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Precursors of young adults' world beliefs across cultures: A machine learning approach☆

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ABSTRACT

Primal world beliefs ("primals") capture individuals' basic understanding of what sort of world this is and are strongly associated with a wide range of behaviors and outcomes, yet we have little understanding of how primals come to be. This study used a data-driven machine learning approach to examine what individual, parenting, family, and cultural factors in childhood best predict young adults' beliefs that the world is *Abundant, Alive, Enticing, Good, Hierarchical, Progressing*, and *Safe*, contributing a long-term longitudinal perspective to the nascent work in developmental science on primal world beliefs ("primals"). Participants included 770 young adults from eight countries (Colombia, Italy, Jordan, Kenya, Philippines, Sweden, Thailand, United States). During childhood, participants and parents reported on 76 factors available as potential predictors of primals. Factors at individual, parenting, family, and cultural levels all had some predictive value in relation to specific primals, but no single factor or cluster of factors was predictive of all primals. Developmental pathways to perceiving the world as *Abundant, Alive, Enticing, Good, Hierarchical, Progressing*, and *Safe* are not uniform. The current data-driven approach successfully unearthed several promising leads for developmentalists to probe in further research.

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Schemas about the general character of local situations are thought to influence perceptions, attention, behavior, affect, and even physiology (Wilson, 2022). For example, if a pub is seen as dangerous, then, while in said pub, a person should perceive more threats, reluctantly relinquish suspicions, antagonize others, and struggle to relax. What if a person sees the whole world as dangerous? If world beliefs functioned like beliefs about local situations, world beliefs would be (a) uniquely impactful (by systematically influencing outcomes across all situations) and (b) uniquely likely to be overlooked (because it becomes impossible to observe the individual in situations where the schema does not apply).

To explore this possibility, researchers in personality and social psychology have launched a new body of theoretical and empirical work to understand primal world beliefs ("primals"), which capture individuals' basic understanding of what sort of world this is (e.g., Clifton et al., 2019). An analysis of more than 1700 descriptions of the world in 385 Western and non-Western sacred texts, philosophical treatises, novels, political speeches, and films as well as more than 80,000 tweets beginning "The world is…" revealed an overarching primal of whether individuals believe the world is *Good*, with slightly more specific primals that the world is *Safe* (as opposed to dangerous), *Enticing* (as opposed to dull), and *Alive* (as opposed to mechanistic) (Clifton et al., 2019). Seventeen tertiary primals stem from the secondary primals of *Safe*, *Enticing*, and *Alive*, and an additional five primals capture beliefs about the world not subsumed by seeing it as good or bad. This empirically-derived taxonomy integrated previously studied primals (e.g., belief the world is just; Lerner, 1980) that have long been thought to impact educational, clinical, health, and social outcomes. The taxonomy also identifies new primals that may have a similarly broad impact (e.g., *Enticing* world belief; Kerry et al., 2024). However, as literatures advance in several fields, work on primals remains nascent in developmental psychology, with explorations of several top-down, theory-driven developmental hypotheses bearing little fruit (Lansford et al., 2025). Therefore, the present study attempts an alternative, more bottom-up, data-driven machine learning approach to address the question of how a wide array of variables measured during childhood might predict primals in early adulthood.

Primals are strongly associated with a wide range of behaviors and outcomes that primals theoretically should influence (Clifton & Meindl, 2022; Stahlmann et al., 2020). Past research on belief in a just world—the belief that the world is a place where people get what they usually deserve and deserve what they usually get—has already found connections to many educational, clinical, and social outcomes. These include grades in school (why work hard if the world is unfair?; Peter et al., 2012), bullying (why be kind in a world where kindness is for suckers?; Donat et al., 2012), and happiness (it is difficult to be happy in contexts perceived as unfair; Correia et al., 2024; Hafer et al., 2020). Several newly discovered primals have similarly vast potential to influence a wide range of outcomes. For example, seeing the world as dangerous is tied to being untrusting (more than Big Five traits; Clifton et al., 2019) and *Enticing* world belief may be a crucial precursor to exploratory behaviors, the development of curiosity, and increasing wellbeing (Clifton & Crum, 2025; Clifton & Meindl, 2022; Hämpke et al., 2024; Tsang et al., 2025).

Many parents, educators, and educational systems may be unwittingly encouraging a range of damaging primal world beliefs. One survey of Manhattan parents found that 52 % thought that teaching children that the world is dangerous is the right parenting decision, and almost no parents wanted especially positive world beliefs for their children (Clifton & Meindl, 2022). Policy analysts have also expressed concern that education actively encourages negative primals by focusing student attention on everything wrong with the world (Pondiscio, 2025). Unpublished data from thousands of subjects also indicate that, among 46 professions, students see the world as more negative than most other groups (University of Pennsylvania, 2025). There is now growing awareness that primals are important and are already being influenced by educators and parents. Scholars have called for further efforts to understand their developmental origins (Clifton et al., 2024; Lansford et al., 2024).

However, primals are not always related to constructs one would anticipate might predict primals if individuals' beliefs about the general nature of the world are simply a direct reflection of their experiences. For example, even when the world became objectively more dangerous during the COVID-19 pandemic, people's belief that the world is *Safe* did not markedly change (Ludwig et al., 2023). Likewise, people who are currently poor or grew up in poor households do not differ from people in more affluent circumstances in their belief that the world is *Abundant* (Kerry, White, O'Brien, Perry, & Clifton, 2024). Developmental scientists also have documented many other examples of ways in which individuals' beliefs do not match objective reality, such as when individuals with distorted body images believe themselves to be overweight when they are dangerously underweight (Sattler et al., 2020).

A major gap in knowledge in the burgeoning primals literature is an understanding of how primals develop. Indeed, so far, hypothesis-driven approaches have largely failed to identify developmental precursors to primals, and no long-standing, extensive, developmental studies have been leveraged. Therefore, the present study uses long-term longitudinal data to examine experiences during childhood as predictors of young adults' primals. Due to the lack of established a priori predictors, we cast a wide net and adopted a data-driven machine learning approach given that so little is yet known about which predictors might be important. Machine learning models are typically developed to make predictions in real-life applications; we adopted machine learning as an objective, data-driven framework to analyze the data and investigate relations between primals and several childhood predictors.

Our aim is not the maximization of the predictive performance, but the extraction of knowledge from the data. Specifically, the adoption of machine learning in this study is motivated by three key advantages: first, the partitioning of data into different independent sets allows the assessment of the robustness and reproducibility of the findings; second: trained machine learning models can be inspected to obtain an indication of the importance of individual predictors and the relation with the investigated variables; finally, simpler predictive models, although sometimes inferior in terms of predictive capability, offer more interpretable results and are less vulnerable to over-fitting. Machine learning therefore provides greater flexibility than traditional analytic techniques and can overcome limitations of traditional inferential approaches (Dwyer et al., 2018). In this study, machine learning techniques facilitated the identification of the unique combination of individual, parenting, family, and cultural characteristics experienced in childhood that predict primals in early adulthood across cultures.

Possible individual, parenting, family, and cultural precursors of primals

We used a data-driven approach in selecting variables to enter in the predictive models yet were informed by variables included in other machine learning studies by developmental scientists (Rothenberg et al., 2023). In terms of predictors related to individuals' own characteristics, we included gender, several aspects of executive functioning, intelligence, school performance, pubertal development, risky behavior, prosocial behavior, social competence, and internalizing and externalizing problems. These characteristics predict numerous aspects of adult development. For example, better self-regulation in childhood is related to several positive outcomes in adulthood, including less unemployment, criminality, depression, and substance use (Robson et al., 2020), whereas internalizing and externalizing problems in childhood are related to several maladaptive outcomes in early adulthood (Vergunst et al., 2023).

In terms of predictors related to parenting, we included parental warmth, hostility, neglect, rejection, behavioral control, rules/limit-setting, knowledge solicitation, discipline practices, positive parenting, psychological control, and autonomy granting. These aspects of parenting capture many of the central foci in the parenting literature. For example, parental warmth, hostility, neglect, and rejection are cornerstones of interpersonal acceptance-rejection theory (Rohner, 2021); a review of 12 meta-analyses of 551 studies from 31 countries on five continents demonstrated the importance of high warmth and low hostility, neglect, and rejection for children's and adults' well-being worldwide (Khaleque & Ali, 2017). Likewise, behavioral control and monitoring strategies such as knowledge solicitation and reasonable limit-setting are related to better child adjustment, whereas psychological control is related to worse child adjustment across cultures (Yan et al., 2020). It is unclear whether these diverse aspects of parenting that are related to the well-being of children and adolescents also predict the development of primal world beliefs. One analysis found that parental warmth was related to belief that the world is *Good*, *Safe*, *Enticing*, *Abundant*, and *Progressing*, but harsh parenting, psychological control, and autonomy granting were unrelated to primals (Lansford et al., 2025). The present study expands the range of parenting predictors examined in relation to primals and compares their predictive value in relation to individual, family, and cultural predictors.

In terms of predictors related to the family, we included parents' education level, household income, changes in household income, the number of people in the household, whether the parents had divorced or separated, how important religion is to the family, expectations regarding children's family obligations, family life events, and the safety of the family's neighborhood. These family-level predictors represent a range of socioeconomic factors, such as education and income, that are often treated as covariates in psychological studies but that might serve as substantive predictors of beliefs about the world (e.g., that the world is *Abundant*). The family-level predictors also include other characteristics that are often developmental risk factors, such as neighborhood danger (Baranyi et al., 2021) and stressful life events (Rnic et al., 2023), as well as characteristics that in particular cultural contexts can be either protective or risk factors, such as religiosity (Bornstein et al., 2017; Lucchetti et al., 2021) and familial obligations (Milan & Wortel, 2015).

