 questions total.

To allow for comparison across groups, participants' overall DOSPERT scores were normalized by summing responses across the five domains and dividing by the number of items on the measure for their age group (Somerville et al., 2017). Within this sample, DOSPERT scores demonstrated good internal consistency for both the adolescent version (Cronbach's $\alpha = .92$, 95% confidence interval [CI] = [.85, .95]) and the adult version (Cronbach's $\alpha = .83$, 95% CI = [.70, .89]). In the CARE questionnaire, participants used a 7-point Likert scale to indicate their likelihood of engaging in a given activity in the next 6 months (1 = *not likely at all*, 4 = *somewhat likely*, 7 = *extremely likely*). The 34 items on the questionnaire assessed risky behaviors from seven domains: illicit drug use, aggressive and illegal behaviors, risky sexual activities, heavy drinking, high-risk sports, academic or work behaviors, and gambling. Adults and adolescents were administered the same version of the CARE questionnaire. As with the DOSPERT,

participants' overall CARE scores were totaled across the domains and divided by the total number of items to obtain an indicator of likelihood of engaging in risky behavior in the near future (Galván et al., 2007). Within this sample, CARE scores demonstrated good internal consistency (Cronbach's $\alpha = .88$, 95% CI = [.82, .92]). After this normalization, both the DOSPERT and CARE were z -scored across participants. We did not have domain-specific hypotheses, so only the total scores from the two measures were analyzed, in line with prior work that has used these measures to assess risk taking in developmental samples (Galván et al., 2007; Somerville et al., 2017).

Age differences

There are several ways to conceptualize possible age differences when considering exploration and its relation to affect, social networks, and risky behaviors. Here we consider two accounts. First, because biological developmental processes occur continuously, we may expect our measures of interest to change with age in a linear or quadratic pattern. Second, the transition to legal independence (at 18 years old in the United States) is discontinuous and defined socioculturally rather than biologically. At this age, regardless of biological maturation, individuals are often expected to leave home and assume adult responsibilities (Arnett, 1998; Arnett et al., 2014). Although the legally defined distinction between adolescence and adulthood is arbitrary (Cohen et al., 2016; Nelson & Luster, 2015), societal expectations and sociocultural factors that map onto this age-based discretization may play an important role in modulating effects of interest. To disentangle these two accounts, we fitted three models in each of our age-related analyses: one that treated age discontinuously (adolescents ages 13–17 vs. adults ages 18–27), one that included linear (z -scored) age alone, and one that included linear as well as quadratic age (z -scored age squared). We then compared Akaike information criterion (AIC; Akaike, 1974) values for each of the three age models, reporting and interpreting results from the favored model (i.e., lowest AIC value). If one model was not clearly favored (i.e., if the AIC difference between two leading models is less than 2; Burnham & Anderson, 2004), we report results from both leading models. For each analysis, we report the AIC values for all three age models.

Control variables

For the mixed-effects model examining within-participant associations between roaming entropy and positive affect, we conducted an analysis to determine whether observed effects remained after including a set of covariates that

we hypothesized could potentially affect both roaming entropy and affect. Covariates included day of the week, precipitation and temperature at the participant's modal location for that day, distance traveled, and the time of day in which the EMA survey was completed. We used historical weather data from Dark Sky (darksky.net) to extract the temperature and precipitation levels. The R function "weekdays" was used to convert dates to days of the week (R Core Team, 2020). To index the total distance traveled each day, we calculated the sum of distances between successive points visited in a given day. Distance was calculated using the `rdist.earth` function in the R package *fields* (Nychka et al., 2017).

Statistical models

Daily roaming entropy, daily novelty, and positive affect were all repeated measures (nested within participant). For our linear mixed-effects analyses of the relationship between daily roaming entropy and positive affect, we used the *lme4* package in R (Bates et al., 2015; R Core Team, 2020). Linear mixed-effects models estimated participant-specific intercepts and slopes for each effect of interest. To model the association between daily roaming entropy and novelty, we used the R package *glmmTMB* (Brooks et al., 2017) to implement a multi-level regression specifying a zero-inflated negative binomial distribution based on the observed distribution of the dependent variable, novelty.

For between-subjects analyses (i.e., in which each participant had a single observation for predictor and outcome variables), we conducted robust regression analyses to minimize the effect of outliers (Ho & Naugher, 2000; Li, 1985). We used the R package *MASS* (Venables & Ripley, 2002) to conduct robust multiple regressions using iterated reweighted least squares for all between-subjects analyses. For these models, we estimated model significance using the Wald *F* test for robust multiple regression in the R package *sfsmisc* (Maechler, 2020). In reporting results from statistical models, the standardized coefficients are denoted as β . In cases in which the unstandardized term is more interpretable (e.g., categorical age group, daily positive affect), the unstandardized coefficient (*b*) is provided instead. We used the `confint` function from the R package *stats* (R Core Team, 2020) to calculate bootstrapped 95% CIs for all analyses.

Results

Roaming entropy and novelty

To verify that the previously reported positive relation between roaming entropy and location novelty was also

present in this sample (Heller et al., 2020), we tested whether higher roaming-entropy days were also days in which exposure to novel locations was greater. We implemented a multilevel regression with a zero-inflated negative binomial distribution specified with daily roaming entropy (*z*-scored within participants) as a predictor and daily number of novel locations (excluding the first 10 days of data; see the Assessment of Location-Based Novelty section) as the outcome. This model revealed a significant positive association between daily roaming entropy and daily novelty exposure ($b = 0.74$, 95% CI = [0.71, 0.78], $z = 41.62$, $p < .001$). Moreover, the effect remained significant when total distance traveled was added to the model (roaming entropy: $b = 0.69$, 95% CI = [0.66, 0.73], $z = 38.44$, $p < .001$; distance traveled: $b = 0.002$, 95% CI = [0.002, 0.003], $z = 9.01$, $p < .001$). Replicating our prior finding, this suggests that daily roaming entropy and novelty are positively related, even after accounting for the total distance traveled within a day.

Age differences in roaming entropy

We hypothesized that adolescents would exhibit heightened average roaming-entropy levels compared with adults. Comparison of the between-subjects robust regression models indicated that both the categorical age-group model and the quadratic-age model were favored over the linear-age model (age-group model AIC = 164.53; linear-age model AIC = 168.78; quadratic-age model AIC = 164.73). Results from the age-group model suggest that the adult group (age ≥ 18 years old) exhibited higher average roaming entropy than the adolescent group (mean roaming entropy for adolescents = 4.54; mean roaming entropy for adults = 5.23; $b = 0.67$, 95% CI = [0.22, 1.13], $F(56) = 8.46$, $p = .005$; Fig. 2a). The quadratic-age model revealed that quadratic age was a significant predictor of roaming entropy levels ($\beta = -0.26$, 95% CI = [-0.51, -0.02], $F(55) = 4.51$, $p = .038$), with the greatest levels of exploration evident in 18- to 21-year-olds (Fig. 2b). However, given our small sample size, the quadratic effect of age should be interpreted with caution (see the Supplemental Material for a priori power analyses).

