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Computational Signatures of Inequity Aversion in Children Across Seven Societies

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Inequity aversion is an important factor in fairness behavior. Previous work suggests that children show more cross-cultural variation in their willingness to reject allocations that would give them more rewards than their partner—*advantageous inequity*—as opposed to allocations that would give them less than their partner—*disadvantageous inequity*. However, as past work has relied solely on children's decisions to accept or reject these offers, the algorithms underlying this pattern of variation remain unclear. Here, we explore the computational signatures of inequity aversion by applying a computational model of decision-making to data from children ($N = 807$) who played the Inequity Game across seven societies. Specifically, we used drift-diffusion models to formally distinguish evaluative processing (i.e., the computation of the subjective value of accepting or rejecting inequity) from alternative factors such as decision speed and response strategies. Our results suggest that variation in the development of inequity aversion across societies is best accounted for by variation in the *drift rate*—the direction and strength of the evaluative preference. Our findings underscore the utility of looking beyond decision data to better understand behavioral diversity.

Public Significance Statement
This study suggests that different cultural contexts help shape children's preferences about fairness, which in turn fundamentally alter their decision-making.

Keywords: inequity aversion, cross-cultural, reaction time, drift-diffusion model

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Human cooperation is possible only when people are willing to redress unfair inequities. This willingness, known as inequity aversion (Fehr & Schmidt, 1999), cannot be taken for granted. Far from being an inevitable and universal feature of human psychology, inequity aversion varies widely across development and between cultures. What are the computational mechanisms underlying this variation? The answer to this question remains a mystery, presenting a major obstacle to understanding the psychological origins of fairness, cooperation, and successful human society. Here, we address this mystery by using, for the first time, a computational model of decision-making to explore the algorithmic underpinnings of inequity aversion across development in seven diverse countries. In doing so, we aim to advance the broader scientific aim of illuminating the ontogeny of human fairness, complementing related research on topics including, but not limited to, how children develop notions of deservedness, such as merit (Baumard et al., 2012) and need (Wörle & Paulus, 2018); the role of collaboration and mutual respect in children's adherence to fairness norms (Corbit et al., 2017; Engelmann & Tomasello, 2019); and children's reasoning about fairness outside of distributional contexts, such as those that call upon procedural (Shaw & Olson, 2014) and retributive (Smith & Warneken, 2016) concerns.

Our investigation into inequity aversion begins with the premise that inequity aversion is not a unitary construct. There are at least two psychologically distinct types of inequity aversion that follow different patterns of developmental and cultural variation. One is *advantageous inequity (AI) aversion*: a willingness to redress inequity that favors oneself by paying a personal cost (Fehr & Schmidt, 1999). The other is *disadvantageous inequity (DI) aversion*: a willingness to redress inequity that favors another by imposing a cost on the advantaged party.

Numerous lines of research have converged on the conclusion that AI and DI aversions are distinct psychological constructs. In work with nonhuman animals, some species show responses that are broadly consistent with DI aversion (Brosnan & de Waal, 2014; Brosnan et al., 2005; Massen et al., 2012; Talbot et al., 2011), whereas few, if any, species show an aversion to AI (McAuliffe & Santos, 2018). Among humans, Western adults display stronger aversion to disadvantage over advantage across a range of situations (Loewenstein et al., 1989), consistent with work showing that as the personal cost of an action increases, a person's likelihood of performing it tends to decrease (Dovidio et al., 1991; Imas, 2014; Sullivan-Toole et al., 2019). AI and DI aversions also appear to have distinct neural signatures (Fliessbach et al., 2012; Gao et al., 2018; Tricomi et al., 2010).

Most relevant to the present investigation is work documenting variation in the behavioral expression of the two types of inequity aversion across ages and across societies. Starting in infancy, humans expect windfalls to be divided equitably and are surprised when they are not (Geraci & Surian, 2011; Sloane et al., 2012). By the age of three, most children will explicitly state that resources should be shared equally, rather than unequally (Smith et al., 2013), but react differently to AI versus DI, displaying more negative affect when receiving less (LoBue et al., 2011). Children's aversion to DI is strong in social contexts—where there is another recipient present—but also shows up in nonsocial contexts, such as when a child simply receives the lesser of two payoffs, with no other recipient involved (McAuliffe et al., 2013, 2017). As humans age, responses to inequity undergo maturational changes that reflect a gradual progression from a more self-focused aversion to inequity to a more generalized aversion to inequity (Damon, 2008; McAuliffe et al., 2017). Specifically, DI aversion appears to be a foundational response, emerging early in development and consistently across cultures (Blake et al., 2015; Blake & McAuliffe, 2011), while AI aversion emerges later in development and more variably across cultures (Blake et al., 2015; Blake & McAuliffe, 2011; Corbit et al., 2017; Shaw et al., 2016; Shaw & Olson, 2014). Results convergently point to an early-emerging unwillingness to accept less than a partner, though at the youngest ages, children appear more than willing to accept *more* than a partner (Blake & McAuliffe, 2011; McAuliffe et al., 2017; Sheskin et al., 2014). This pattern begins to shift in some societies in middle childhood. In the United States, for instance, around the age of eight, many children begin to consistently reject allocations of AI, incurring a cost to themselves to prevent their peer from receiving less than them (Blake & McAuliffe, 2011; McAuliffe et al., 2013). Additionally, children's reaction times (RTs) are much slower when faced with AI, as opposed to equal allocations, suggesting that children may be experiencing conflict or tension when faced with receiving more than a partner (Blake & McAuliffe, 2011). However, these patterns do not appear to be consistent across all societies (Paulus, 2015), suggesting a role for cultural norms in shaping inequity aversion. Comparative research with chimpanzees and human children suggests that while children sometimes sacrifice to equalize when they receive more—exhibiting AI aversion—no such behavior is observed among chimpanzees, who focus primarily on maximizing their own resources (Ulber et al., 2017). Thus, AI aversion may be uniquely important among humans.