Finally, in terms of cultural predictors, we included parents' reports of individualism and collectivism, which for decades has been one of the main frameworks for understanding cultural differences (e.g., Hofstede, 1980; Lansford et al., 2021; Triandis, 1995). We also included families from 11 cultural groups in eight countries (Colombia, Italy, Jordan, Kenya, the Philippines, Sweden, Thailand, and the United States). The eight countries vary widely not only in terms of individualism/collectivism (Hofstede Insights, 2024) but also in terms of predominant religious and secular orientations (Pew Research Center, 2022) and sociodemographic factors such as average life expectancy and gross national income per capita (United Nations, 2024), which might be related to beliefs about the world.

The present study

Machine learning is adopted as a data-driven analysis framework to identify the optimal subset of childhood predictors that best classify developmental outcomes. Our aim, though, is not the development of a model to be used in real-life applications to make predictions on novel data points, but the answer to one overarching question: What individual, parenting, family, and cultural factors in childhood best predict beliefs that the world is *Safe*, *Enticing*, *Alive*, *Abundant*, *Progressing*, *Hierarchical*, and *Good*? Our purpose is inherently more exploratory, and we do not pose specific hypotheses, as previous primals research has struggled to identify developmental precursors of primal world beliefs, showing many initial intuitions to be weak (e.g., Kerry, White, O'Brien, Perry, & Clifton, 2024). Leveraging machine learning approaches, we test a wide array of variables measured during childhood as prospective predictors of primals in early adulthood to identify the top predictors, which may lead to surprising findings about what contributes to the development of primals that we would not have hypothesized a priori.

Method

Participants

Data for the current study were drawn from the Parenting Across Cultures Project, which originally recruited children (M_{age} = 8.59 years, *SD* = 0.68, range = 7–11 years; 50 % girls), their mothers, and their fathers in 2008 to participate in a longitudinal study. Families were recruited through schools in nine countries including: Jinan (*n* = 120) and Shanghai (*n* = 122), China; Medellín, Colombia (*n* = 108); Naples (*n* = 102) and Rome (*n* = 111), Italy; Zarqa, Jordan (*n* = 114); Kisumu, Kenya (*n* = 100); Manila, Philippines (*n* = 120); Trollhättan/Vänersborg, Sweden (*n* = 129); Chiang Mai, Thailand (*n* = 120); and Durham, NC, United States (*n* = 110 White, *n* = 102 Black, *n* = 99 Latino). Most parents lived together (82 %) and were biological parents (97 %); nonresidential and non-biological parents also provided data. Sampling included families from each country's majority ethnic group, except in Kenya where we sampled Luo (13 % of the population), and in the United States, where we sampled equal proportions of White, Black, and Latino families. Families from different socioeconomic backgrounds were sampled in proportions representative of each recruitment area.

Procedure and measures

Data for the current study were collected via self-reports from children, mothers, and fathers when children were 10 years old (see Table 1) and from self-reports from the original child participants when they were age 22, on average. Primals data (the outcome of interest in the present study) could not be collected in China, so the present study does not include China.

Measures were administered in Spanish (Colombia and the United States), Italian (Italy), Arabic (Jordan), Dholuo (Kenya), Filipino (the Philippines), Swedish (Sweden), Thai (Thailand), and English (the Philippines and the United States), following forward- and back-translation, cultural adaptation, and meetings to resolve any item-by-item ambiguities in linguistic or semantic content (Erkut, 2010). In translating the Primals Inventory, we followed the guidelines in Clifton et al. (2023). Parents provided informed consent; children provided assent at age 10 and provided their own informed consent at age 22. Families were given modest monetary compensation for participating or compensated in other ways deemed appropriate by local institutional review boards (IRBs). Procedures and measures were approved by IRBs in each participating country.

Individuals' own characteristic predictors

Executive functioning. Child executive functioning was assessed with the Balloon Analog Risk Task, the Modified Iowa Gambling Task, the Stoplight Task, and the Tower of London Task. The *Balloon Analog Risk Task* is a computerized task developed by Lejuez et al. (2002). On each trial, the participant decides how much air to "pump" into a balloon on the computer screen. For each successful pump of air, more points are accrued. However, at some point, the addition of more air causes the balloon to burst, leading to the loss of all points accrued during that trial. The average inflation ratio, which is the percent of a balloon an adolescent inflated relative to the maximum, is used in analyses. Higher scores indicate more impulsivity and risk-taking.

In the computerized *Modified Iowa Gambling Task (IGT)*, individuals attempt to earn points by playing or passing cards from four different decks (Bechara et al., 1994; see Icenogle et al., 2017 for modifications). Two of the decks are associated with relatively small gains, but the small gains exceed losses over the course of the task, resulting in a net gain. The other two decks produce larger gains than the first two decks, but in the long run, these decks produce a net loss due to larger losses. In addition, within each type of deck (net gain vs. net loss), there is one

Table 1
List of the predictors in the original and processed datasets by respondent.

Original dataset				Processed dataset		
Predictor	Resp.	Target	N MD	Predictor	Resp.	Target
Child Gender	Child	Child	0	Child Gender	Child	Child
Mother Individualism	Mother	Mother	4	Individualism	Parents	Parents
Father Individualism	Father	Father	129			
Mother Collectivism	Mother	Mother	4	Collectivism	Parents	Parents
Father Collectivism	Father	Father	129			
Neighborhood Danger	Mother	Other	4	–		
Neighborhood Danger	Father	Other	130	–		
Neighborhood Danger	Child	Other	29	Neighborhood Danger	Child	Other
Mother Education	Mother	Mother	11	Education	Parents	Parents
Father Education	Father	Father	72			
Family Income	Parent	Other	14	Family Income	Parents	Other
Family Income Change	Parent	Other	9	Family Income Change	Parents	Other
Number of Household Members	Parent	Other	1	Number of Household Members	Parents	Other
Parents Divorced	Parent	Other	6	Parents Divorced	Parents	Other
Religious Importance	Parent	Other	21	Religious Importance	Parents	Other
Family Obligations	Mother	Child	4	–		
Family Obligations	Father	Child	130	–		
Family Obligations	Child	Child	0	Family Obligations	Child	Child
Life Events	Mother	Other	5	Life Events	Parents	Other
Life Events	Father	Other	128			
Mother Warmth	Mother	Mother	4	–		
Father Warmth	Father	Father	128	–		
Mother Warmth	Child	Mother	2	Parent Warmth	Child	Parents
Father Warmth	Child	Father	43			
Mother Hostility	Mother	Mother	4	–		
Father Hostility	Father	Father	128	–		
Mother Hostility	Child	Mother	2	Parent Hostility	Child	Parents
Father Hostility	Child	Father	43			
Mother Neglect	Mother	Mother	4	–		
Father Neglect	Father	Father	128	–		
Mother Neglect	Child	Mother	2	Parent Neglect	Child	Parents
Father Neglect	Child	Father	43			
Mother Rejection	Mother	Mother	4	–		
Father Rejection	Father	Father	128	–		
Mother Rejection	Child	Mother	2	Parent Rejection	Child	Parents
Father Rejection	Child	Father	43			
Mother Behavioral Control	Mother	Mother	4	–		
Father Behavioral Control	Father	Father	128	–		
Mother Behavioral Control	Child	Mother	2	Parent Behavioral Control	Child	Parents
Father Behavioral Control	Child	Father	43			
Rules/Limit-setting	Mother	Parents	4	–		
Rules/Limit-setting	Father	Parents	129	–		
Rules/Limit-setting	Child	Parents	0	Rules/Limit-setting	Child	Parents
Knowledge Solicitation	Mother	Parents	4	–		
Knowledge Solicitation	Father	Parents	129	–		
Knowledge Solicitation	Child	Parents	0	Knowledge Solicitation	Child	Parents
Mother Physical Punishment	Mother	Mother	6	Physical Punishment	Parents	Parents
Father Physical Punishment	Father	Father	130			
Mother Severe Physical Punishment	Mother	Mother	6	Severe Physical Punishment	Parents	Parents
Father Severe Physical Punishment	Father	Father	129			
Mother Positive Parenting	Mother	Mother	4	Positive Parenting	Parents	Parents
Father Positive Parenting	Father	Father	128			
Parents' Psychological Control	Child	Parents	0	Parents' Psychological Control	Child	Parents
Parents' Autonomy Granting	Child	Parents	0	Parents' Autonomy Granting	Child	Parents
Balloon Analog Risk Task	Child	Child	118	–		
Overall Assessment of Risk	Child	Child	119	–		
IGT Reward Sensitivity Good Decks	Child	Child	117	–		
IGT Reward Sensitivity Bad Decks	Child	Child	117	–		
Stoplight Task Risk Propensity	Child	Child	124	–		
Stoplight Task Response Inhibition	Child	Child	134	–		
Impulse Control	Child	Child	122	–		
Matrix Reasoning	Child	Child	124	–		
Working Memory Task	Child	Child	116	–		
Verbal Fluency	Child	Child	117	–		
Pubertal Development	Child	Child	124	–		
Prosocial Behaviors	Child	Child	0	Prosocial Behaviors	Child	Child
Social Competence	Mother	Child	6	Social Competence	Parents	Child
Social Competence	Father	Child	128			
Internalizing Behavior	Mother	Child	4	–		
Internalizing Behavior	Father	Child	128	–		
Internalizing Behavior	Child	Child	0	Internalizing Behavior	Child	Child
Externalizing Behavior	Mother	Child	4	–		
Externalizing Behavior	Father	Child	128	–		

(*continued on next page*)

Table 1 (*continued*)

Original dataset				Processed dataset		
Predictor	Resp.	Target	N MD	Predictor	Resp.	Target
Externalizing Behavior	Child	Child	0	Externalizing Behavior	Child	Child
School Performance	Mother	Child	5	School Performance	Parents	Child
School Performance	Father	Child	130			

Note. The column "N MD" indicates the number of missing values that were present before the original dataset was created.

deck in which the loss is infrequent but large, and the other deck produces losses that are consistent and small. The ability to choose to pass on bad decks and play on good decks is a measure of decision-making under conditions of uncertainty and risk evaluation. The preference to play the decks with more variance in the outcome is taken as a measure of risk preference. This task assesses decision-making relatively free of prior experience. We measured both reward sensitivity (based on change in percent of plays on good decks from the first to the last blocks) and cost sensitivity (based on change in percent plays on bad decks from the first to the last blocks) in the current study.