Roaming entropy and affect

Positive-affect ratings were assessed on a scale from 0 to 100 (Fig. 1). Across participants, the mean positive-affect rating across all days of EMA data was 67.93 with an average within-subjects standard deviation of 21.57. We first examined whether age predicted average positive affect (*z*-scored across participants). Comparison of models indicated that both the categorical age-group model and the linear-age model were favored over the

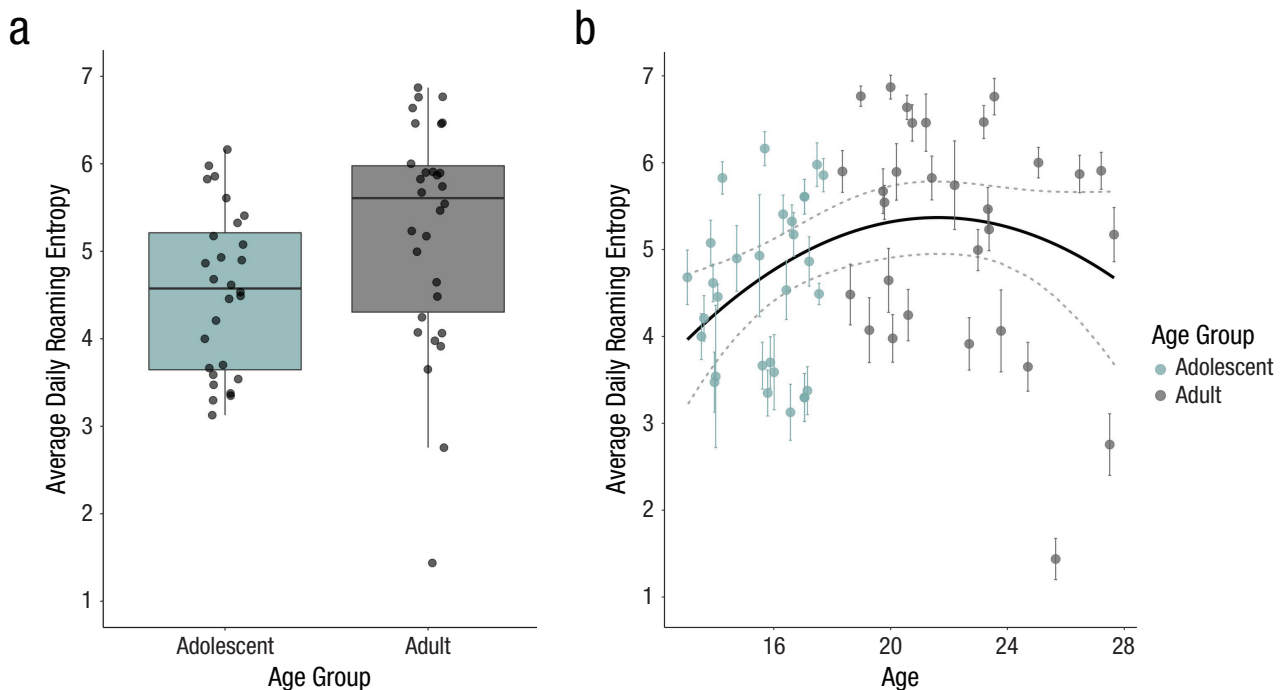


Fig. 2. (a) When age is treated categorically, average roaming entropy is higher for adults than for adolescents. Points represent individual participants. (b) When age is treated continuously, average roaming entropy displays a quadratic function, with the greatest mean roaming entropy levels evident in 18- to 21-year-olds. Points represent individual participants, colored by age group; the line represents the predicted effect of quadratic age from the robust regression model. Bars represent standard errors within participants. Dotted lines represent 95% confidence intervals.

quadratic-age model (age-group model: AIC = 169.53; linear-age model: AIC = 169.66; quadratic-age model: AIC = 171.79). Age was not associated with mean positive affect regardless of whether age was treated categorically, $b = 0.08$, 95% CI = $[-0.44, 0.60]$, $F(56) = 0.09$, $p = .76$, or continuously, $\beta = 0.02$, 95% CI = $[-0.24, 0.27]$, $F(56) = 0.02$, $p = .88$.

In order to investigate whether days of higher roaming entropy were associated with variation in affect and whether this relation varied with age, we tested a linear mixed-effects model with positive affect (0–100 rating) as the dependent variable and age as a moderator. To adjust for between-subjects differences in mean roaming entropy, we z -scored daily roaming entropy within participants and included it as a fixed effect. The model including age group (vs. linear or quadratic age) as the moderator had the lowest AIC value (age-group model: AIC = 11,201.55; linear age: AIC = 11,204.37; quadratic age: AIC = 11,204.30). Replicating the effect reported in Heller et al. (2020), there was a significant positive relationship between daily roaming entropy and positive affect so that on days in which participants experienced higher roaming entropy, they also reported higher levels of positive affect, $b = 3.54$, 95% CI = $[1.46, 5.60]$, $t(59.21) = 3.25$, $p = .002$ (Fig. 3a). The effect of roaming entropy on positive affect was robust to the

inclusion of a number of factors which we hypothesized might have influenced one or both of these measures (temperature, precipitation levels, time of day, distance traveled, and day of the week, $b = 3.77$, 95% CI = $[1.65, 5.94]$, $t(60.81) = 3.44$, $p < .01$). Moreover, none of these additional covariates significantly predicted positive affect (see Table S1 in the Supplemental Material). Contrary to our hypotheses, however, results did not reveal a significant interaction between roaming entropy and age group, $b = -0.63$, 95% CI = $[-3.66, 2.27]$, $t(54.97) = -0.42$, $p = .67$, in predicting positive affect. Thus, although we observed a positive relationship between daily roaming entropy and positive affect, an effect that holds after accounting for potential confounding variables, we did not detect age-related differences in the magnitude of this effect (Fig. 3b).

Average roaming entropy and social network size

To examine whether real-world exploration relates to social connectedness, we next performed a series of analyses to investigate age differences in social network size and the relationship between social network size and average daily roaming entropy. We first examined whether there were age differences in self-reported