In what follows, we review prior research on developmental and cultural differences in the Inequity Game—a standardized task to measure inequity aversion—and highlight outstanding questions about the computational mechanisms underlying this variation. Then, we introduce a computational model of decision-making and use it to glean novel insights into the nature of inequity aversion, both advantageous and disadvantageous.

The Inequity Game Across Age and Culture

Much of the research on inequity aversion has employed a standardized resource allocation task called the Inequity Game, designed to capture children's responses to AI and DI relative to equality. The Inequity Game is played by two children: an actor and a recipient. The actor makes decisions to accept or reject different allocations of food rewards. Some offers reflect AI (e.g., four food items for the actor vs. one food item for the recipient), some reflect DI (e.g., one food item for the actor vs. four food items for the recipient), and some are equitable (e.g., one food item for both children). AI aversion is indexed by higher rejection rates for advantageously inequitable offers relative to equitable offers; DI aversion is indexed by higher rejection rates for disadvantageously inequitable offers relative to equitable offers.

The Inequity Game was used first by Blake and McAuliffe (2011) in research on the development of inequity aversion among American children. The results of this study revealed evidence for the early emergence of DI aversion, with AI aversion emerging later in development. Specifically, 8-year-old children, but not 4- to 7-year-old children, rejected advantageously inequitable allocations at a higher rate than equitable allocations. This was not true of disadvantageously inequitable allocations, which children of all ages rejected more often than equitable allocations.

In addition to analyzing rejection rates, Blake and McAuliffe (2011) analyzed RTs—how quickly children chose to accept or reject each allocation. These analyses, like those of rejection rates, suggest that, among American children, the willingness to reject advantageously inequitable allocations is weak early in life, but increases later in development. Specifically, 4- to 7-year-olds were faster to accept advantageously inequitable allocations than they were to reject such allocations, whereas 8-year-old children accepted and rejected advantageously inequitable allocations with similar speed. Analyses of RTs further corroborated the analyses of rejection rates by implying that DI aversion emerges early: Children of all ages were just as fast to accept disadvantageously inequitable offers as they were to reject such offers.

Recently, researchers have begun examining the development of inequity aversion in children across societies (Blake et al., 2015; Huppert et al., 2019; Rochat et al., 2009). This work addresses a critical gap in a literature that, for many years, focused almost exclusively on individuals living in Western, Educated, Industrialized, Rich, and Democratic (WEIRD) societies (Henrich et al., 2010). Even now, in developmental science, the vast majority of samples—over 90%—come from WEIRD societies that represent less than 5% of the world's population (Nielsen et al., 2017). While the dichotomy implied by the WEIRD/non-WEIRD distinction does not capture the full diversity of human variation—there is often more variation within a society than between societies—it serves as a useful reminder that there are constraints on the generalizability of findings from exclusively Western participants. Given the pivotal role of culture in the evolutionary history of humankind and its unique function as a determinant of psychological and behavioral variation, an exclusive focus on a small subset of cultures severely limits our understanding of the diversity of human behavior (Amir & McAuliffe, 2020; Kline et al., 2018). Psychological investigations studying more diverse participant populations frequently find striking levels of variation in domains ranging from judgment (Fu et al., 2007; Lobel et al., 2001) and decision-making (Amir et al., 2019; Blake et al., 2015; House et al., 2020; Huppert et al., 2019) to reasoning (Christie et al., 2020), attention (Kuwabara & Smith, 2012), and memory (Santos et al., 2005).

Inequity aversion varies across cultures too. Adopting both a cross-cultural and developmental research design, members of our research team previously used the Inequity Game to investigate the ontogeny of inequity aversion (Blake et al., 2015). Looking across 866 pairs of children across seven diverse societies, Blake et al. (2015) uncovered two key findings: (a) DI aversion emerged across all populations by middle childhood, but (b) AI aversion was more variable, emerging only later in development, and only in three populations—Uganda, Canada, and, replicating the results of Blake and McAuliffe (2011), the United States.

These results may seem to point to cultural variation in the development of *evaluative preferences* for equity over different types of inequity. Specifically, they may seem to suggest that, early in development, children across societies value equity over DI, and only later in development, and in fewer societies, do children come to value equity over AI. The truth is, however, that the results reviewed thus far do not permit inferences about evaluative preferences. This is because evaluative preferences cannot be inferred directly from raw behavioral data, such as choices and RTs in the Inequity Game.