In the computerized *Stoplight Task*, an individual must "drive" a car to a destination under time pressure (Steinberg et al., 2008). Along the way are crossroads, and at each one the person must decide whether to run a yellow light, which turns red after a variable amount of time, or to stop and wait for the light to turn red and then green. The goal is to get to a destination as quickly as possible in order to win a prize. Time is saved if the person successfully runs the yellow light, whereas time is lost when the light turns red and the person crashes into another car at the intersection. The relative gain of successfully running the light vs. the loss of crashing are varied across trials. Risk preference was measured by how many times an individual chose to run the red as compared to stopping.

In the computerized *Tower of London Task* (Shallice, 1982), the child viewed a series of three balls on a peg in a start position that must be moved to a pre-specified goal configuration on three other pegs, one of which can support one ball, one of which can support two balls, and one of which can support three balls. The child was instructed to replicate the goal configuration using the smallest number of moves. The number of moves and time required to reach the goal position is the dependent measure. The task measures not only how well an individual can organize sequential behavior to reach a goal but also whether one can inhibit acting before a plan is fully formed. We measured impulse control on this task by measuring the amount of time in seconds to first move on hard problems (i.e., 6 and 7 move problems). Higher scores indicate more impulse control.

Child intelligence. Measures of child intelligence were subscales derived from the Wechsler Abbreviated Scale of Intelligence (WASI; Psychological Corporation, 1999). First, the Matrix Reasoning subtest of the WASI was used to produce an estimate of nonverbal intellectual ability. Matrix Reasoning t-scores were calculated and used in the present analyses. Second, the Spatial Working Memory task examines both the ability to maintain information in working memory as well as to retrieve it. The participant is presented with a series of items, one at a time. In the 2-back version of the task, individuals indicate whether the current item in a sequence of items (forms, letters, digits) is the same as that mentioned two items previously. Thus, individuals must not only hold in mind the current item but also that one and two items back for comparison purposes. On each trial, information in working memory must be updated and a comparison must be performed. A count of the greatest number of items that were recalled in correct serial order, and an overall average of the number of items recalled on each task trial were both utilized as measures of working memory in this study. Third, a measure of Verbal Fluency asked participants to generate, in one minute, as many words as possible that either began with a specific letter or were members of a category. A verbal fluency score was computed by averaging the number of words generated for each of six lists.

School performance. Mothers and fathers were asked to rate their child's school performance in reading, writing, math, social studies, spelling, science, and other subjects. These seven areas were used because they are common to curricula in every country. The questions were adapted from the performance in academic subjects section of the Child Behavior Checklist. Parents rated whether children were 1 = *failing*, 2 = *below average*, 3 = *average*, or 4 = *above average* in each area. A single scale was computed as the average of the items to capture total school performance ($\alpha = 0.89$ for mother and 0.90 for father report).

Pubertal development. Adolescents completed the Pubertal Development Scale (Petersen et al., 1988), a widely used and well-validated self-report measure of physical development that is correlated with measures of pubertal development derived from physical examination. Five items asked about perceived pubertal changes in skin, height, body hair, and either breast growth and menstruation (for girls) or facial hair growth and voice (for boys). Items were scored on a 0 = *has not yet started* to 3 = *definitely completed* scale, with the exception of the menstruation item, which was scored 0 = *no* or 3 = *yes*. In line with prior multicultural studies using this measure in this and other samples (Icenogle et al., 2017), item scores were averaged to create a continuous measure for physical maturation ranging from 0 = *puberty has not started* to 3 = *puberty seems complete*. The IRB in Sweden did not allow puberty to be assessed before age 12, so age 10 pubertal status in Sweden could not be measured.

Benthin risk perception scale. This scale, adapted from an instrument developed by Benthin et al. (1993), is designed to measure the extent to which an individual recognizes and evaluates the risks inherent in activities that are potentially dangerous or harmful. The measure employed in this study presents the respondent with eight activities: Riding in a car with a drunk driver, smoking cigarettes, drinking alcohol, vandalizing property, getting into a physical fight, going into a dangerous part of town, threatening or injuring someone with a weapon, and having unprotected sex. The procedure asks the respondent to indicate five things for each of these activities: How "scary" the activity is (affective component), how risky the activity is (likelihood component), how much the risks of the activity outweigh its benefits (comparative value component), how serious the consequences of the activity would be if something "bad" happened as a result (salience component), and if he or she has engaged in the activity previously and in the past 6 months. Each of these ratings is made on a 4-point scale; evaluations of riskiness and the relative risk-benefit ratio are reverse-scaled and reverse-scored. A single risk perception score was computed by averaging 16 responses (the four evaluation dimensions for four activities).

Child prosocial behavior. Children completed a 9-item scale composed of items such as "I try to help others," which was adapted from Pastorelli et al. (1997). Items were rated as 1 = *never*, 2 = *sometimes*, or 3 = *often*. Items were averaged to create a prosocial behavior scale ($\alpha = 0.77$).

Child social competence. Mothers and fathers completed a 7-item social competence scale adapted from Pettit et al. (1991) indicating how socially skilled the child was in several kinds of interpersonal interactions (e.g., understanding others' feelings, generating good solutions to interpersonal problems). Items were rated on a 5-point scale from 1 = *very poor* to 5 = *very good*. Items were averaged to create a child social competence scale (α = 0.89 and 0.90 for mother and father reports, respectively).

Child externalizing and internalizing behavior. Mothers and fathers completed Achenbach's (1991) Child Behavior Checklist, and children completed the Youth Self Report. Participants were asked to rate how true each item was of the child during the last six months (0 = *not true*, 1 = *somewhat or sometimes true*, 2 = *very or often true*). The externalizing behavior scale used 33 items (for parent reports) or 30 items (for youth reports) to capture behaviors such as lying, truancy, vandalism, bullying, drug and alcohol use, disobedience, and physical violence. The internalizing behavior scale used 31 items (for parent reports) or 29 items (for youth reports) to measure behaviors and emotions such as loneliness, self-consciousness, nervousness, sadness, and anxiety. Items were summed to create composite externalizing (α = 0.88 for mother, 0.86, and 0.85 for child report) and internalizing (α = 0.87 for mother, 0.85 for father, and 0.87 for child report) scales.

Parenting predictors

Parent warmth, hostility, neglect, undifferentiated rejection, and behavioral control. All five of these parenting constructs were measured using the appropriate subscales of the Parental Acceptance-Rejection/Control Questionnaire-Short Form (PARQ/Control-SF; Rohner, 2005). Mother, father, and child reports (separately for each parent) on each construct were collected. Participants rated items on a modified scale: 1 = *never or almost never*, 2 = *once a month*, 3 = *once a week*, or 4 = *every day*. Eight warmth items (e.g., parents say nice things to the child; α = 0.83 for mother report, 0.83 for father report, 0.81 for child report about the mother, and 0.84 for child report about the father), 6 hostility items (e.g., punish child severely when angry; α = 0.66 for mother report, 0.71 for father report, 0.72 for child report about the mother, and 0.70 for child report about the father), 6 neglect items (e.g., pay no attention to the child; α = 0.61 for mother report, 0.66 for father report, 0.65 for child report about the mother, and 0.67 for child report about the father), 4 undifferentiated rejection items (e.g., resent the child; α = 0.44 for mother report, 0.59 for father report, 0.62 for child report about the mother, and 0.61 for child report about the father), and 5 behavioral control items (e.g., always tell the child how to behave; α = 0.54 for mother report, 0.52 for father report, 0.47 for child report about the mother, and 0.51 for child report about the father) were averaged to create scales. Although some of the alphas were low in this sample, we included the scales because meta-analytic work has demonstrated good psychometric properties of the scales in a range of countries and languages, and the measure is one of the most widely used in international studies of parenting (Khaleque & Rohner, 2002). A review of 12 meta-analyses that included 551 studies of 149,440 respondents in 31 countries on five continents concluded that these measures are reliable for use in cross-cultural studies (Khaleque & Ali, 2017).

Parent rules/limit-setting and parent knowledge solicitation. Parent rules/limit-setting and knowledge solicitation were assessed by subscales of the 10-item parental monitoring scale derived from the work of Conger et al. (1994) and Steinberg et al. (1992). To measure parent rules/limit-setting, mothers, fathers, and children answered 5 questions that captured the frequency with which parents impose limits on their child's activities on a 0 = *never* to 3 = *always* scale. To measure parent knowledge solicitation, mothers, fathers, and children answered 5 questions that examined the extent to which parents tried to find out about their child's activities and whom their child spends time with on a 0 = *do not try*, 1 = *try a little*, 2 = *try a lot* scale. Both parent rules/limit-setting and parent knowledge solicitation were assessed by asking about the same 5 child activities (e.g., with whom the child spends time, how the child spends free time, how the child spends money, where the child goes right after school, and the type of homework the child receives). Items were averaged to create rules/limit-setting (α = 0.84 for mother, 0.84 for father, and 0.80 for child report) and knowledge solicitation (α = 0.85 for mother, 0.84 for father, and 0.74 for child report) scales.