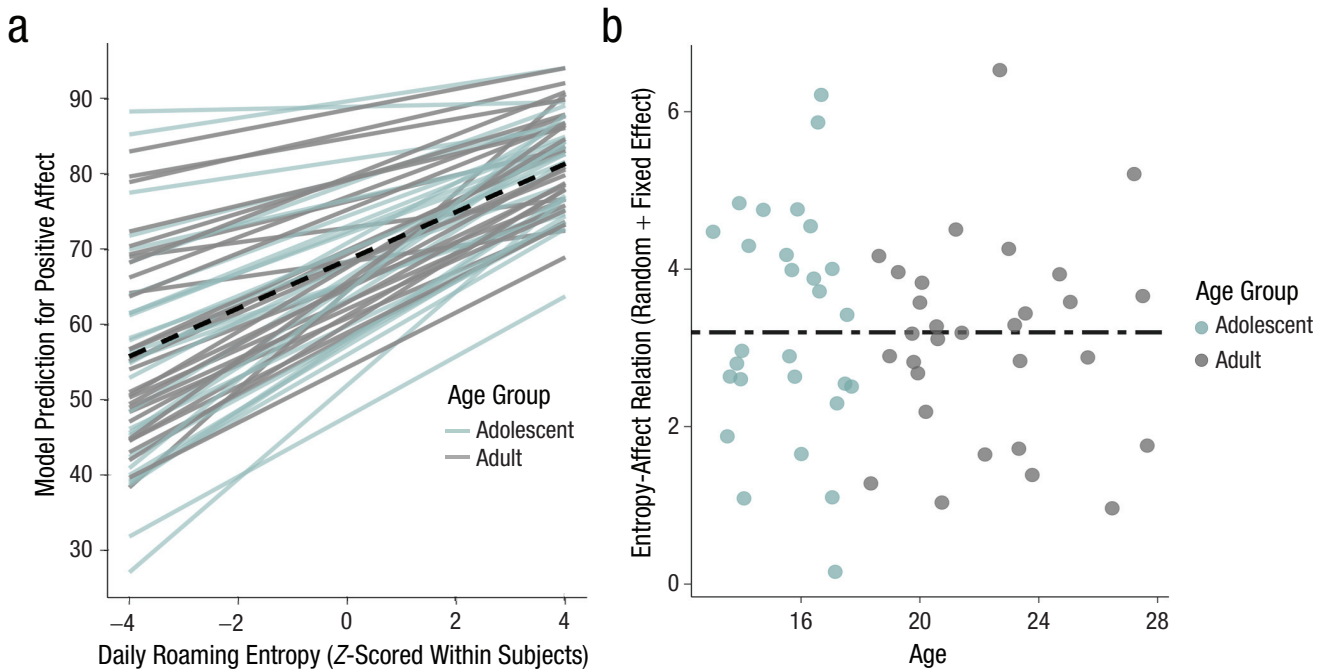


Fig. 3. (a) Daily increases in roaming entropy relate to greater positive affect (on a scale from 0–100). Individual lines represent per-participant random slopes from a model that does not include age. Lines are colored by age group for illustration. The dashed black line represents the fixed effect of daily roaming entropy on positive affect. (b) The relation between roaming entropy and positive affect does not differ with respect to age. Points represent the sum of fixed and random-effect estimates of this relation for individual participants, colored by age group for illustration. The dashed black line represents the fixed effect of roaming entropy on positive affect.

social connectivity. Social network size values (i.e., sum of the number of people called and messaged in the last month) ranged from 9 people to 250 people across participants with a mean of 60.39 and a standard deviation of 53.08. Two participants had values that were more than 2.5 standard deviations above the mean (reporting interactions with 214 and 250 people, respectively). These participants were not excluded, but as with the other between-subjects analyses, we conducted robust regressions to minimize the effect of outliers (Ho & Naugher, 2000; Li, 1985). There were minimal differences in AIC for the three models assessing the relationship between age and social network size (age-group model: AIC = 137.63; linear-age model: AIC = 137.56; quadratic-age model: AIC = 139.48). Average social network size did not differ by age group, $b = 0.01$, 95% CI = $[-0.38, 0.40]$, $F(44) = 0.003$, $p = .96$; linear age, $\beta < 0.01$, 95% CI = $[-0.20, 0.20]$, $F(44) < 0.01$, $p = .99$; or quadratic age, $\beta = -0.04$, 95% CI = $[-0.24, 0.16]$, $F(43) = 0.16$, $p = .69$. Additionally, we tested for age-associated differences in the use of different forms of social communication (i.e., the use of phone calls vs. texts), which could pose a confound in the age analyses when these two measures were combined. To test this, we calculated the difference between the reported number of text-based interactions (including messaging

via social media) and the reported number of phone-call-based interactions for each participant and tested whether these difference scores varied by age. Robust regressions comparing these difference scores (text – phone) revealed no significant difference in this variable by age group, $b = -0.21$, 95% CI = $[-0.64, 0.22]$, $F(44) = 0.93$, $p = .34$; linear age, $\beta = -0.14$, 95% CI = $[-0.35, 0.08]$, $F(44) = 1.57$, $p = .22$; or quadratic age, $\beta = -0.01$, 95% CI = $[-0.22, 0.20]$, $F(43) = 0.01$, $p = .92$.

To test whether mean level of exploration is linked to larger social network size, we assessed the relation between average roaming entropy and self-reported social connectivity. A robust linear regression demonstrated a significant positive relationship between average roaming entropy and social network size, $\beta = 0.30$, 95% CI = $[0.11, 0.50]$, $F(44) = 9.93$, $p = .003$ (Fig. 4). We then tested whether this effect was moderated by age. Comparison of the between-subjects robust interaction models indicated that both the categorical age-group model and the linear-age model were favored over the quadratic-age model (age-group model: AIC = 135.14; linear-age model: AIC = 135.58; quadratic-age model: AIC = 139.63). Contrary to our hypothesis, the relationship between social network size and roaming entropy did not differ between age groups, $b = -0.28$, 95% CI = $[-0.67, 0.12]$, $F(42) = 1.83$, $p = .18$, or by linear age,

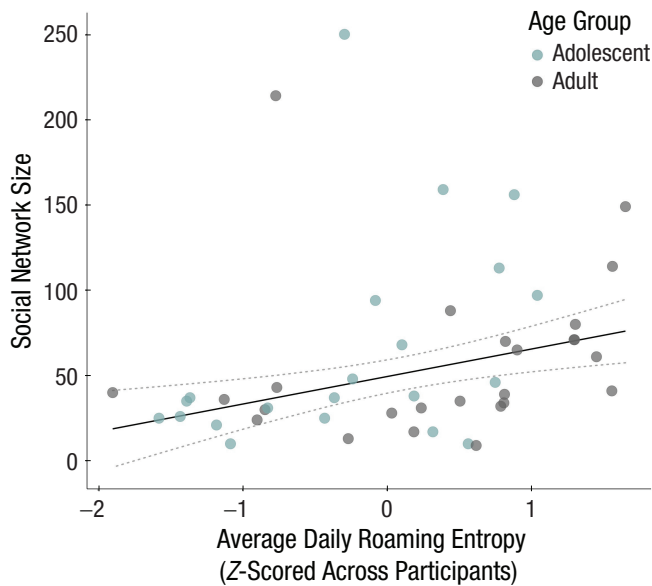


Fig. 4. Greater average daily roaming entropy is associated with larger social network size. Social network size values represent the number of people participants conversed with via phone calls or messaging platforms. Points represent individual participants (including outliers), colored by age group. The black line is the regression line from the robust regression, without age included as a covariate or moderator. Dotted lines represent 95% confidence intervals.

interaction $\beta = -0.14$, 95% CI = $[-0.34, 0.06]$, $F(42) = 2.06$, $p = .16$.

Average roaming entropy and risk taking

Next, we tested whether individual differences in the propensity for exploration, reflected by higher mean roaming entropy, relates to a heightened tendency to engage in potentially risky behaviors (as indicated by CARE and DOSPERT scores) and whether this association differed by age. To do this, we used robust regressions to test whether normalized DOSPERT was predicted by z -scored average roaming entropy and was moderated by age (group, linear, or quadratic). The same process was conducted for CARE scores. For both the DOSPERT and CARE models, the model including age group (vs. linear or quadratic age) as the moderator had the lowest AIC value (DOSPERT—age-group model: AIC = 159.70; linear-age model: AIC = 164.78; quadratic-age model: AIC = 166.03; CARE—age-group model: AIC = 156.55; linear-age model: AIC = 162.04; quadratic-age model: AIC = 164.76). The DOSPERT interaction model demonstrated that average random entropy, $\beta = 0.77$, 95% CI = $[0.29, 1.25]$, $F(53) = 9.69$, $p = .003$, but not age group, $b = -0.22$, 95% CI = $[-0.78, 0.33]$, $F(53) = 0.61$, $p = .44$, significantly predicted mean DOSPERT scores. Average item scores on the DOSPERT did not differ by group

(mean adolescent DOSPERT item score = 2.92; mean adult DOSPERT item score = 2.97). Further, there was a significant interaction between age group and average roaming entropy: Higher roaming entropy was associated with greater reported risk taking in the adolescent group, $b = -0.76$, 95% CI = $[-1.34, -0.17]$, $F(53) = 6.43$, $p = .01$ (Fig. 5a). In the CARE interaction model, both average roaming entropy, $\beta = 0.97$, 95% CI = $[0.54, 1.39]$, $F(54) = 18.89$, $p < .001$, and age group, $b = -0.71$, 95% CI = $[-1.20, -0.22]$, $F(54) = 7.66$, $p < .01$, significantly predicted mean CARE scores, with adults reporting greater risk taking (mean adolescent total CARE score = 75.67; mean adult total CARE score = 79.75). Additionally, this CARE model replicated the interaction effect present in the DOSPERT model, so higher roaming entropy was associated with greater risk taking in the adolescent group, $b = -0.80$, 95% CI = $[-1.31, -0.28]$, $F(54) = 8.95$, $p < .01$ (Fig. 5b).