For many reasons, choices do not always reflect people's underlying preferences. For instance, the choice to accept an offer may reflect a prepotent response bias to accept allocations in general, rather than an evaluative preference for the specific allocation on offer. RTs are amenable to multiple interpretations as well (Baron et al., 2012; Donders, 1969; Evans et al., 2015; Fong, 2006; Rand, 2016; Simon, 1990; Sternberg, 1969; Wong et al., 2017). For instance, if someone is faster to accept an allocation than to reject that allocation, this may reflect an evaluative preference for accepting (Diederich, 2003; Jamieson & Petrusic, 1977; Konovalov & Krajbich, 2019; Tversky & Shafir, 1992), but it could also reflect variation in other factors, such as nondecision time (i.e., the time it takes to visually process the allocation and recruit motor processes) or simple impatience.

To summarize, the development of inequity aversion varies systematically across societies; DI aversion emerges early and in most cultures, whereas AI aversion emerges later and in a smaller subset of cultures. However, the computational mechanisms underlying this variation cannot be gleaned from prior studies, which have relied solely on raw behavioral data. Accordingly, in the present investigation, we adopt a computational approach designed to disentangle evaluative preferences from alternative mechanisms that might account for cultural variation in the development of inequity aversion. We describe this approach, known as drift diffusion modeling, in detail below.

Drift-Diffusion Modeling

Computational models can link behavioral data to specific components of their underlying psychological mechanisms. When behavioral data characterize binary decisions, such as accepting or rejecting allocations of resources, the most popular model of the underlying decision-making process is the *drift-diffusion model* (DDM; Forstmann et al., 2016; Ratcliff et al., 2016; Ratcliff & McKoon, 2008). This model formally distinguishes *evaluative processing* (i.e., the computation of the subjective value of the two response options) from factors external to the evaluative process that influence the decisions people make and the speed with which they make them. These external factors include *response strategies*, such as opting to make fast, intuitive responses versus slow, deliberative responses, or a prepotent response bias toward favoring one option (e.g., "accept") over the other (e.g., "reject") regardless of the specific offer on hand. External factors also include *nondecision time*, or the time it takes people to start the decision-making process and to act on their decisions. DDMs can provide insight into each individual component of the decision-making process, identifying which component, or combination thereof, underpins variation in inequity aversion across age and between cultures (Large et al., 2019). In other words, a DDM could reveal whether the variation observed in the original Blake et al. (2015) investigation reflects variation in evaluative preferences for equity over different types of inequity, or something else entirely.

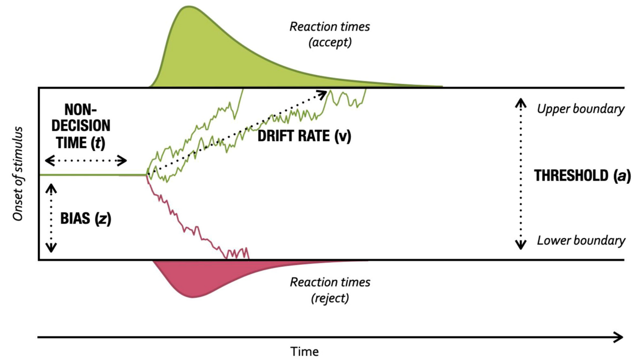
The same cannot be said of analyses of pure choice or RT data. To see why, consider a situation in which older children are found to reject disadvantageous inequality more than younger children. This effect could reflect age-related differences in evaluations of DI, but it could also emerge exclusively from age-related differences in response strategies. Specifically, older children may simply spend more time evaluating their choices; if children of all ages dislike DI to the same degree, but also have a prepotent bias to accept any offer, then simply by evaluating their options for longer, older children would be more likely to accumulate enough evidence (i.e., information of any sort that favors one response over another) to overrule their initial response bias. Ultimately, younger and older children would exhibit different choice patterns despite sharing the same underlying evaluative preferences. This is the sort of ambiguity that DDMs can resolve.

In addition to mapping effects of development and culture to underlying computational mechanisms, DDMs can detect effects of development and culture that are invisible to traditional analytic approaches. As an example, suppose two decision-making parameters vary across cultures in a way that produces equal and opposite effects on mean RT—the effect of one parameter cancels out the effect of the other, resulting in identical mean RTs across cultures, despite substantive cross-cultural differences in the underlying cognitive process. These cross-cultural differences would go unnoticed by a simple regression model that uses culture to predict RT. The DDM obviates these limitations by taking advantage of the fact that the entire shape of a RT distribution changes in predictable ways as a function of evaluative processing, response strategies, and nondecision time. For instance, a change in evaluative preferences will alter not just the mean of a RT distribution, but also variance and skewness, whereas changes in nondecision time will alter only the mean. By accounting for the unique contribution of each component of decision-making to the entire shape of the response time distribution, the DDM can uncover effects of development and culture on the computational mechanisms underlying inequity aversion that do not show up in mean-level patterns of behavior.

The DDM makes several assumptions. It assumes that people make decisions by estimating the subjective value of each response option (e.g., “accept” and “reject”) and then selecting the response option whose estimated value is greatest. It also assumes that estimates of subjective value fluctuate throughout the decision-making process due to variation in the strength and focus of attention and the stochastic nature of neuronal firing; in other words, DDMs assume that evaluation is noisy. In the DDM, fluctuating estimates of subjective value are represented as random draws from probability distributions whose means denote the subjective value of each response option. Thus, the estimated value of one response option relative to the other (i.e., the “evidence” for that response option) fluctuates randomly around a fixed value corresponding to the difference between the means of the two value distributions. This fixed value is called the drift rate, denoted as v, and it can be thought of as the subjective preference (e.g., how much a child prefers to accept vs. reject an offer). The DDM further assumes that decision-makers average out the noise in the evaluation process by repeatedly sampling estimates of their subjective preference and aggregating over time until enough evidence has been acquired to make a decision. Thus, in addition to the drift rate (i.e., the subjective preference), the DDM involves a decision threshold, denoted as a, which quantifies the amount of evidence required before a decision is made. The final two elements of the DDM are the starting point (or “bias”) of the drift-diffusion process, denoted as z, which quantifies the degree to which one response option is favored before evidence is available, and nondecision time, denoted as t, which quantifies the time consumed by perception and motor processes (e.g., how long it takes the child to count the number of candies on each tray, or to pull the lever after arriving at a decision).