Parent physical punishment. Physical punishment was assessed using parent reports on items developed by UNICEF for their Multiple Indicator Cluster Survey. Parents were asked whether they or another adult in the household had used each form of physical punishment in the last month (0 = *no*, 1 = *yes*). UNICEF (2006) scoring guidelines were followed to create composite scales of physical punishment (4 items, e.g., hitting or slapping on the hand, arm, or leg; α = 0.71 for mothers and 0.69 for fathers) and severe physical punishment (2 items, e.g., hitting or slapping the child on the face, head, or ears; $r = 0.44$ for mothers and 0.26 for fathers).

Positive parenting. Positive parenting was measured with items adapted from Capaldi and Patterson (1989). Parents rated how many days per week they talk with their child (0–7) and how much they engage in positive parenting behaviors, such as praising the child for doing a good job (0–4 scale). Items were standardized and averaged to create a positive parenting scale (α = 0.65 for mother and 0.70 for father reports).

Parents' psychological control and autonomy granting. Children rated the extent to which their parents make decisions for them versus let them make their own decisions and how often parents try to control how adolescents think or feel or manipulate them psychologically (Barber, 1996). This measure yields two subscales, the 7-item Psychological Control subscale (α = 0.64) and the 3-item Autonomy Granting subscale (α = 0.54), which are both scored on a 4-point scale ranging from 1 = *strongly disagree* to 4 = *strongly agree*, with higher scores indicating more psychological control and autonomy granting.

Family predictors

Years of education. Both mother and father total years of education completed were reported.

Family annual income. The family's annual income over the past year was reported by parents on a 1–10 scale that is scaled such that within each country, 5 = average income for the country, 1 = well below average income for the country, and 10 = well above average income for the country.

Annual income change. The family's change in annual income over the past year was reported by parents on a 5-point scale with 1 *≥25 % drop in income*, 2 = *5 %–25 % drop in income*, 3 = *No change in income*, 4 = *5 %–25 % increase in income*, 5 *≥25 % increase in income*.

Number of individuals in household. Parents reported the number of individuals living in the household.

Divorce or separation. Parents indicated whether they were divorced or separated at the time of the interview (0 = *not divorced/separated*, 1 = *divorced/separated*).

Family religious importance. Parents reported on a 5-point scale how important their religion is to the family (1 = *not at all important*, 5 = *extremely important*).

Family obligations. Using the Family Obligations Scale adapted from Fuligni et al. (1999), parents and children rated a series of statements related to how important it is for children to spend time with their families, help their families, and to respect older members of their families. The first 11 statements ask the parent and child to rate on a scale from 1 = *almost never* to 5 = *almost always* how often the child is expected to spend time with and help their family. The other 7 statements ask the parent and child to rate on a scale from 1 = *not important* to 5 = *very important* how important certain family practices and relationships are. Items were averaged to create a composite family obligations score (α = 0.84, 0.86, and 0.83 for mother, father, and child reports, respectively).

Family life events. Using a list of major life events adapted from Dodge et al. (1994), parents indicated whether each of 19 major life events (such as a move, birth of a child, divorce, death of a close family member) had occurred in the last year, indicating either 0 = *no* or 1 = *yes*. A sum score out of 19 for both father and mother reports of life events over the last year was calculated. As discrete indicators of life events, no alpha is provided because the items are better treated as an index rather than a scale.

Neighborhood danger. Mothers, fathers, and children rated four items adapted from Griffin et al. (1999) and O'Neil et al. (2001) on a 4-point scale from 0 = *never true* to 3 = *always true* indicating whether youth get in trouble in the neighborhood, there are drugs and gangs in the neighborhood, the neighborhood is dangerous, and whether they feel scared in the neighborhood. Items were averaged to create a neighborhood danger scale (α = 0.88 for mother, 0.86 for father, and 0.74 for child reports).

Cultural predictors

Individualism and collectivism items were adapted from Singelis et al. (1995), Tam et al. (2003), and Triandis (1995). Mothers and fathers rated the importance of different values related to their autonomy and belonging to a social group. Parents were asked whether they 1 = *strongly disagree*, 2 = *disagree*, 3 = *agree*, or 4 = *strongly agree* with a series of 16 statements, 8 reflecting individualism (e.g., "I'd rather depend on myself than others") and 8 reflecting collectivism (e.g., "To me, pleasure is spending time with others"). Items were averaged to create an individualism scale score (αs = 0.70 and 0.71 for mothers and fathers, respectively) and a collectivism scale score (αs = 0.65 and 0.70 for mothers and fathers, respectively).

Primal world beliefs

When young adults were approximately age 22, on average, we administered a 30-item version of the Primals Inventory (Clifton et al., 2019). The instrument is a brief version developed from the 99-item Primals Inventory, which measures basic (i.e., primal) beliefs about the world. The current study focuses on seven primal word beliefs: *Abundant* (4 items; e.g., "The world is an abundant place with tons and tons to offer"), *Progressing* (4 items; e.g., "Though the world has problems, on the whole things are definitely improving"), *Hierarchical* (5 items; e.g., "Most things in the world could be ranked in order of importance"), *Safe* (6 items; e.g., "I tend to see the world as pretty safe"), *Enticing* (7 items; e.g., "No matter where we are, incredible beauty is always around us"), *Alive* (5 items; e.g., "What happens in the world is meant to happen"), as well as one overarching primal *Good*, which as an overarching primal also includes some items on the other scales (15 items; e.g., "Most things in the world are good"). After reversing negative belief items, we created the primals scores by averaging participants' answers (α for *Abundant* = 0.70, α for *Progressing* = 0.80, α = 0.72 for *Hierarchical*, α for *Safe* = 0.70, α for *Enticing* = 0.71, α = 0.70 for *Alive*, α for *Good* = 0.78).

Analytic plan

Datasets. A subset of 770 young adults completed the Primals Inventory; among these, 311 had missing data on one or more of the 76 prospective predictors (Table 1), resulting in 459 participants with complete data. A first dataset, called "Original" was therefore created, including all 76 predictors and data of all 459 participants with no missing values. We opted for avoiding the imputation of missing data to avoid the influence of the data imputation algorithm (a machine learning model itself) on the outcomes.

Considering the original dataset included only 59.6 % of the sample with primals data, a second dataset was created to reduce the impact of missing values and maximize the number of participants included in the study. The analysis of missing values highlighted that values are mainly missing in father-related predictors (when the respondent was the father or when the respondent was the child, but the target of the measure was the father). To overcome these issues, the 76 predictors in the original dataset were aggregated using the following guidelines. When a questionnaire was administered to the mother, father, and child, only the score from the child was used. When a questionnaire was administered to both the mother and the father, their scores were averaged; if either score was missing, the score of the available parent was used. When a questionnaire about both parents was administered to the child, the average score was computed to obtain an overall parenting score; if either score was missing, the score for the available parent was used.

Finally, some measures with a large amount of missing values were removed (although retained in the Original dataset): Balloon Analog Risk Task, Benthin Risk Perception Scale, Modified Iowa Gambling Task, Stoplight Task, Tower of London Task, Matrix Reasoning, Spatial Working Memory, and Verbal Fluency. An additional dataset that incorporated all these changes was obtained, called "Processed," including 29 predictors and data from 696 young adults (Table 1).

Data partitioning. Following machine learning (ML) best practices, both the original and the processed datasets were divided into two data partitions: the "Train set" (75 % of the sample) and the "Test set" (remaining 25 % of the sample). The data points in the Train set are used in the model training procedure, to optimize the model parameters and fit the model weights. The data points in the Test set are only used for the evaluation of the predictive performances of the ML models, and for model inspection. The partitioning was performed randomly, and the same partitions were used for all primals.

Target. Being the first study to apply ML approaches to primals, a binary classification task (instead of regression) was preferred, to simplify the ML experiments and the interpretation of the results. Primals scores, which are numerical values from 0 to 5, were therefore dichotomized to obtain two classes: "Low" for participants with lower scores in the primal dimension and "High" for participants with higher scores in the primal dimension. The dichotomization was performed with the following two approaches. First, for the median approach, the median primal score (computed on the Train set) was used as the threshold value. The "Low" class includes participants who scored lower than the threshold value; the "High" class includes participants who scored higher than or equal to the threshold value. Second, for the three-levels approach, the 33rd and 66th percentile primal scores (computed on the Train set) were used as the threshold values. The "Low" class includes participants who scored lower than the 33rd percentile; the "High" class includes participants who scored higher than or equal to the 66th percentile.

The two approaches were selected aiming at two distinct objectives. The median approach allows using all data points and obtaining a balanced distribution of participants across the two classes. The three-levels approach drops about a third of the sample (data points with a primal score between the 33rd and 66th percentile) but allows focusing on the key differences between the more extreme groups in terms of primal scores.

In summary, this study used two datasets (original and processed) and two dichotomization approaches (median and three-levels). The two datasets and the two dichotomization approaches serve different purposes (Fig. 1). Whereas the original dataset aims at maximizing the *information* used, the processed dataset aims at maximizing the sample size. The median dichotomization approach focuses on assessing patterns of the whole population, whereas the three-levels approach focuses on identifying the key patterns that differentiate the extremes of each primal scale. For each primal scale, four independent ML experiments were conducted: for both datasets and both dichotomization approaches.

Model training. The ML procedure used for training the model was based on a standardized pipeline used in previous studies (e.g., Rothenberg et al., 2023). Briefly, the main steps were: model optimization and selection of the optimal set of predictors, model fit, model evaluation, and model inspection. A Support Vector Machine (SVM) with linear kernel was the reference predictive model, used for all ML experiments, however, Logistic Regression models (with and without ridge regularization) were also used in the study. Tables SM1 and SM2 in the Supplementary Material report the results obtained with the SVM and Logistic Regression models in terms of performance and best features. This article focuses on SVM models as, in terms of interpretability and predictive capability they stand in between more interpretable models (e.g., logistic regression) and more powerful but opaque models (e.g., deep learning).