Discussion

A broad literature suggests that exploration fosters engagement with novelty (Nunnally & Lemond, 1974) and relates to affect (Heller et al., 2020), social behaviors (Arakawa, 2003; Crone & Dahl, 2012; Dindo et al., 2009), and risky decision-making (Bardo et al., 1996; Bevins, 2001; Wingo et al., 2016) across development. Although recent work has underscored the importance of assessing these behaviors in naturalistic contexts (Berman et al., 2019; Mobbs et al., 2018; Tost et al., 2015), adolescent exploration remains relatively understudied outside of controlled laboratory settings. Consistent with the notion that roaming entropy may provide an objective index of environmental exploration, our results showed that roaming entropy was associated with greater novelty exposure and that mean roaming-entropy levels were associated with age, with individuals at the lower bounds of legal adulthood (e.g., ages 18–21) exhibiting the highest roaming-entropy levels. Our findings replicate a previously reported relationship between exploratory behavior and positive affect in adults (Heller et al., 2020), and demonstrate that this relation is also evident in adolescents. Moreover, levels of exploration were positively associated with social network size in both adolescents and adults but were linked to risk taking selectively among adolescents. Together, these findings evidence the interplay of naturalistic exploratory behavior and affect across development and highlight how individual differences in exploration relate to risk taking and social connectivity.

Increases in exploratory behavior are proposed to facilitate adolescents' transition toward independence (Spear, 2000a). Our objective measure of environmental exploration revealed evidence of such increases across

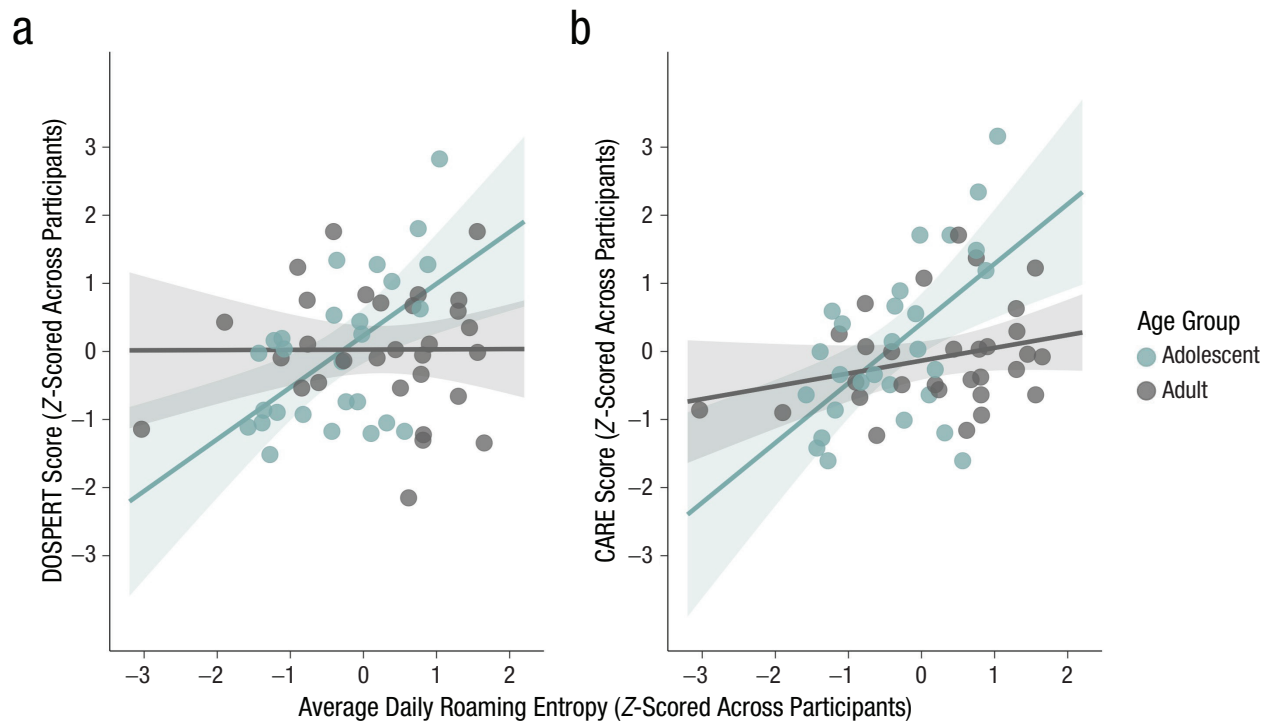


Fig. 5. Average daily roaming entropy relates to self-reported risk taking on both the Domain-Specific Risk-Taking Scale (DOSPERT; a) and the CARE questionnaire (b) in adolescents. Points represent individual participants (including outliers), colored by age group. Lines represent the regression lines from a robust regression in which age group was treated as a moderator. The simple slopes for DOSPERT shown in (a) are $\beta_{\text{adolescents}} = 0.77$, $\beta_{\text{adults}} = 0.01$. The simple slopes for CARE shown in (b) are adolescent $\beta_{\text{adolescents}} = 0.97$, $\beta_{\text{adults}} = 0.17$. Shaded regions represent 95% confidence intervals.

human adolescence. Mean levels of roaming entropy exhibited a quadratic relation with age: Individuals at the transition to legal adulthood (i.e., 18- to 21-year-olds) exhibited the highest levels of entropy, supporting the notion that exploration increases as individuals acquire autonomy (Spear, 2000a). Peak levels of exploration at the onset of legal adulthood may reflect, in part, adolescents' release from societal constraints placed on minors. Minors typically spend a large proportion of each day in geographically constrained, structured activities (e.g., school, extracurricular activities; Hofferth & Sandberg, 2001; Larson & Verma, 1999; U.S. Department of Labor, Bureau of Labor Statistics, 2019). The increased independence afforded during the culturally defined transition to adulthood may enable greater expression of a developmentally heightened propensity toward exploration. Additional cross-cultural research (particularly across countries in which the legal age of adulthood differs; Arnett, 2015) or studies in which other factors that foster or constrain autonomy are recorded (e.g., going to college, obtaining a driver's license, school attendance vs. summer breaks) may provide insight into how societal norms shape the expression of exploratory behavior across adolescence (Duell et al., 2018). Although quadratic age was a significant predictor of exploration, given the cross-sectional

nature of our data (which can be prone to cohort effects), we were unable to draw strong conclusions about the precise trajectory of exploratory behavior that might occur for a given individual across adolescence. In particular, given the limited sample size, the current evidence of a peak in exploration at the legal transition to adulthood should be treated as provisional. Future attempts to replicate the current findings in a larger longitudinal sample, with focal sampling of individuals transitioning to adulthood, could provide greater clarity into the normative trajectory of age-related change in environmental exploration.