Estimating the parameters of the DDM can reveal how culture and development shape each component of the decision-making process. The evaluative component of decision-making corresponds to the drift rate (v); its sign (positive for accept, or negative for reject) denotes which of the two response options is preferred (a value of zero corresponds to no preference), and its magnitude denotes the strength of the preference (Figure 1). The threshold (a) and starting point (z) capture response strategies. The threshold (a) captures the speed-deliberation tradeoff such that smaller values correspond to a preference for speed and larger values correspond to a preference for deliberation. The starting point (z) captures prepotent response bias by determining which of the two response options are favored before decision-making begins. By finding the values of v, a, z, and t that provide the best fit to participants' choice and RT data, we can quantify how these parameters vary across age and culture, thereby revealing the computational mechanisms of developmental and cultural effects on inequity aversion. That is, we can ask: to what extent are cross-cultural and age-related effects in inequity aversion driven by evaluative processing (v), response strategies (a and/or z), and nondecision time (t)?

Figure 1
The Four Parameters of the DDM



Note. Each zig-zag line represents the evidence accumulation process on a single trial. DDM = drift-diffusion model. See the online article for the color version of the figure.

The Present Study

In this study, we examine the computational signatures of inequity aversion across age and diverse societies. In these analyses, we use DDMs to quantify the contributions of evaluative processing, response strategies, and nondecision time on the behavior of 807 children in the Inequity Game across seven countries. Specifically, we test between three possibilities: That cultural and developmental variation in the behavioral expression of inequity aversion (a) results entirely from differences in evaluative preferences, (b) is not at all related to differences in evaluative preferences, or (c) results in part from differences in evaluative preferences, and in part from other mechanisms. Testing between these possibilities is critical for identifying the specific aspects of cognition that explain cultural differences in the development of inequity aversion.

Method

Participants

In the full sample, 866 pairs of children between 4 and 15 years were recruited from seven different societies: Canada ($n = 96$), India ($n = 104$), Mexico ($n = 68$), Peru (n= 149), Senegal ($n = 128$), Uganda ($n = 114$), and the United States ($n = 207$). In Canada, participants were recruited from the small, rural university town of Antigonish in Nova Scotia. The vast majority of this population is White-Caucasian, English-speaking, and economically centered around the local university, hospital, agriculture, and fishing. In India, participants were recruited from three villages located near the city of Vijayawada, Andhra Pradesh in the Southeast of India. The core occupation is seasonal agricultural labor, and the dominant language in the villages is Telugu. In Mexico, participants were recruited in a small rural village in Puuc region of the Yucatan Peninsula. Families practice subsistence agriculture and primarily speak Maya. In Peru, participants were primarily recruited from the village of San Pedro de Saño. Livelihood among these communities is typically gained through agriculture, traditional crafts, service work, or labor, and the dominant local language is Spanish. In Senegal, participants were recruited from the Dakar region, a peninsula off the Atlantic coast of West Africa. The main economy is foreign exchange, including the export of fish and petrol, as well as tourism. The main ethnic groups in the region are Wolof and Lebou. The official language is French, with people in addition speaking their ethnic languages (mostly Wolof in the areas where the research was conducted). In Uganda, participants were recruited in the Kabarole District in Western Uganda, near the border to the Democratic Republic of Congo. The people are predominantly Batooro with a small number of Bakiga, speaking the related Bantu languages of Rutooro and Rukiga. Most adults are engaged in subsistence farming, growing much of their own food. A more detailed breakdown of the sample—with variables like gender and familiarity—in addition to further information about the research sites can be found in the online supplemental materials.

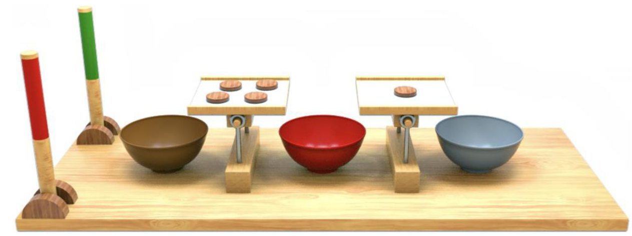
Children in the full sample received both test trials and practice trials. As RT data was coded from video recordings, the DDM analyses were based on a subset of approximately 93% of the total sample ($n = 807$): Canada ($n= 92$), India ($n = 100$), Mexico (n= 49), Peru ($n = 145$), Senegal ($n = 121$), Uganda ($n = 112$), and the United States (n= 188).