Model optimization and feature selection. A standard 10 × 5-fold cross-validation scheme (10x5CV) was used for the model optimization and selection of the optimal set of predictors, based only on data points from the Train set. The optimal value of the SVM regularization parameter C was selected from a set of candidate values (10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}, 0.1, 1, 10, 100). The optimal set of predictors was identified by recursively eliminating the less important predictor. Specifically, the training process started with all predictors, and the 10x5CV procedure was performed for each candidate value of the C parameter. The importance of the predictor was then computed, using the C value that achieved the highest average performance across the 50 performance values resulting from the 10x5CV procedure. The importance of a predictor is a measure of how much the model relies on the information provided by that predictor to perform the prediction. The importance was computed by permutation in which the values of a given predictor are randomly shuffled between the data points, and the corresponding difference in model performance is computed. The assumption is that the more important a predictor is, the larger the drop in the model performance. The predictor with the lowest importance was then removed from the dataset, and the 10x5CV procedure to select the optimal C value was repeated again on the reduced dataset, until one predictor remained. After the process was completed, the set of predictors that achieved the highest performance and the corresponding C value was selected and used to fit the model weights.

Model fit and model evaluation. With the optimal value of the C parameter, and the optimal set of predictors, the weights of the SVM model are computed using the data points of the whole Train set. To measure the model predictive performance, the Matthews correlation coefficient (MCC) was calculated on both the Train and Test sets. The MCC is a performance metric that ranges from −1 to 1, with higher values associated with better performance. Positive values indicate that the model's predictive performance is better than a random classifier, and thus, that the model was able to learn some patterns in the data.

The predictive performance of the model is computed on both the Train and Test set to assess model overfitting. If performance on the Test set is comparable to that on the Train set, it indicates that the learned patterns effectively generalize to unseen data. Conversely, if performance on the Test set is not comparable to that on the Train set and lower, it suggests that the model has overfitted to specific patterns that are only present in the train set and not in the general population.

For a more conservative model evaluation and to assess the stability of the predictive performance, a bootstrap evaluation was employed. The MCC was computed on 1000 subsets of the original Train and Test sets, obtaining a distribution of MCC values for both sets. The sample size of the subsets was 25 % of the original set, with data points randomly selected with replacement. Finally, the median and 5 %–95 % confidence intervals (5 %CI, 95 %CI) for the MCC were computed. Confidence intervals provide a robust estimation of the range of the expected variability in model performance. Specifically, the value of the 5 %CI on the Test set (5 %TEST) was considered representative of the expected performance on the general population in the worst-case scenario and was used as a reference to assess the reliability of the model. This approach ensures that the patterns learned by the model are informative and relevant to the general population.

A positive 5 %CI value was considered as indicating that the predictive performance was better than that of a random classifier, thereby suggesting that the learned patterns were reliable. Conversely, a non-positive 5 %CI value indicated that, in the worst case scenario, the predictive performance was no better than that of a random classifier, suggesting that the interpretation of the learned patterns should be more cautious.

Model inspection. The final step aimed at investigating the learned patterns to extract knowledge from the trained models. Specifically, for each ML experiment, the ranking of the optimal predictors was obtained, and the top five most important predictors were selected. Then, the set of predictors that appeared most frequently across the four ML experiments was identified. Subsequently, the inspection focused on the top 5 most important predictors of the ML experiment that achieved the best predictive performance. First, Partial Dependence Plots (PDPs) were obtained for each of the top 5 most important features. Partial Dependence Plots show the marginal effect each predictor has on the predicted outcome. PDPs take the form of lines: PDPs with positive slopes indicate that higher values of the predictor are associated with the "High" class;

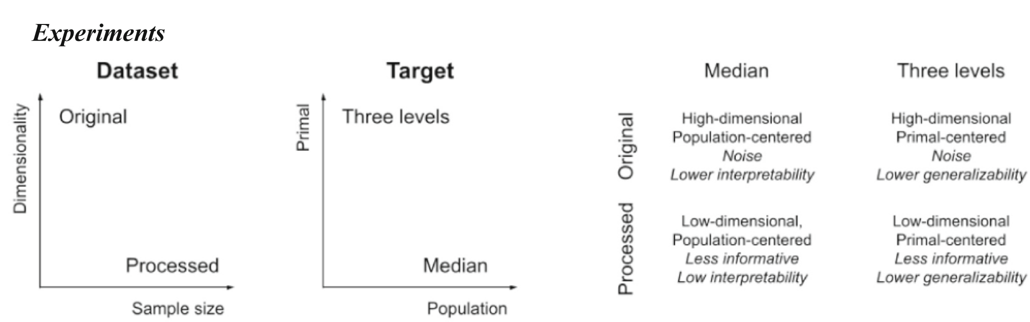

Fig. 1. Representation of the main characteristics of the two datasets and two dichotomization approaches, with a summary of the main advantages and disadvantages of the four Machine Learning experiments.

conversely, PDPs with negative slopes indicate that higher values of the predictor are associated with the "Low" class. Finally, for each of the top 5 most important predictors, a Kruskal-Wallis test was applied on data points from the Test set to assess if any statistically significant differences exist in the distribution of the predictor values between the primal classes (Low vs High).

Transparency and openness

Research measures are available at parentingacrosscultures.org. Data were analyzed in Python (v3.10) using custom code developed based on the ML package *sklearn* (v1.3.2). This study's design and its analysis were pre-registered (https://osf.io/syrc4/?view_only=35c2cbfcd66c4d3f871246e13139f1e3).

Results

Evaluation of the predictive performance

We computed the predictive performance in terms of MCC values on the Train and Test sets for all ML experiments (Table 2). For each primal, we then identified the ML experiment that achieved the best predictive performance, by considering the 5 %CI value on the Test set. For five primals, the best result is achieved with the processed dataset, either with the three-levels categorization approach (*Abundant*, *Enticing*, *Hierarchical*, *Progressing*) or with the median categorization approach (*Good*). For two primals (*Alive*, *Safe*), the best result is achieved with the original dataset, with the three-levels categorization approach. The minimum MCC score on the Train set is always positive, and ranges between 0.158 (*Abundant*) and 0.523 (*Alive*). However, the *Abundant*, *Good*, and *Progressing* primals have a negative 5 %CI value on the Train set; for these primals, the information extracted from the following model inspection should be considered very preliminary and requires confirmation from other studies.

Model inspection

The predictive models trained in the ML experiments are inspected to extract knowledge from the learned patterns. Specifically, for each primal, we obtained the top five most important features for all ML experiments to be able to observe any recurring predictors (see Table 3). Then, for the best predictive model of each primal, the direction of the effects was analyzed (Fig. 2) and statistical tests were applied to assess differences between the two primals classes in the Test set (Table 4). In the following paragraphs, we present the results and main outcomes for each primal, focusing on patterns emerging from the model inspection.

Abundant

None of the experiments conducted for the *Abundant* primal yielded robust results; thus, the interpretation of the findings should be approached with caution. The experiment that demonstrated the best performance used the processed dataset with the three-levels dichotomization. In this experiment, the Train set showed an MCC of 0.317 (CI: 0.15 to 0.46); the Test set had an MCC of 0.158 (CI: −0.14 to 0.44).

The poor performance of the models on the Test set implies that the dataset may not contain features that can accurately predict the *Abundant* primal, suggesting that a diverse approach with other variables might yield better results. Additionally, the discrepancy between Train and Test performance indicates potential overfitting.

Alive

In contrast with the *Abundant* primal, all experiments with the *Alive* primal achieved good performance. The best result was obtained with the three-levels approach using the original dataset. For this approach, the MCC was 0.577 (CI: 0.40 to 0.74) in the Train set and 0.523 (CI: 0.16 to 0.77) in the Test set. The performance values suggest good generalizability and overall robust performance. The most important features for the model's performance were the Balloon Analog Risk Task and Pubertal Development, with higher scores associated with the Low *Alive* class, and father-reported rules/limit-setting, with high scores associated with the High *Alive* class; however, none of these predictors showed significant statistical differences between the Low *Alive* and High *Alive* class in the Test set. The following most important predictors were the Working Memory Task (higher scores associated with the Low *Alive* class), which significantly differed between the two classes ($H = 4.92$, $p = 0.027$), and Religious Importance (higher scores associated with the High *Alive* class), which significantly differed between the two classes ($H = 21.07$, $p < 0.001$).

Table 2
MCC values (Median [5 %CI; 95 %CI]) on the Train and Test sets for all ML experiments. In bold, the experiment that achieved the best predictive performance.