Consistent with a cross-species literature suggesting that novelty is rewarding (Berlyne, 1970; Bevins, 2001), our results showed that exposure to novelty was greater on high entropy days and that positive affect varied with day-to-day fluctuations in real-world exploration. Although we replicated the positive association between exploration and positive affect that we previously observed in adults (Heller et al., 2020), we did not find evidence for age-related differences in this effect. This result stands in apparent contrast to research demonstrating heightened sensitivity to rewards during adolescence (e.g., Barkley-Levenson & Galván, 2014; Braams et al., 2015; Doremus-Fitzwater & Spear, 2016; Galván, 2013; Somerville et al., 2010; van Duijvenvoorde

et al., 2016). Past studies observing heightened adolescent reward reactivity have typically quantified phasic responses to discrete stimuli (see Galván, 2010; van Duijvenvoorde et al., 2016). In our study, we lacked a temporally precise measure of affective responses to novel environments. This may have obscured our ability to detect potential age differences in phasic reward reactivity (Heller & Casey, 2016). Future studies examining phasic affective responses to novel experiences with higher temporal resolution (e.g., using dense experience-sampling approaches; Villano et al., 2020) may clarify whether adolescents indeed exhibit heightened reactivity to environmental novelty. Moreover, the study's cross-sectional design and limited number of participants at each age further preclude strong conclusions that the association between entropy and affect is indeed age invariant. However, it is notable that on the individual (random-slope) level, all participants demonstrate a positive association between entropy and affect despite their wide range of ages (Fig. 3b). This suggests that the association between entropy and positive affect previously observed in a large sample of adults (Heller et al., 2020) is similarly evident in adolescents.

Consistent with our hypothesis that motivation to explore one's geographic environment might be paralleled by a drive to seek diverse social interactions (but see results from Freund et al., 2015 in mice, which support alternative hypotheses), our results showed a positive relationship between average roaming entropy and social network size. Exploration of physical and social environments may emerge from a common trait-like motivation to seek out novel and rewarding experiences (Dölen et al., 2013; Spear, 2000a). On the basis of findings that adolescents exhibit heightened novelty seeking (Adriani et al., 1998; Laviola et al., 1999, 2003; Philpot & Wecker, 2008; Stansfield & Kirstein, 2006) and greater sensitivity to the rewarding properties of social interaction (Blakemore & Mills, 2014; Douglas et al., 2004; Foulkes & Blakemore, 2016; Somerville, 2013; Walker et al., 2017; Yates et al., 2013), we hypothesized that this relation might be strongest during adolescence. However, we did not observe age differences in the relation between exploration and social network size. Future ecological studies providing richer characterizations of social interaction than our network-size measure might better capture aspects of social affiliation that are uniquely linked to adolescent exploration. Notably, our results suggest that individuals who communicate via mobile technology are also those most likely to explore their physical environments. This result lends support to a growing literature suggesting that, despite popular belief, digital technology does not necessarily hinder real-world engagement during adolescence (Orben et al., 2019; Orben & Przybylski, 2019).

Intriguingly, whereas the relation between mean entropy and social connectivity was evident in both age groups, mean entropy was associated only with greater risk taking within adolescents. Adolescents lack prior experience with many situations familiar to adults (e.g., attending parties, going on first dates). In such novel contexts, adolescents may have greater uncertainty about the potential outcomes of their actions and thus may be more likely to take risks (Rosenbaum & Hartley, 2019). Indeed, epidemiological statistics suggest that such uncertain contexts are precisely those in which adolescents exhibit heightened risky decision making (e.g., unsafe driving, or experimentation with drugs, alcohol, or sex; Arnett, 1992). These results suggest that the tendency to explore one's environment, reflected in higher levels of mean entropy, may foster greater exposure to situations in which adolescents' lack of prior experience makes them particularly prone to take risks (Romer et al., 2017; Spielberg et al., 2014).

There are several important factors to consider when interpreting the current findings. Although our study focused on individuals' exploration of their physical environments, it is important to note that exploration is not strictly geolocational—a given physical location can also afford novel and diverse experiences (e.g., social interactions, activities). Detailed accounts of daily experiences (e.g., diary methods) may supplement location-based measures to provide more comprehensive estimates of real-world exploratory behavior. Furthermore, without manipulation of exploration, we cannot draw definitive conclusions about causality in the relation between exploration and positive affect. Additionally, individuals who are willing to allow their behavior to be tracked may represent a unique group, therefore limiting generalizability. Last, although risk taking can be conceptualized as a normative behavior that facilitates the transition toward independence (Romer et al., 2017; Sercombe, 2014; Spear, 2000a), given that this sample exhibited limited heterogeneity in risk taking, it is important for future work—particularly in samples that examine age-related changes in risk taking from childhood to young adulthood (Rosenbaum et al., 2022)—to determine the features of exploration that differentiate adaptive and maladaptive risk-taking behavior during this formative stage of development.

The current study leveraged geolocation data to translate rodent models of roaming entropy to humans and provides evidence of age-related increases in real-world exploration during adolescence. The current findings replicate the association between exploration and positive affect previously seen in adults and suggest that exploration may play a role in sustaining adolescent well-being, social connectivity, and risk taking. Together, these results demonstrate the interplay of real-world exploration, affect, social affiliation, and risk

taking across development and highlight the roles of both biological maturation and sociocultural factors in shaping adolescent behavior.

Transparency

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Author Contributions

A. S. Heller and C. A. Hartley designed the study with input from A. O. Cohen and N. M. Saragosa-Harris. A. O. Cohen and N. M. Saragosa-Harris led recruitment and data collection. T. R. Reneau and W. J. Villano led automated collection of ecological momentary assessment (EMA), GPS, and weather data. N. M. Saragosa-Harris, A. O. Cohen, and T. R. Reneau analyzed the data. N. M. Saragosa-Harris, A. O. Cohen, A. S. Heller, and C. A. Hartley wrote the manuscript with input from the other authors. All authors approved the final manuscript for submission.

Declaration of Conflicting Interests

The authors declared no conflicts of interest with respect to the authorship or the publication of this article.

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Open Practices

All processed data and analysis scripts have been made publicly available via OSF and can be accessed at <https://osf.io/qw4b3/>. The design and analysis plans for the study were not preregistered. This article has received the badge for Open Data. More information about the Open Practices badges can be found at <http://www.psychologicalscience.org/publications/badges>.



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Supplemental Material

Additional supporting information can be found at <http://journals.sagepub.com/doi/10.1177/09567976221102070>

References

- Adriani, W., Chiarotti, F., & Laviola, G. (1998). Elevated novelty seeking and peculiar d-amphetamine sensitization in periadolescent mice compared with adult mice. *Behavioral Neuroscience*, 112(5), 1152–1166. <https://doi.org/10.1037/0735-7044.112.5.1152>
- Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, 19(6), 716–723.
- Arakawa, H. (2003). The effect of isolation rearing on open-field behavior in male rats depends on developmental stages. *Developmental Psychobiology*, 43(1), 11–19.
- Arnett, J. (1992). Reckless behavior in adolescence: A developmental perspective. *Developmental Review*, 12(4), 339–373.
- Arnett, J. J. (1998). Learning to stand alone: The contemporary American transition to adulthood in cultural and historical context. *Human Development*, 41(5–6), 295–315.
- Arnett, J. J. (2015). The cultural psychology of emerging adulthood. In L. A. Jensen (Ed.), *The Oxford handbook of human development and culture: An interdisciplinary perspective* (pp. 487–501). Oxford University Press.
- Arnett, J. J., Žukauskienė, R., & Sugimura, K. (2014). The new life stage of emerging adulthood at ages 18–29 years: Implications for mental health. *The Lancet Psychiatry*, 1(7), 569–576.
- Bardo, M. T., Donohew, R. L., & Harrington, N. G. (1996). Psychobiology of novelty seeking and drug seeking behavior. *Behavioural Brain Research*, 77(1–2), 23–43.
- Bardo, M. T., Neisewander, J. L., & Pierce, R. C. (1989). Novelty-induced place preference behavior in rats: Effects of opiate and dopaminergic drugs. *Pharmacology Biochemistry and Behavior*, 32(3), 683–689.
- Barkley-Levenson, E., & Galván, A. (2014). Neural representation of expected value in the adolescent brain. *Proceedings of the National Academy of Sciences, USA*, 111(4), 1646–1651.
- Bates, D., Maechler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1). <https://doi.org/10.18637/jss.v067.i01>
- Berlyne, D. E. (1970). Novelty, complexity, and hedonic value. *Perception & Psychophysics*, 8(5), 279–286.
- Berman, M. G., Kardan, O., Kotabe, H. P., Nusbaum, H. C., & London, S. E. (2019). The promise of environmental neuroscience. *Nature Human Behaviour*, 3(5), 414–417.
- Bevins, R. A. (2001). Novelty seeking and reward: Implications for the study of high-risk behaviors. *Current Directions in Psychological Science*, 10(6), 189–193.