Inequity Game

The Inequity Game is a standardized resource allocation task designed to isolate concerns for distributional inequity in the absence of other concerns, such as those for deservedness or merit. In the Inequity Game, the experimenter recruits two children to sit face-to-face with the Inequity Game apparatus (Figure 2) between them. This apparatus consists of two trays—one for the actor and one for the recipient—and a green and red handle that can be used to accept (green) or reject (red) different allocations of rewards in the form of small food items. The experimenter assigns pairs of children to the AI or DI condition and assigns one child to the role of *actor* and the other to the role of *recipient*. In the AI condition, the actor receives four rewards, while the recipient receives one (4–1). In the DI condition, the actor receives one reward, while the recipient receives four (1–4). In addition to the unequal trials, children are presented with equal trials in which both the actor and recipient receive one reward (1–1) to allow comparison of children's responses to equity and inequity. The actor is then given a choice between accepting or rejecting the allocation. If the actor accepts the allocation, the rewards are paid out accordingly into the actor's and recipient's bowls. If the actor rejects the allocation, the rewards are discarded into the center bowl and neither receives any rewards. The position of the levers does not change across trials.

Figure 2

A Depiction of the Inequity Game Apparatus Showing an Advantageous Inequity Distribution



Note. The actor is on the left and has the ability to pull one of two handles—green (on actor's left) or red (on actor's right)—to accept or reject the distribution, respectively. See the online article for the color version of the figure.

Design

Test trials were carried out according to a 2×2 design with Inequity Type (DI or AI) as a between-subjects variable and Distribution (Equal or Unequal) as a within-subject variable. The AI condition consisted of a 4–1 distribution of resources which favored the decider, while the DI condition consisted of a 1–4 distribution that favored the recipient. In both cases, rejections went against immediate self-interest and deprived a peer of rewards. In India and Peru, children received 12 test trials: six equal and six unequal trials, which were presented in blocks of six equal and six unequal trials. Blocks were counterbalanced across participants. In India and Peru, children received the same kind of candy across all trials. In Canada, Mexico, Senegal, Uganda, and the United States, children received 16 test trials. Trials were blocked according to food value (see the online supplemental materials), with a block of eight high value trials and a block of eight low value trials. Within value blocks, children were randomly presented with four equal and four unequal trials. Although procedural variation may have inflated variation across cultures, none of the cross-cultural effects we observed were unique to Peru and India, which suggests that our results are not reducible to differences in superficial features of the task. Age range groupings were created prior to testing and consisted of the following groups: 4- to 6-year-olds, 7- to 9-year-olds, 10- to 12-year-olds, and 13- to 15-year-olds.

All study procedures and protocols were approved by Institutional Review Boards of Harvard University (IRB F18470-108, F18470-118, and F18643-105), St. Francis Xavier University, Antigonish, Canada (IRB #21630), the University of Utah (IRB #00065740), the Cheik Anta Diop University in Senegal, and the Uganda National Council for Science and Technology (IRB #SS 2761), respectively (Blake et al., 2015).

Procedure

Participants were matched by gender for each session and by age as closely as possible based on the children who were available for each session. The local experimenter at each site assigned each pair of children to the AI or DI condition within their age group, and designated one child as the *actor* and the other as the *recipient*. As described above, the two children sat face-to-face and were presented with the Inequity Game apparatus (Figure 1), which consisted of two trays—one for the actor and one for the recipient—and two handles that could be used to accept or reject different allocations of rewards. If the actor pulled the green handle, they accepted the offer and the rewards were paid out accordingly into the actor and recipient's bowls. If the actor pulled the red handle, they rejected the offer and the rewards were discarded into the center bowl. The rewards used in this study varied by site, but always consisted of small food items (see the online supplemental materials).

Once children were seated on either side of the apparatus, the experimenter explained the basic rules of the game. Children were not to touch the apparatus when the resources were being distributed, not to talk during the game, and to wait until the game ended to eat the treats. Children were introduced to a stick that rested atop the trays and instructed to wait until the stick had been removed before pulling a handle. The experimenter then explained how the handles worked by reciting the following instructions: "You can either pull the green handle or the red handle. If you pull the green handle, look what happens [*Experimenter pulls green handle to demonstrate*]. The [treats] fall into your bowls and you get to keep those. You move those over to the side bowls and you get to take those home at the end of the game." To demonstrate the red handle the experimenter said: "If you pull the red handle, look what happens [*Experimenter pulls red handle to demonstrate*]. They drop into the middle and nobody gets those treats." During the task, rewards gained on trials were moved to side bowls so that children could clearly see the rewards for both children gained by accepting on a trial and also see the accumulation of rewards over the course of the session.

After the demonstration phase, the experimenter presented three practice trials to the children: one equal (one candy for the actor, one candy for the recipient, 1–1), and two unequal trials (one candy for the actor, no candies for the recipient, 1–0; no candies for the actor, one candy for the recipient, 0–1). The equal practice trial was always presented first while the order of the second and third practice trials was counterbalanced between participants. The experimenter placed allocations of rewards on both sides of the apparatus, always placing the rewards on the recipient's side first to ensure that the actor paid attention to the recipient's payoff before attending to their own. If a participant pulled only one handle during the practice trials, rejecting or accepting all offers, they were then given one extra 1–1 allocation and asked to demonstrate their knowledge of the handle they had not pulled (e.g., "Show me how you would make the treats fall into the middle bowl"). For each child, we recorded whether they accepted or rejected each of the practice trials. Children's behavior in the practice trials, and related exploratory analyses, can be found in the online supplemental materials. Following practice trials, children were presented with test trials (see above for description of test trials). For each trial, we recorded whether the participant accepted or rejected an allocation (decision data were originally reported in Blake et al., 2015). Following the test trials, the experimenter probed children's justifications for their behavior in a series of open-ended questions. These, and analyses digging more deeply into children's verbal responses, can be found in the online supplemental materials.