	Original						Processed					
	Median			Three-levels			Median			Three-levels		
Primal	N	Train	Test	N	Train	Test	N	Train	Test	N	Train	Test
Abundant	459	0.334 [0.18; 0.49]	−0.022 [−0.31; 0.26]	301	0.507 [0.33; 0.66]	0.045 [−0.32; 0.41]	696	0.223 [0.11; 0.35]	−0.03 [−0.26; 0.20]	**460**	**0.317 [0.15; 0.46]**	**0.158 [−0.14; 0.44]**
Alive	459	0.431 [0.28; 0.57]	0.358 [0.07; 0.61]	**280**	**0.577 [0.40; 0.74]**	**0.523 [0.16; 0.77]**	696	0.312 [0.19; 0.45]	0.248 [0.02; 0.47]	474	0.396 [0.24; 0.53]	0.303 [0.03; 0.54]
Enticing	459	0.398 [0.27; 0.53]	0.063 [−0.23; 0.32]	300	0.535 [0.35; 0.69]	0.368 [−0.00; 0.67]	696	0.292 [0.17; 0.42]	0.250 [0.02; 0.46]	**446**	**0.414 [0.26; 0.56]**	**0.320 [0.04; 0.58]**
Good	459	0.373 [0.21; 0.52]	0.215 [−0.05; 0.47]	308	0.604 [0.42; 0.74]	0.153 [−0.15; 0.49]	**696**	**0.337 [0.21; 0.45]**	**0.209 [−0.02; 0.42]**	452	0.412 [0.28; 0.55]	0.214 [−0.10; 0.49]
Hierarchical	459	0.265 [0.12; 0.42]	0.246 [−0.04; 0.49]	300	0.559 [0.39; 0.72]	0.257 [−0.11; 0.58]	696	0.174 [0.04; 0.29]	0.292 [0.07; 0.48]	**457**	**0.306 [0.16; 0.46]**	**0.375 [0.08; 0.62]**
Progressing	459	0.489 [0.35; 0.62]	0.149 [−0.13; 0.44]	363	0.522 [0.36; 0.66]	0.032 [−0.30; 0.33]	696	0.309 [0.19; 0.43]	0.151 [−0.09; 0.39]	**539**	**0.341 [0.19; 0.48]**	**0.185 [−0.06; 0.45]**
Safe	459	0.449 [0.31; 0.58]	0.227 [−0.04; 0.51]	**318**	**0.503 [0.32; 0.67]**	**0.328 [0.02; 0.61]**	696	0.241 [0.11; 0.37]	0.124 [−0.08; 0.34]	435	0.317 [0.16; 0.47]	0.149 [−0.13; 0.41]

Note. N refers to the number of datapoints in the dataset used for the ML experiment.

Table 3
Top five most important features for each primal and ML experiment. In bold, the ML experiment with the best predictive performance.

		Original		Processed	
	Rank	Median	3 levels	Median	3 levels
Abundant	#1	(Child) Mother Warmth	Prosocial Behaviors	(Parents' avg.) Individualism	**(Child) Rules/Limit-setting**
	#2	Family Income	(Mother) Mother Behavioral Control	(Parents' avg.) Collectivism	**(Parents' avg.) Collectivism**
	#3	(Father) Father Warmth	Mother Education	(Child) Prosocial Behaviors	**(Parents' avg.) Individualism**
	#4	(Father) School Performance	Child Gender	(Parents' avg.) School Performance	**(Child) Prosocial Behaviors**
	#5		(Child) Father Neglect	(Child) Parents' Behavioral Control	**(Child) Internalizing Behavior**
Alive	#1	Child Gender	**Balloon Analog Task**	(Child) Internalizing Behavior	Religious Importance
	#2	Religious Importance	**Pubertal Development**	Religious Importance	(Parents' avg.) Adverse Life Experiences
	#3	(Mother) Social Competence	**(Father) Rules/Limit-setting**	(Child) Family Obligations	Child Gender
	#4	Verbal Fluency	**Working Memory Task**	(Parents' avg.) Social Competence	(Parents' avg.) Social Competence
	#5	(Father) Adverse Life Experiences	**Religious Importance**	Number Household Members	(Child) Internalizing Behavior
Enticing	#1	(Child) Mother Warmth	(Mother) Mother Individualism	(Child) Prosocial Behaviors	**(Child) Prosocial Behaviors**
	#2	(Child) Father Warmth	Family Income	Family Income	**(Child) Internalizing Behavior**
	#3	(Mother) Mother Rejection	(Mother) Mother Rejection	(Child) Internalizing Behavior	**Family Income**
	#4	(Mother) Mother Hostility	Prosocial Behaviors	(Parents' avg.) Individualism	**(Parents' avg.) Adverse Life Experiences**
	#5	Prosocial Behaviors	(Child) Mother Neglect	(Parents' avg.) Social Competence	**(Parents' avg.) Social Competence**
Good	#1	(Father) Father Warmth	(Mother) Social Competence	**(Parents' avg.) Social Competence**	(Parents' avg.) Social Competence
	#2	Stoplight Task Risk Propensity	(Child) Internalizing Behavior	**(Parents' avg.) Physical Punishment**	(Child) Internalizing Behavior
	#3	(Father) Neighborhood Danger	Matrix Reasoning	**(Child) Internalizing Behavior**	(Child) Parents' Neglect
	#4	(Father) Social Competence	(Mother) School Performance	**Religious Importance**	Number of Household Members
	#5	(Father) Physical Punishment	IGT Reward Sensitivity on Bad decks	**(Child) Parents' Neglect**	(Parents' avg.) School Performance
Hierarchical	#1	(Mother) Mother Behavioral Control	Prosocial Behaviors	Family Income	**Family Income**
	#2	Prosocial Behaviors	(Child) Mother Behavioral Control	Religious Importance	**(Child) Prosocial Behaviors**
	#3	(Child) Mother Hostility	(Father) School Performance		**(Child) Parents' Rejection**
	#4	(Child) Father Hostility	Family Income		**(Parents' avg.) Individualism**
	#5	Family Income	(Child) Father Behavioral Control		**(Child) Internalizing Behavior**
Progressing	#1	Working Memory Task	Working Memory Task	Religious Importance	**Religious Importance**
	#2	(Child) Father Hostility	Prosocial Behaviors	(Child) Parents' Hostility	**(Child) Internalizing Behavior**
	#3	(Father) Knowledge Solicitation	(Child) Father Hostility	Number of Household Members	**Number of Household Members**
	#4	(Mother) Positive Parenting	(Father) Knowledge Solicitation	(Child) Internalizing Behavior	**(Parents' avg.) Individualism**
	#5	(Mother) Mother Neglect	(Father) Father Individualism	(Parents' avg.) Adverse Life Experiences	**(Child) Parents' Hostility**
Safe	#1	(Child) Neighborhood Danger	**(Child) Internalizing Behavior**	(Parents' avg.) Social Competence	(Child) Internalizing Behavior
	#2	(Child) Internalizing Behavior	**(Child) Father Hostility**	(Child) Internalizing Behavior	Religious Importance
	#3	(Father) Father Collectivism	**(Father) Positive Parenting**	(Child) Family Obligations	(Child) Parents' Hostility
	#4	(Father) Father Rejection	**(Father) Father Collectivism**	(Child) Neighborhood Danger	(Child) Parents' Behavioral Control
	#5	(Mother) Social Competence	**(Mother) Mother Rejection**	Number of Household Members	(Child) Externalizing Behavior

Note. Mother, father, and child labels in parentheses indicate the reporter of the construct.

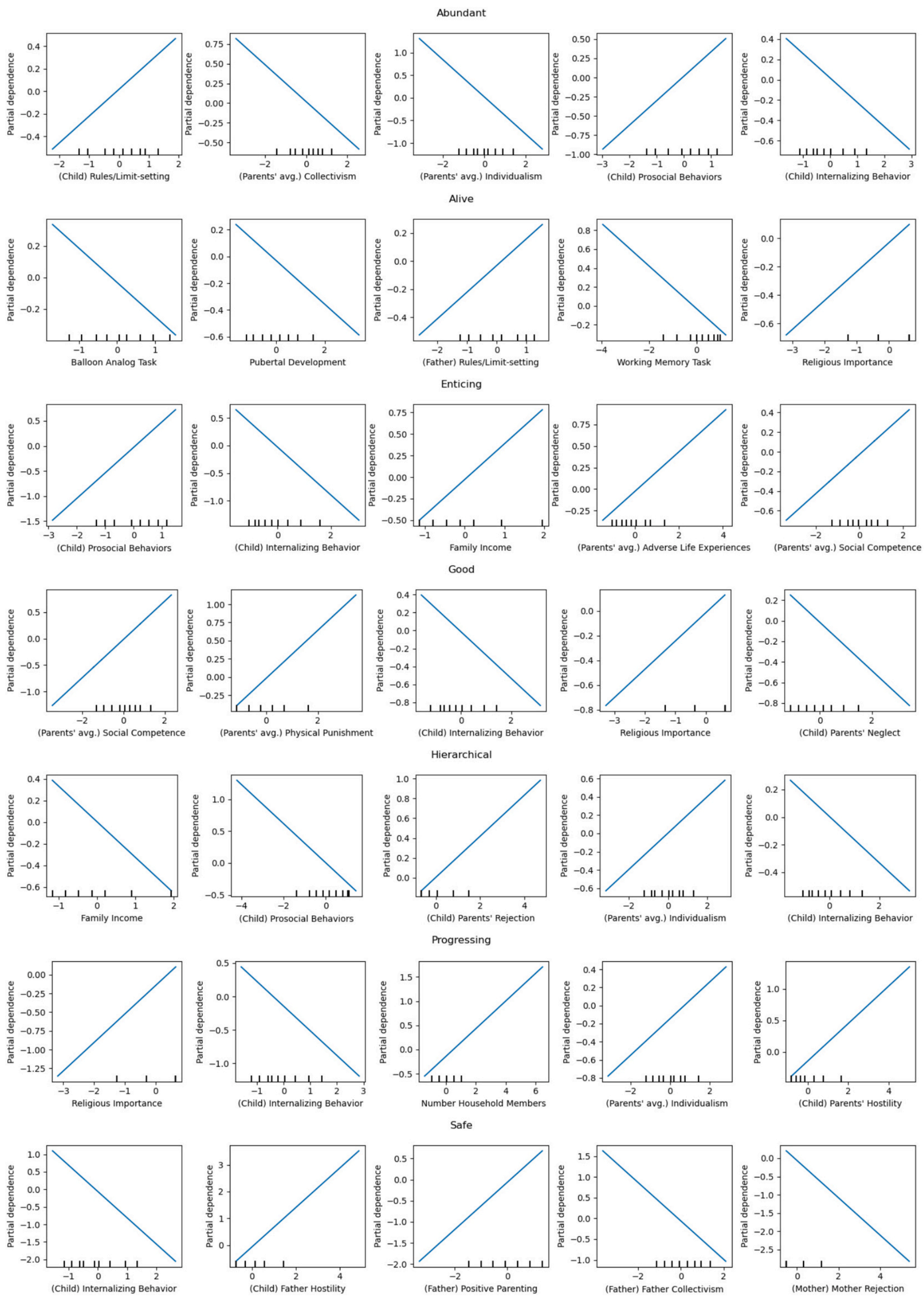

Fig. 2. Partial dependence plots of the top five most important predictors for each Primal to show the direction of the effects between (normalized) predictor values and the outcome class. Positive slopes indicate that higher values of the predictor are associated with the "High" class; conversely, partial dependence plots with negative slopes indicate that higher values of the predictor are associated with the "Low" class.