- Bevins, R. A., & Bardo, M. T. (1999). Conditioned increase in place preference by access to novel objects: Antagonism by MK-801. *Behavioural Brain Research*, 99(1), 53–60.
- Blais, A.-R., & Weber, E. U. (2006). A domain-specific risk-taking (DOSPERT) scale for adult populations. *Judgment and Decision Making*, 1(1), 33–47.
- Blakemore, S. J., & Mills, K. L. (2014). Is adolescence a sensitive period for sociocultural processing? *Annual Review of Psychology*, 65, 187–207.
- Bowker, A. (2004). Predicting friendship stability during early adolescence. *The Journal of Early Adolescence*, 24(2), 85–112.
- Braams, B. R., van Duijvenvoorde, A. C., Peper, J. S., & Crone, E. A. (2015). Longitudinal changes in adolescent risk-taking: A comprehensive study of neural responses to rewards, pubertal development, and risk-taking behavior. *Journal of Neuroscience*, 35(18), 7226–7238.
- Brooks, M. E., Kristensen, K., van Benthem, K. J., Magnusson, A., Berg, C. W., Nielsen, A., Skaug, H. J., Maechler, M., & Bolker, B. M. (2017). glmmTMB balances speed and flexibility among packages for zero-inflated generalized linear mixed modeling. *The R Journal*, 9(2), 378–400.
- Brown, B. B. (2004). Adolescents' relationships with peers. In R. M. Lerner & L. Steinberg (Eds.), *Handbook of adolescent psychology* (pp. 363–394). John Wiley.
- Bunzeck, N., Doeller, C. F., Dolan, R. J., & Duzel, E. (2012). Contextual interaction between novelty and reward processing within the mesolimbic system. *Human Brain Mapping*, 33(6), 1309–1324.
- Burnham, K. P., & Anderson, D. R. (2004). Multimodel inference: Understanding AIC and BIC in model selection. *Sociological Methods & Research*, 33(2), 261–304.
- Calcagnetti, D. J., & Schechter, M. D. (1992). Place conditioning reveals the rewarding aspect of social interaction in juvenile rats. *Physiology & Behavior*, 51(4), 667–672.
- Casey, B. J. (2015). Beyond simple models of self-control to circuit-based accounts of adolescent behavior. *Annual Review of Psychology*, 66, 295–319.
- Christakou, A., Gershman, S. J., Niv, Y., Simmons, A., Brammer, M., & Rubia, K. (2013). Neural and psychological maturation of decision-making in adolescence and young adulthood. *Journal of Cognitive Neuroscience*, 25(11), 1807–1823.
- Cohen, A. O., Breiner, K., Steinberg, L., Bonnie, R. J., Scott, E. S., Taylor-Thompson, K. A., Rudolf, M. D., Chein, J., Richeson, J. A., Heller, A. S., Silverman, M. R., Dellarco, D. V., Fair, D. A., Galván, A., & Casey, B. J. (2016). When is an adolescent an adult? Assessing cognitive control in emotional and nonemotional contexts. *Psychological Science*, 27(4), 549–562.
- Crews, F., He, J., & Hodge, C. (2007). Adolescent cortical development: A critical period of vulnerability for addiction. *Pharmacology Biochemistry and Behavior*, 86(2), 189–199.
- Crone, E. A., & Dahl, R. E. (2012). Understanding adolescence as a period of social-affective engagement and goal flexibility. *Nature Reviews Neuroscience*, 13(9), 636–650. <https://doi.org/10.1038/nrn3313>
- Dellu, F., Piazza, P. V., Mayo, W., Le Moal, M., & Simon, H. (1996). Novelty-seeking in rats-biobehavioral characteristics and possible relationship with the sensation-seeking trait in man. *Neuropsychobiology*, 34(3), 136–145. <https://doi.org/10.1159/000119305>
- Dindo, M., Whiten, A., & de Waal, F. B. M. (2009). Social facilitation of exploratory foraging behavior in capuchin monkeys (*Cebus apella*). *American Journal of Primatology*, 71(5), 419–426. <https://doi.org/10.1002/ajp.20669>
- Dölen, G., Darvishzadeh, A., Huang, K. W., & Malenka, R. C. (2013). Social reward requires coordinated activity of nucleus accumbens oxytocin and serotonin. *Nature*, 501(7466), 179–184. <https://doi.org/10.1038/nature12518>.
- Doremus-Fitzwater, T. L., & Spear, L. P. (2016). Reward-centricity and attenuated aversions: An adolescent phenotype emerging from studies in laboratory animals. *Neuroscience & Biobehavioral Reviews*, 70, 121–134. <https://doi.org/10.1016/j.neubiorev.2016.08.015>
- Doremus-Fitzwater, T. L., Varlinskaya, E. I., & Spear, L. P. (2010). Motivational systems in adolescence: Possible implications for age differences in substance abuse and other risk-taking behaviors. *Brain and Cognition*, 72(1), 114–123.
- Douglas, L. A., Varlinskaya, E. I., & Spear, L. P. (2003). Novel-object place conditioning in adolescent and adult male and female rats: Effects of social isolation. *Physiology & Behavior*, 80(2–3), 317–325.
- Douglas, L. A., Varlinskaya, E. I., & Spear, L. P. (2004). Rewarding properties of social interactions in adolescent and adult male and female rats: Impact of social versus isolate housing of subjects and partners. *Developmental Psychobiology: The Journal of the International Society for Developmental Psychobiology*, 45(3), 153–162.
- Duell, N., Steinberg, L., Icenogle, G., Chein, J., Chaudhary, N., Di Giunta, L., Dodge, K. A., Fanti, K. A., Lansford, J. E., Oburu, P., Pastorelli, C., Skinner, A. T., Sorbring, E., Tapanya, S., Uribe Tirado, L. M., Alampay, L. P., Al-Hassan, S. M., Takash, H. M. S., Bacchini, D., & Chang, L. (2018). Age patterns in risk taking across the world. *Journal of Youth and Adolescence*, 47(5), 1052–1072.
- El Rawas, R., Klement, S., Kummer, K. K., Fritz, M., Dechant, G., Saria, A., & Zernig, G. (2012). Brain regions associated with the acquisition of conditioned place preference for cocaine vs. social interaction. *Frontiers in Behavioral Neuroscience*, 6, Article 63. <https://doi.org/10.3389/fnbeh.2012.00063>
- FollowMee. (2020). FollowMee [Mobile application software]. <https://www.followmee.com>
- Foulkes, L., & Blakemore, S. J. (2016). Is there heightened sensitivity to social reward in adolescence? *Current Opinion in Neurobiology*, 40, 81–85.
- Freund, J., Brandmaier, A. M., Lewejohann, L., Kirste, I., Kritzler, M., Krüger, A., & Kempermann, G. (2013). Emergence of individuality in genetically identical mice. *Science*, 340(6133), 756–759.
- Freund, J., Brandmaier, A. M., Lewejohann, L., Kirste, I., Kritzler, M., Krüger, A., Sachser, N., Lindenberger, U., & Kempermann, G. (2015). Association between exploratory activity and social individuality in genetically