RT Coding

For sessions that were video recorded (approximately 93% of the full sample), research assistants used Interact v.9 to code the beginning of each trial—when the experimenter lifted the stick—and the ending of each trial—when the decider began to pull the handle which resulted in the decision to accept or reject (Blake & McAuliffe, 2011). The brief window of time between the presentation of the stimulus and the lifting of the stick was not measured, but was kept as short as possible and was not varied across conditions to ensure that it cannot account for any effects of condition. In cases in which children pulled one handle slightly and then switched to the other handle, we coded the decision time between stick removal and the handle pull that was associated with their final decision. If children were reluctant to pull, the experimenter would prompt them to make a decision: for example, by reminding them of the actions associated with the green and red handles. Prompts of this kind were rare, occurring in fewer than 2% of trials overall.

Analysis

To establish how culture and development shape each component of the decision-making process in the Inequity Game, we used the hierarchical drift diffusion model (HDDM) toolbox (Wiecki et al., 2013) to perform hierarchical Bayesian estimation of four DDM parameters (v, z, a, and t). Hierarchical Bayesian estimation is ideal when relatively few observations are collected from each subject, as it simultaneously estimates parameters at the subject and group levels, which enhances statistical power.

Data Preprocessing

Following past recommendations, trials were excluded for extreme RTs ($<$150 ms, $>$2,500 ms), or if the remaining (log transformed) RT exceeded the participant's mean RT by ± 3 *SD* Participants' data were excluded if fewer than two trials of each type (equal and unequal) remained after exclusions. A total of 79% of all trials were retained, leading to the final *N* of 722.

To ensure we could detect nonlinear effects of age (e.g., lower values of v among 7- to 9-year-olds relative to 4- to 6-year-olds and 10- to 12-year-olds), we treated age as a discrete variable with three levels: 4- to 6-year-olds, 7- to 9-year-olds, and 10- to 12-year-olds. These age groups were already formed a priori for recruitment purposes and reutilized to meet the requirements of the statistical procedure. Data were collected from 13- to 15-year-olds as well, but most countries did not include this age group, so these data were not used to fit any DDMs.

Our final sample included no 10- to 12-year-olds from Mexico in the DI condition. Accordingly, although data from 10- to 12-year-olds were used to fit all DDMs, parameter estimates for children from Mexico were excluded from subsequent analyses comparing effects of condition (AI vs. DI) among 10- to 12-year-olds.

Convergence

HDDM is initialized with informative priors that reflect the range of plausible values of each parameter as established by past research (Matzke & Wagenmakers, 2009). It then uses Markov Chain Monte Carlo methods to draw samples from the joint posterior distribution over all parameters. We drew 20,000 samples from the posterior, discarding the first 5,000 as burn-in. We also applied thinning, discarding four out of every five samples. Checks for convergence included both visual inspection of histograms and autocorrelation plots (see the online supplemental materials) and calculation of the R-hat (Gelman–Rubin) statistic ($<$1 for all parameters in the winning model, indicative of successful convergence).

Model Selection

Following past recommendations (Wiecki et al., 2013), we used the Deviance Information Criterion (DIC; Spiegelhalter et al., 2002) for model comparison. Models with lower DIC values are favored. All models included person-specific estimates for the *v*, *a*, and *t* parameters. The *z* parameter was estimated only at the group level to support convergence. Responses were coded such that positive values of *v* correspond to an evaluative preference for the "accept" option and negative values of v correspond to an evaluative preference for the "reject" option; values of *z* above .5 correspond to a prepotent bias to accept offers, and values of *z* below 0.5 correspond to a prepotent bias to reject offers.

For each subject, the value of each parameter was modeled as a random draw from a group-level distribution centered on a mean μ and standard deviation σ. For instance, a particular subject's drift rate parameter value (*v*) was modeled as a random draw from a group-level Gaussian distribution with mean μ_v and standard deviation σ_v. As we are interested in the group-level parameters (e.g., the average value of *v* among Canadians) rather than individual-level parameters (e.g., the value of *v* for a particular Canadian), model selection involved comparing DIC values for multiple model variants in which group-level parameters were either fixed or allowed to vary by condition (i.e., country, age group, inequity type, and/or distribution).

Results

An evaluative preference for inequity corresponds to a more positive drift rate (one that more strongly favors the "accept" option) on unequal trials versus equal trials. So, if evaluative preferences for inequity vary across countries, the best fitting model should allow *v* to vary by country and distribution, and if evaluative preferences for inequity vary by age, the best fitting model should allow *v* to vary by age group and distribution. Since previous work outlined earlier in this paper suggests that responses to DI versus AI are psychologically, neurologically, and evolutionarily dissociable, we modeled evaluative preferences as a function of inequity type (AI or DI). If the influence of country or age on evaluative preferences for inequity depends on the type of inequity—AI or DI—then, in the best fitting model, *v* should also be free to vary by inequity type in addition to distribution, country, and/or age. However, if cultural and developmental variation in choice behavior do not reflect cultural and developmental variation in evaluative processing, the winning model should not let *v* vary by distribution and distribution type.