Religious Importance appeared among the top five most important features in all ML experiments with more religious importance related to the High *Alive* class. Social Competence (either mother-reported or parent-reported) appeared three times; Child Gender, Adverse Life Experiences (either father-reported or parent-reported), and child-reported Internalizing Behavior appeared two times (Table 3). Additionally, the median dichotomization approach with the original dataset resulted in an MCC of 0.431 (CI: 0.28 to 0.57) for the Train set and an MCC of 0.358 (CI: 0.07 to 0.61) for the Test set, and good performances were achieved with the processed datasets (both dichotomization approaches) as well, reflecting strong performance in both sets and suggesting that the models generalize fairly well with some degree of variability.

Table 4
Results of the Kruskal-Wallis tests for the top five features of the best ML experiment for each primal.

Primal	Feature #1 Name	H	p-corr	Feature #2 Name	H	p-corr	Feature #3 Name	H	p-corr	Feature #4 Name	H	p-corr	Feature #5 Name	H	p-corr
Abundant	(Child) Rules/ Limit-setting	0.01	0.939	(Parents' avg.) Collectivism	2.53	0.264	(Parents' avg.) Individualism	0.01	0.939	(Child) Prosocial Behaviors	2.57	0.264	(Child) Internalizing Behavior	1.99	0.264
Alive	Balloon Analog Task	0.99	0.531	Pubertal Development	0.59	0.059	(Father) Rules/ Limit-setting	0.09	0.767	*Working Memory Task*	*4.92*	*0.066*	**Religious Importance**	**21.07**	**<0.001**
Enticing	*(Child) Prosocial Behaviors*	*4.54*	*0.083*	(Child) Internalizing Behavior	1.08	0.298	*Family Income*	*6.42*	*0.056*	(Parents' avg.) Adverse Life Experiences	1.81	0.224	(Parents' avg.) Social Competence	2.64	0.1734
Good	*(Parents' avg.) Social Competence*	*4.37*	*0.061*	(Parents' avg.) Physical Punishment	0.32	0.572	**(Child) Internalizing Behavior**	**7.68**	**0.028**	Religious Importance	0.44	0.572	*(Child) Parents' Neglect*	*5.09*	*0.060*
Hierarchical	**Family Income**	**18.27**	**<0.001**	**(Child) Prosocial Behaviors**	**12.05**	**0.001**	**(Child) Parents' Rejection**	**14.39**	**<0.001**	(Parents' avg.) Individualism	0.06	0.800	(Child) Internalizing Behavior	0.31	0.719
Progressing	Religious Importance	1.25	0.439	(Child) Internalizing Behavior	0.46	0.624	Number of Household Members	0.01	0.913	(Parents' avg.) Individualism	3.15	0.190	**(Child) Parents' Hostility**	**7.76**	**0.027**
Safe	*(Child) Internalizing Behavior*	*6.05*	*0.070*	(Child) Father Hostility	0.83	0.614	(Father) Positive Parenting	0.14	0.710	(Father) Father Collectivism	0.81	0.614	(Mother) Mother Rejection	0.3	0.710

Note. Mother, father, and child labels in parentheses indicate the reporter of the construct.
P-values have been corrected with the Benjamini-Hochberg method. Results that remained significant after correction are in bold font; results that were originally significant but not after correction are in italics.

Enticing

For this primal, the three-levels dichotomization using the processed dataset yielded the best results. The Train set showed an MCC of 0.414 (CI: 0.26 to 0.56), and the Test set had an MCC of 0.320 (CI: 0.04 to 0.58). This indicates good generalizability and reliability. Distinctively, the features that contributed the most to its performance were child-reported prosocial behaviors, child-reported internalizing behavior, and family income (see Fig. 2, Table 3). For Prosocial Behavior, higher scores were associated with the High *Enticing* class, which also showed significant differences between the two classes (H = 4.54, $p = 0.033$). For Internalizing Behavior, higher scores were associated with the Low *Enticing* class, which, however, showed no significant difference between classes. For Family Income, higher income was associated with the High *Enticing* class, which showed significant differences between the two classes (H = 6.42, $p = 0.011$). The following two predictors showed no significant differences between the two classes: parent-reported Adverse Life Experiences (higher scores associated with the High *Enticing* class) and parent-reported Social Competence (higher scores associated with the High *Enticing* class).

Child-reported Prosocial Behaviors appeared among the top five most important features in all ML experiments. Family Income appeared in three ML experiments. Mother-reported Mother Rejection, Individualism (either mother's or the parents' average), parent-reported Social Competence, and child-reported Internalizing Behaviors appeared two times. Finally, we note the role of predictors derived from the Parental Acceptance-Rejection/Control questionnaire (Parent warmth, hostility, neglect, undifferentiated rejection, and behavioral control), which appeared six times. The results were also good for the median dichotomization using the processed dataset, with an MCC of 0.292 (CI: 0.17 to 0.42) in the Train set and an MCC of 0.250 (CI: 0.02 to 0.46) in the Test set. This indicates moderate performance in both sets, suggesting some variability but generally reliable performance. Sub-optimal results were obtained with the original dataset (both dichotomization approaches), indicating that the processed dataset contained features with greater predictive performance. The superior performance of the three-levels approach compared to the median approach suggests that the model is better at predicting more extreme values of the *Enticing* primal, rather than cases close to the median.

Good

For *Good* world belief, the three-levels approach yielded unsatisfactory results using both datasets, whereas the median approach showed moderate performance. The best performance was achieved using the processed dataset, with an MCC of 0.337 (CI: 0.21 to 0.45) in the Train set and an MCC of 0.209 (CI: −0.02 to 0.42) in the Test set, indicating moderate performance with higher levels of uncertainty in the Test set.

The top 5 most important features for this experiment were: parent-reported child Social Competence (higher scores associated with the High *Good* class), which also showed significant differences between the two classes (H = 4.37, $p = 0.037$); parent-reported Physical Punishment (higher scores associated with the High *Good* class, but no significant difference between the two classes); child-reported Internalizing Behavior (higher scores associated with the Low *Good* class), which also showed significant differences between the two classes (H = 7.68, $p = 0.006$); Religious Importance (higher scores associated with the High *Good* class, no significant differences between classes); and child-reported Parents' Neglect (higher scores associated with the Low *Good* class), which showed significant differences between the two classes (H = 5.09, $p = 0.024$).

Hierarchical

The ML experiments based on the processed dataset yielded the best results for this primal with both approaches, but the three-levels approach was the best overall. The Train set showed an MCC of 0.306 (CI: 0.16 to 0.46), and the Test set had an MCC of 0.375 (CI: 0.08 to 0.62). This indicates good generalization to new data, although there is substantial variability. The top features contributing to its performance were: Family Income (higher scores associated with the Low *Hierarchical* class), which showed significant differences between the two classes ($H = 18.27$, $p < 0.001$); child-reported Prosocial Behavior (higher scores associated with the Low *Hierarchical* class), which also showed significant differences between the two classes ($H = 12.05$, $p = 0.001$); child-reported Parents' Rejection (higher scores associated with the High *Hierarchical* class), which also showed significant differences between the two classes ($H = 14.39$, $p < 0.001$).

The following two predictors showed no statistically significant differences between the two classes: parent-reported Individualism (higher scores associated with the High *Hierarchical* class); child-reported Internalizing Behaviors (higher scores associated with the Low *Hierarchical* class).

Family Income appeared among the top five most important features in all ML experiments; child-reported Prosocial Behaviors and Parent Behavioral Control-related predictors appeared three times.

Progressing

With this primal, low predictive performance was achieved in all ML experiments; the one using the processed dataset with the three-levels approach provided the best overall performance (MCC = 0.341 [0.19 0.48] on the Train set; MCC = 0.185 [0.06, 0.45] on the Test set). The low predictive performances across all ML experiment results indicate that the model struggles to generalize properly, showing poor performance on unseen data.

For this experiment the top five features were: Religious Importance (higher scores associated with the High *Progressing* class); child-reported Internalizing Behavior (higher scores associated with the Low *Progressing* class); Number of Household Members (higher number of members associated with the High *Progressing* class); parent-reported Individualism (higher scores associated with the High *Progressing* class); and child-reported Parents' Hostility (higher scores associated with the High *Progressing* class). Only child-reported Parents' Hostility showed significant differences between the two classes ($H = 7.76$, $p = 0.005$).

Safe

The best predictive performance for this primal was obtained using the original dataset with the three-levels dichotomization approach. The MCC was 0.503 (CI: 0.32 to 0.67) in the Train set and 0.328 (CI: 0.02 to 0.61) in the Test set. Despite considerable variability, the model shows good overall performance. The top five most important predictors were: child-reported Internalizing Behavior (higher scores associated with the Low *Safe* class), which was the only one to show significant differences between the two classes ($H = 6.05$, $p = 0.014$); child-reported Father Hostility (higher scores associated with the High *Safe* class); father-reported Positive Parenting (higher scores associated with the High *Safe* class); father-reported Collectivism (higher scores associated with the Low *Safe* class); and mother-reported Rejection (higher scores associated with the Low *Safe* class).