- identical mice living in the same enriched environment. *Neuroscience*, 309, 140–152.
- Fromme, K., Katz, E. C., & Rivet, K. (1997). Outcome expectancies and risk-taking behavior. *Cognitive Therapy and Research*, 21(4), 421–442.
- Galván, A. (2010). Adolescent development of the reward system. *Frontiers in Human Neuroscience*, 4, Article 6. <https://doi.org/10.3389/neuro.09.006.2010>
- Galván, A. (2013). The teenage brain: Sensitivity to rewards. *Current Directions in Psychological Science*, 22(2), 88–93.
- Galván, A., Hare, T., Voss, H., Glover, G., & Casey, B. J. (2007). Risk-taking and the adolescent brain: Who is at risk? *Developmental Science*, 10(2), F8–F14.
- Heller, A. S., & Casey, B. J. (2016). The neurodynamics of emotion: Delineating typical and atypical emotional processes during adolescence. *Developmental Science*, 19(1), 3–18.
- Heller, A. S., Shi, T. C., Chiemeka Ezie, C. E., Reneau, T. R., Baez, L. M., Gibbons, C. J., & Hartley, C. A. (2020). Association between real-world experiential diversity and positive affect relates to hippocampal–striatal functional connectivity. *Nature Neuroscience*, 23, 800–804.
- Ho, K., & Naugher, J. (2000). Outliers lie: An illustrative example of identifying outliers and applying robust models. *Multiple Linear Regression Viewpoints*, 26(2), 2–6.
- Hofferth, S. L., & Sandberg, J. F. (2001). How American children spend their time. *Journal of Marriage and Family*, 63(2), 295–308.
- Horvitz, J. C. (2000). Mesolimbocortical and nigrostriatal dopamine responses to salient non-reward events. *Neuroscience*, 96(4), 651–656.
- Houillon, A., Lorenz, R. C., Boehmer, W., Rapp, M. A., Heinz, A., Gallinat, J., & Obermayer, K. (2013). The effect of novelty on reinforcement learning. In V. S. Chandrasekhar Pammi, Narayanan Srinivasan (Eds.), *Progress in brain research* (Vol. 202, pp. 415–439). Elsevier.
- Jepma, M., Schaaf, J. V., Visser, I., & Huizenga, H. M. (2020). Uncertainty-driven regulation of learning and exploration in adolescents: A computational account. *PLOS Computational Biology*, 16(9), Article 1008276.
- Kakade, S., & Dayan, P. (2002). Dopamine: Generalization and bonuses. *Neural Networks*, 15(4–6), 549–559.
- Katz, E. C., Fromme, K., & D'Amico, E. J. (2000). Effects of outcome expectancies and personality on young adults' illicit drug use, heavy drinking, and risky sexual behavior. *Cognitive Therapy and Research*, 24(1), 1–22.
- Krebs, R. M., Schott, B. H., Schütze, H., & Düzal, E. (2009). The novelty exploration bonus and its attentional modulation. *Neuropsychologia*, 47(11), 2272–2281.
- Larson, R. W., & Verma, S. (1999). How children and adolescents spend time across the world: Work, play, and developmental opportunities. *Psychological Bulletin*, 125(6), 701–736. <https://doi.org/10.1037/0033-2909.125.6.701>
- Laviola, G., Adriani, W., Terranova, M. L., & Gerra, G. (1999). Psychobiological risk factors for vulnerability to psychostimulants in human adolescents and animal models. *Neuroscience & Biobehavioral Reviews*, 23(7), 993–1010.
- Laviola, G., Macrì, S., Morley-Fletcher, S., & Adriani, W. (2003). Risk-taking behavior in adolescent mice: Psychobiological determinants and early epigenetic influence. *Neuroscience & Biobehavioral Reviews*, 27(1–2), 19–31.
- Levitt, M. J., Guacci-Franco, N., & Levitt, J. L. (1993). Convoys of social support in childhood and early adolescence: Structure and function. *Developmental Psychology*, 29(5), 811–818. <https://doi.org/10.1037/0012-1649.29.5.811>
- Li, G. (1985). Robust regression. In D. C. Hoaglin, C. F. Mosteller, and J. W. Turkey (Eds.), *Exploring data tables, trends, and shapes* (Vol. 281, p. U340). John Wiley & Sons, Inc.
- Lloyd, A., McKay, R., Sebastian, C., & Balsters, J. (2021). Are adolescents more optimal decision-makers in novel environments? Examining exploration and learning in a patch foraging paradigm. *Developmental Science*, 24(4), Article e13075. <https://doi.org/10.1111/desc.13075>
- Lynn, D. A., & Brown, G. R. (2009). The ontogeny of exploratory behavior in male and female adolescent rats (*Rattus norvegicus*). *Developmental Psychobiology*, 51(6), 513–520.
- Macrì, S., Adriani, W., Chiarotti, F., & Laviola, G. (2002). Risk taking during exploration of a plus-maze is greater in adolescent than in juvenile or adult mice. *Animal Behaviour*, 64(4), 541–546.
- Maechler, M. (2020). sfsmisc: Utilities from “Seminar fuer Statistik” ETH Zurich. R package version 1.1-7. <https://CRAN.R-project.org/package=sfsmisc>
- Mahalik, J. R., Levine Coley, R., McPherran Lombardi, C., Doyle Lynch, A., Markowitz, A. J., & Jaffee, S. R. (2013). Changes in health risk behaviors for males and females from early adolescence through early adulthood. *Health Psychology*, 32(6), 685–694.
- Mobbs, D., Trimmer, P. C., Blumstein, D. T., & Dayan, P. (2018). Foraging for foundations in decision neuroscience: Insights from ethology. *Nature Reviews Neuroscience*, 19(7), 419–427.
- Myers, A. K., & Miller, N. E. (1954). Failure to find a learned drive based on hunger; evidence for learning motivated by “exploration.” *Journal of Comparative and Physiological Psychology*, 47(6), 428–436. <https://doi.org/10.1037/h0062664>
- Nelson, L. J., & Luster, S. S. (2015). “Adulthood” by whose definition?: The complexity of emerging adults' conceptions of adulthood. In J. J. Arnett (Ed.), *The Oxford handbook of emerging adulthood* (p. 421). Oxford University Press.
- Nunnally, J. C., & Lemond, L. C. (1974). Exploratory behavior and human development. In *Advances in child development and behavior* (Vol. 8, pp. 59–109). JAI.
- Nychka, D., Furrer, R., Paige, J., & Sain, S. (2017). *fields: Tools for spatial data* (R package Version 10.3) [Computer software]. GitHub. <https://github.com/NCAR/Fields>
- Orben, A., Dienlin, T., & Przybylski, A. K. (2019). Social media's enduring effect on adolescent life satisfaction. *Proceedings of the National Academy of Sciences, USA*, 116(21), 10226–10228.
- Orben, A., & Przybylski, A. K. (2019). The association between adolescent well-being and digital technology use. *Nature Human Behaviour*, 3(2), 173–182.
- Philpot, R. M., & Wecker, L. (2008). Dependence of adolescent novelty-seeking behavior on response phenotype and effects of apparatus scaling. *Behavioral Neuroscience*, 122(4), 861–875. <http://doi.org/10.1037/0735-7044.122.4.861>