Model comparisons were consistent with the hypothesis that evaluative preferences for inequity vary meaningfully across countries and age groups and that the pattern of variation depends on the type of inequity at hand (see the online supplemental materials for a complete list of model comparisons and more details about model-fitting procedures). Specifically, in the best fitting model, *v* varied by country, age group, distribution, and inequity type. In addition, *a* varied by country (but not age, inequity type, or distribution), *t* varied by inequity type and distribution (but not country or age group), and *z* did not vary across any of our four conditions. These results suggest that cross-cultural and developmental effects on decision-making in the Inequity Game cannot be attributed solely to response strategies and/or nondecision time. Instead, these effects appear to reflect evaluative processing: variation across age and culture in the Inequity Game is largely due to variation in the subjective value children place on accepting or rejecting various allocations (captured by the drift rate *v*) rather than response strategies and nondecision time.

Subsequent analyses revealed that the relationship between country and the underlying decision-making parameters is not reducible to cross-cultural variation in degree of familiarity between participants. When best-fitting modeled was altered so that the country variable was replaced with a familiarity variable (i.e., a binary variable denoting whether each pair of participants did or did not self-identify as friends or acquaintances; see the online supplemental materials for details), the fit of the model was reduced (Increase in DIC = 49). Accordingly, the effects of country on *v* and *a* likely involve more than mere familiarity.

To understand the effect of each condition on *v*, we performed a series of contrasts, allowing us to assess the degree to which *v* differs across unequal and equal offers. This involved subtracting the samples from one (marginal) posterior distribution (e.g., the posterior distribution over *v* for unequal offers among 10- to 12-year-old Canadians in the AI condition) from the samples from a second (marginal) posterior distribution (e.g., the posterior distribution over *v* for equal offers among 10- to 12-year-old Canadians in the AI condition), and then computing the 90% highest density interval (HDI) of the new distribution of difference scores. Ninety percentage of HDIs are Bayesian analogs to confidence intervals; they contain the 90% most credible values of a parameter given the prior information, model, and data. If the 90% HDIs do not contain zero, then the two original distributions are considered credibly different.