Child-reported Internalizing Behaviors appeared among the top five most important features in all ML experiments. Child-reported Neighborhood Danger, father-reported Collectivism, parent-related Rejection and Hostility (either mother's or father's or parents' average), and Social Competence (either mother-reported or parent-reported) appeared two times.

Discussion

Using an international sample from eight countries, we addressed the question of what individual, parenting, family, and cultural factors assessed in childhood best predict primal world beliefs in early adulthood. This data-driven work is important because prior intuitions about predictors of primals have been largely inconclusive, and researchers have struggled to find predictors of primal world beliefs (Kerry, White, O'Brien, Perry, & Clifton, 2024). Results from the *Abundant* models did not yield robust results, but for the other six primals examined, the machine learning analyses generated results that are informative in their own right as well as useful guides for replication attempts in future hypothesis-driven studies.

The most consistent predictor of *Alive* across machine learning models was the importance of religion to the family, although additional predictors emerged as being important in some models. Young adults who grew up in families where religion was important are more likely to believe the world is *Alive* than those who grew up in families where religion was not important. Items that assess the *Alive* primal, such as "Everything happens for a reason and on purpose" and "The universe needs me for something important," refer to purpose in life events, which are often cornerstones of religious messages in a number of different faiths (Prinzing et al., 2023). Beliefs about the world that are connected to religion may also be especially open to prior experiences because parents often explicitly try to socialize religious beliefs in their children (Voas & Storm, 2021).

The most consistent predictor of *Enticing* across machine learning models was child prosocial behavior, followed by higher household income. It is likely that more money makes it possible for families to surround themselves with possessions and experiences that make the world appear more enticing, and a large literature documents the importance of family income for a range of developmental outcomes (e.g., Cooper & Stewart, 2021). Behaving prosocially elicits positive responses from others (Chávez et al., 2022), which in turn may contribute to the belief that the world is an enticing place.

Predictors that most consistently distinguished young adults who were high versus low in the *Good* primal were child social competence, child internalizing behavior, and child-reported parental neglect. As with prosocial behavior in relation to *Enticing*, it is possible that children's social competence elicits responses from others (Guo et al., 2023), which then help children perceive the world as a good place. Internalizing behavior encompasses anxiety and depressive symptoms that contribute to negatively biased ways of perceiving the world (Bell et al., 2023). Parental neglect may be a global indicator that interferes with the ability for children to develop belief that the world is good.

The most consistent predictor of *Hierarchical* across machine learning models was family income. Young adults were more likely to believe the world is hierarchical when they grew up in lower-income families. In lower-SES families, parents are more likely than in higher-SES families to socialize children to be obedient rather than to think more independently (Alwin & Tufiş, 2021), which could contribute to the belief that the world is hierarchical.

The most consistent predictor of *Safe* across machine learning models was child internalizing behavior. Child-reported neighborhood danger, father-reported collectivism, parent-reported rejection and hostility, and child social competence also emerged as predictors in some of the models. These findings suggest that in addition to experiencing objectively safe childhood conditions, such as living in a low-crime neighborhood, researchers should prioritize understanding how *Safe* world belief can come from having non-hostile parents and parents that children believe will not reject them. Parental hostility was also the most important predictor of *Progressing*, suggesting further probing parenting as a predictor of the development of a range of beliefs about the world.

The factors that emerged in the top five for each primal are especially good candidates for future research to test the replicability of the current data-driven findings. It is especially striking that child internalizing behaviors appeared in the top five predictors of the best machine learning experiment for six out of seven primals (all except *Alive*), always with higher internalizing scores associated with the low class of the primal. It was also noteworthy that some of the most intuitive potential predictors did not emerge as important in these data-driven models. For example, young adults who grew up in higher-income families did not as young adults believe the world is more *Abundant*, consistent with prior research finding no concurrent correlations between poverty and the *Abundant* primal (Kerry, White, O'Brien, Perry, & Clifton, 2024). Likewise, parenting variables emerged as consistently as growing up in a dangerous neighborhood as predictors of believing the world is *Safe*, consistent with prior concurrent correlations suggesting that objective factors that make the world less safe are not necessarily correlated with believing the world is less safe (Ludwig et al., 2023).

Although the current aim is basic research to stimulate further exploration before policy recommendations would be appropriate, findings speak to potential for eventual application in educational and family contexts. The factors that predicted primals were often more controllable (i.e., child and parent behaviors) than not (e.g., income, neighborhood crime). If so, a range of activities—and policies that support those activities—could encourage adaptive primals. Initial intervention research is likewise showing that some primals can be changed, not by making the world different, but by redirecting attention via short daily reflection, resulting in increased wellbeing (Snook et al., 2025). Further, several top predictors were not just controllable but deeply social in nature (or anti-social). For example, processing negative emotions internally and alone, and not socially, was a top predictor of lower *Good*, lower *Safe*, and lower *Enticing*; child prosocial behavior (i.e., kindness) was tied to increased *Enticing*; and child social competence was tied to increased *Good*. These findings appear consistent with the discovery that positive interactions with loved ones predicted adopting more positive primals a year later, whereas positive social interactions with the broader world (strangers and acquaintances) had no impact (Lemay Jr. et al., 2025). If primals are birthed by social connection over and above material circumstance, this finding can help parents, educators, and policymakers make difficult decisions about how to allocate limited resources and time (e.g., teaching math skills versus social skills).

Key strengths of the current study include the long-term longitudinal design with reports from youth, mothers, and fathers in eight countries as well as the four different machine learning models tested for each primal to capitalize on strengths and mitigate limitations of each specific ML approach related to different thresholds for categorizations and different datasets. The study also has limitations. The relatively small sample sizes within each culture limited the number of predictors that could be utilized for machine learning purposes and the number of people who could be withheld from the machine learning training sample. The within-country sample sizes were also too small to replicate the analyses separately for each cultural group. Additionally, samples are not representative of the nations from which they are derived, so national-level inferences cannot be permitted. Future research is needed to probe whether the predictors that emerged as being most important in the full international sample hold in different individual cultural groups. We also chose a developmental snapshot in middle childhood as the assessment point for predictors of young adults' primals, but other predictors earlier in childhood (perhaps before primals develop if they are already in place by middle childhood) or later in adolescence (perhaps when they are developmentally more proximal to primals in early adulthood) might be fruitful to examine in future research. In addition, primals are fairly stable (Clifton et al., 2019). Thus, childhood measures may not be precursors of a primal if the primal is held already and influencing outcomes. For example, internalizing behavior in relation to believing the world is dangerous may have been a result of seeing the world as dangerous, and not a precursor of the belief. Finally, we caution that alphas were low for some of the measures, especially parental neglect, rejection, and control, suggesting the need for replication in other samples and possibly using different measures.

The study leads to two main conclusions. First, a range of individual, parenting, family, and cultural factors in childhood are related to young adults' beliefs that the world is *Alive, Enticing, Good, Hierarchical, Progressing*, and *Safe*. Second, factors at individual, parenting, family, and cultural levels all have some predictive value in relation to specific primals, but no single factor or even cluster of factors emerged as being predictive of all primals. The developmental pathways to perceiving the world as *Abundant, Alive, Enticing, Good, Hierarchical, Progressing*, and *Safe* are not uniform, reinforcing the importance of adopting a wide lens to understand the full range of individual, parenting, family, and cultural factors that contribute to individuals' beliefs about the world. However, the current wide-lens data-driven approach successfully unearthed several promising leads for developmentalists to probe in further research, such as the relation between *Alive* and religiosity, the relation between *Safe* and parent-child relationships, and the relation of *Hierarchical* to low rather than high family income.

CRediT authorship contribution statement

Jennifer E. Lansford: Writing – review & editing, Writing – original draft, Investigation, Funding acquisition, Conceptualization. **Andrea Bizzego:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Julio Daniel Bermúdez Chinea:** Methodology, Formal analysis. **Gianluca Esposito:** Writing – review & editing, Supervision, Methodology. **W. Andrew Rothenberg:** Writing – review & editing, Writing – original draft, Conceptualization. **Jeremy D.W. Clifton:** Writing – review & editing, Methodology, Funding acquisition, Conceptualization. **Dario Bacchini:** Writing – review & editing, Data curation. **Lei Chang:** Writing – review & editing, Data curation. **Kirby Deater-Deckard:** Writing – review & editing, Investigation. **Laura Di Giunta:** Writing – review & editing, Data curation. **Kenneth A. Dodge:** Writing – review & editing, Investigation. **Sevtap Gurdal:** Writing – review & editing, Data curation. **Daranee Junla:** Writing – review & editing, Data curation. **Paul Oburu:** Writing – review & editing, Data curation. **Concetta Pastorelli:** Writing – review & editing, Data curation. **Ann T. Skinner:** Writing – review & editing, Project administration, Data curation. **Emma Sorbring:** Writing – review & editing, Data curation. **Laurence Steinberg:** Writing – review & editing, Investigation. **Marc H. Bornstein:** Writing – review & editing, Investigation. **Liliana Maria Uribe Tirado:** Writing – review & editing, Data curation. **Saengduean Yotanyamaneewong:** Writing – review & editing, Data curation. **Liane Peña Alampay:** Writing – review & editing, Data curation. **Suha M. Al-Hassan:** Writing – review & editing, Data curation.

Author statement

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.appdev.2025.101858.

Data availability

Data will be made available on request.

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