- Poulin, F., & Chan, A. (2010). Friendship stability and change in childhood and adolescence. *Developmental Review*, 30(3), 257–272.
- R Core Team. (2020). R: A language and environment for statistical computing. *R Foundation for Statistical Computing*. <https://www.R-project.org/>
- Rebec, G. V., Christensen, J. R., Guerra, C., & Bardo, M. T. (1997). Regional and temporal differences in real-time dopamine efflux in the nucleus accumbens during free-choice novelty. *Brain Research*, 776(1–2), 61–67.
- Reed, P., Mitchell, C., & Nokes, T. (1996). Intrinsic reinforcing properties of putatively neutral stimuli in an instrumental two-lever discrimination task. *Animal Learning & Behavior*, 24(1), 38–45.
- Romer, D. (2010). Adolescent risk taking, impulsivity, and brain development: Implications for prevention. *Developmental Psychobiology*, 52(3), 263–276.
- Romer, D., Reyna, V. F., & Satterthwaite, T. D. (2017). Beyond stereotypes of adolescent risk taking: Placing the adolescent brain in developmental context. *Developmental Cognitive Neuroscience*, 27, 19–34.
- Rosenbaum, G. M., Grassie, H. L., & Hartley, C. A. (2022). Valence biases in reinforcement learning shift across adolescence and modulate subsequent memory. *eLife*, 11, Article e64620. <https://doi.org/10.7554/eLife.64620>
- Rosenbaum, G. M., & Hartley, C. A. (2019). Developmental perspectives on risky and impulsive choice. *Philosophical Transactions of the Royal Society B*, 374(1766), Article 20180133.
- Sercombe, H. (2014). Risk, adaptation and the functional teenage brain. *Brain and Cognition*, 89, 61–69.
- Somerville, L. H. (2013). The teenage brain: Sensitivity to social evaluation. *Current Directions in Psychological Science*, 22(2), 121–127.
- Somerville, L. H., Jones, R. M., & Casey, B. J. (2010). A time of change: Behavioral and neural correlates of adolescent sensitivity to appetitive and aversive environmental cues. *Brain and Cognition*, 72(1), 124–133.
- Somerville, L. H., Sasse, S. F., Garrad, M. C., Drysdale, A. T., Abi Akar, N., Insel, C., & Wilson, R. C. (2017). Charting the expansion of strategic exploratory behavior during adolescence. *Journal of Experimental Psychology: General*, 146(2), 155–164. <https://doi.org/10.1037/xge0000250>
- Spear, L. P. (2000a). The adolescent brain and age-related behavioral manifestations. *Neuroscience & Biobehavioral Reviews*, 24(4), 417–463.
- Spear, L. P. (2000b). Neurobehavioral changes in adolescence. *Current Directions in Psychological Science*, 9(4), 111–114.
- Spear, L. P. (2011). Rewards, aversions and affect in adolescence: Emerging convergences across laboratory animal and human data. *Developmental Cognitive Neuroscience*, 1(4), 390–403.
- Spielberg, J. M., Olino, T. M., Forbes, E. E., & Dahl, R. E. (2014). Exciting fear in adolescence: Does pubertal development alter threat processing? *Developmental Cognitive Neuroscience*, 8, 86–95. <https://doi.org/10.1016/j.dcn.2014.01.004>
- Stansfield, K. H., & Kirstein, C. L. (2006). Effects of novelty on behavior in the adolescent and adult rat. *Developmental Psychobiology*, 48(1), 10–15.
- Subrahmanyam, K., Reich, S. M., Waechter, N., & Espinoza, G. (2008). Online and offline social networks: Use of social networking sites by emerging adults. *Journal of Applied Developmental Psychology*, 29(6), 420–433.
- Tost, H., Champagne, F. A., & Meyer-Lindenberg, A. (2015). Environmental influence in the brain, human welfare and mental health. *Nature Neuroscience*, 18(10), 1421–1431.
- Trezza, V., Campolongo, P., & Vanderschuren, L. J. (2011). Evaluating the rewarding nature of social interactions in laboratory animals. *Developmental Cognitive Neuroscience*, 1(4), 444–458.
- Tymula, A., Belmaker, L. A. R., Roy, A. K., Ruderman, L., Manson, K., Glimcher, P. W., & Levy, I. (2012). Adolescents' risk-taking behavior is driven by tolerance to ambiguity. *Proceedings of the National Academy of Sciences, USA*, 109(42), 17135–17140.
- U.S. Department of Labor, Bureau of Labor Statistics. (2019). *American Time Use Survey—May to December 2019 and 2020 results*. <https://www.bls.gov/news.release/pdf/atus.pdf>
- van den Bos, W., & Hertwig, R. (2017). Adolescents display distinctive tolerance to ambiguity and to uncertainty during risky decision making. *Scientific Reports*, 7, Article 40962. <https://doi.org/10.1038/srep40962>
- van Duijvenvoorde, A. C., Peters, S., Braams, B. R., & Crone, E. A. (2016). What motivates adolescents? Neural responses to rewards and their influence on adolescents' risk-taking, learning, and cognitive control. *Neuroscience & Biobehavioral Reviews*, 70, 135–147.
- Venables, W. N., & Ripley, B. D. (2002). *Modern applied statistics with S* (4th ed.). Springer.
- Vidal-Infer, A., Arenas, M. C., Daza-Losada, M., Aguilar, M. A., Miñarro, J., & Rodríguez-Arias, M. (2012). High novelty-seeking predicts greater sensitivity to the conditioned rewarding effects of cocaine. *Pharmacology Biochemistry and Behavior*, 102(1), 124–132.
- Villano, W. J., Otto, A. R., Chiemeka Ezie, C. E., Gillis, R., & Heller, A. S. (2020). Temporal dynamics of real-world emotion are more strongly linked to prediction error than outcome. *Journal of Experimental Psychology: General*, 149(9), 1755–1766. <https://doi.org/10.1037/xge0000740>
- Wahlstrom, D., Collins, P., White, T., & Luciana, M. (2010). Developmental changes in dopamine neurotransmission in adolescence: Behavioral implications and issues in assessment. *Brain and Cognition*, 72(1), 146–159.
- Walker, D. M., Bell, M. R., Flores, C., Gulley, J. M., Willing, J., & Paul, M. J. (2017). Adolescence and reward: Making sense of neural and behavioral changes amid the chaos. *Journal of Neuroscience*, 37(45), 10855–10866.
- Weber, E. U., Blais, A. R., & Betz, N. E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making*, 15(4), 263–290.
- Wills, T. A., DuHamel, K., & Vaccaro, D. (1995). Activity and mood temperament as predictors of adolescent substance use: Test of a self-regulation mediational model. *Journal of Personality and Social Psychology*, 68(5), 901–916. <https://doi.org/10.1037//0022-3514.68.5.901>

- Wills, T. A., Vaccaro, D., & McNamara, G. (1994). Novelty seeking, risk taking, and related constructs as predictors of adolescent substance use: An application of Cloninger's theory. *Journal of Substance Abuse*, 6(1), 1–20.
- Wingo, T., Nesil, T., Choi, J. S., & Li, M. D. (2016). Novelty seeking and drug addiction in humans and animals: From behavior to molecules. *Journal of Neuroimmune Pharmacology*, 11(3), 456–470.
- Wittmann, B. C., Bunzeck, N., Dolan, R. J., & Düzel, E. (2007). Anticipation of novelty recruits reward system and hippocampus while promoting recollection. *NeuroImage*, 38(1), 194–202.
- Wittmann, B. C., Daw, N. D., Seymour, B., & Dolan, R. J. (2008). Striatal activity underlies novelty-based choice in humans. *Neuron*, 58(6), 967–973.
- Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: A meta-analysis. *Psychological Bulletin*, 139(1), 53–80. <https://doi.org/10.1037/a0028601>
- Yates, J. R., Beckmann, J. S., Meyer, A. C., & Bardo, M. T. (2013). Concurrent choice for social interaction and amphetamine using conditioned place preference in rats: Effects of age and housing condition. *Drug and Alcohol Dependence*, 129(3), 240–246.