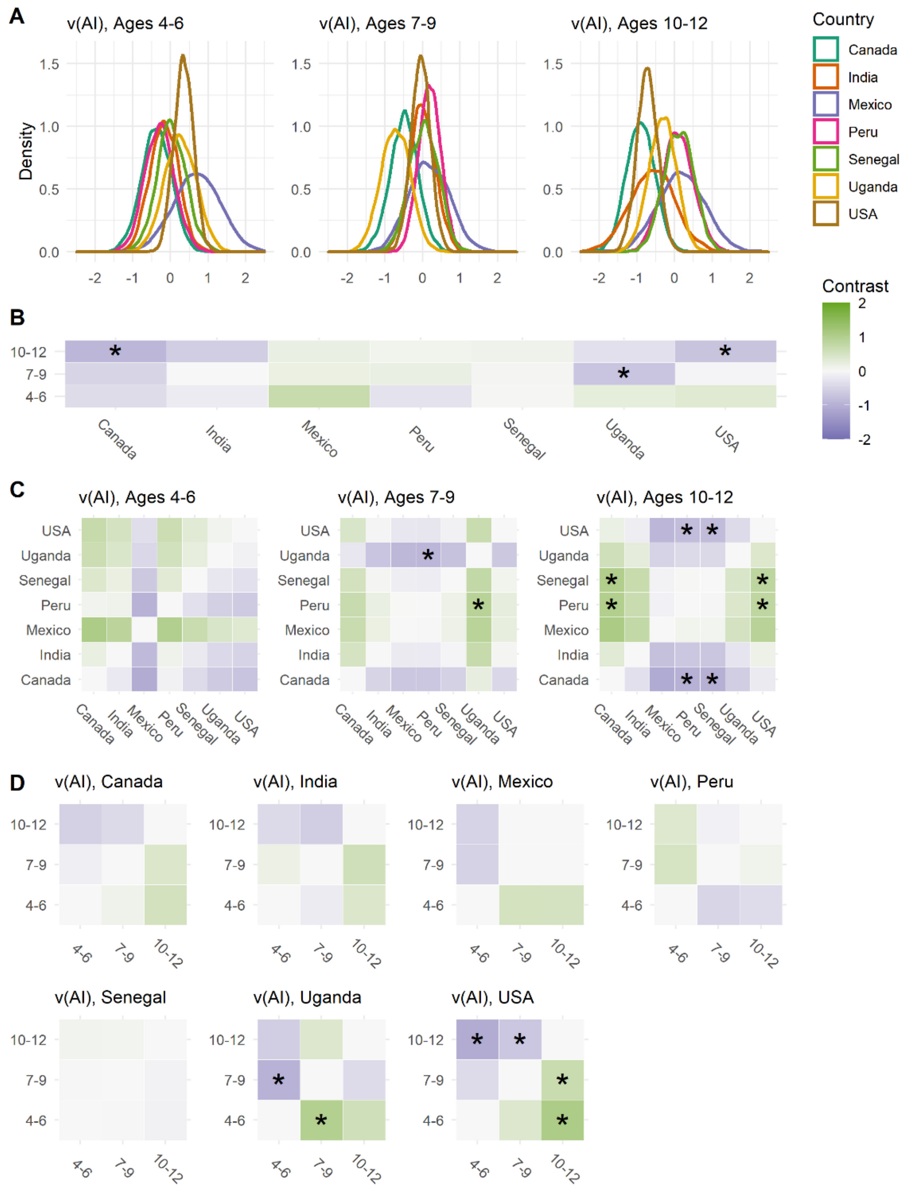
AI Aversion

First, we explored how the evaluative preference for AI varies by country and age. The evaluative preference for AI corresponds to the value of *v* for unequal offers in the AI condition minus the value of *v* for equal offers in the AI condition, denoted as *v*(AI). The more positive the value of *v*(AI), the greater the evaluative preference for AI over equity; the more negative the value of *v*(AI), the greater the evaluative preference of equity over AI.

We found substantial cross-cultural variation in *v*(AI). At younger ages, evaluative preferences for one type of distribution over the other were absent across societies, and at older ages, an evaluative preference for equity over AI emerged in some societies, but not others (Figure 3A and B). More specifically, among 4- to 6-year-olds, *v*(AI) was not credibly different from zero in any society. However, among 7- to 9-year-olds, *v*(AI) was credibly lower than zero in Uganda (90% HDI = −1.36, −.10), and among 10- to 12-year-olds, *v*(AI) was credibly lower than zero in the United States (90% HDI = −1.16, −0.27) and Canada (90% HDI = −1.53, −.30). *v*(AI) was not credibly lower than zero among any other society regardless of age group.

The strongest developmental shifts in *v*(AI) were observed in Uganda and the United States (Figure 3D). In the United States, we observed a credible decrease in *v*(AI) among 10–12 years relative to 7- to 9-year-olds (90% HDI = −1.28 to −.08) and 4- to 6-year-olds (90% HDI = −1.86 to −.45), and in Uganda, we observed a credible decrease in *v*(AI) among 7- to 9-year-olds relative to 4- to 6-year-olds (90% HDI = −1.96 to −.05). These developmental shifts led to different degrees of cross-cultural variation in *v*(AI) at different age groups (Figure 3C). Among 7- to 9-year-olds, *v*(AI) was lower in Uganda versus Peru (90% HDI = −1.72 to −.16), and, among 10- to 12-year-olds, *v*(AI) was lower in the United States and Canada versus Peru and Senegal (United States vs. Peru: 90% HDI = −1.6

Figure 3
Model-Based Analyses of Advantageous Inequity Aversion



Note. Panel A represents posterior distributions over v(AI) (i.e., the contrast between v[Equal, AI] and v[Unequal, AI] by age group and country. Negative values correspond to evaluative preferences for equal offers over AI offers, and positive values correspond to evaluative preferences for AI offers over equal offers. Panel B represents distance of v(AI) from zero by age group and country. Negative values (purple) denote evaluative AI aversion and positive scores (green) denote an attraction to AI. The more opaue the color, the greater the magnitude of the contrast. Credible differences are denoted by an asterisk. Panel C represents the effects of country on v(AI). Cell values denote the difference in v(AI) between countries such that positive values indicate that v(AI) is greater in the country on the y-axis. Credible differences are denoted by an asterisk. Panel D represents effects of age on v(AI) by country. Cell values denote the difference in v(AI) between age groups such that positive values indicate that v(AI) is greater in the age group on the y-axis. Credible differences are denoted by an asterisk. AI = advantageous inequity. See the online article for the color version of the figure.

to −.02; United States vs. Senegal: 90% HDI = −1.64 to −.07; Canada vs. Peru: 90% HDI = −1.91 to −.1; Canada vs. Senegal: 90% HDI = −1.9 to −.11).

Collectively, these results suggest that the developmental emergence of evaluative preferences for equity over AI depends on culture. Further support for this interpretation comes from a direct test of the hypothesis that the relationship between age and v(AI) differs by country. Specifically, using ordinary least squares (OLS) regression, we tested the hypothesis that there is a significant interaction between country and age group on v(AI). For each distribution (equal and unequal) in the AI condition, we extracted the mean of each subject-level posterior distribution over v. Next, we subtracted the subject-level means for equal offers from the subject-level means for unequal offers to estimate subject-specific values of v(AI). Finally, we regressed these subject-level estimates of v(AI) on country, age group, and their interaction term. To draw inferences about the cumulative effect of development on evaluative AI aversion across societies, we excluded 7- to 9-year-olds from this analysis (i.e., the age group variable was a binary variable distinguishing between 4- to 6-year-olds and 10- to 12-year-olds).

We found a significant interaction between country and age group, $F(6) = 3.03$, $p = .007$, such that v(AI) decreased with age only in the United States ($b = -1.08$, $SE = .22$, $t = 4.81$, $p < .001$); marginal effects of age on v(AI) were observed in Canada ($b = -.54$, $SE = .32$, $t = 1.66$, $p = .099$) and Uganda ($b = -.6$, $SE = .33$, $t = 1.9$, $p = .074$), and no effects were observed in India, Peru, or Senegal. Moreover, among 4- to 6-year-olds, v(AI) was not credibly lower than zero in any society, but among 10- to 12-year-olds, v(AI) was credibly lower than zero only in Canada ($b = -.91$, $SE = .22$, $t = 4.17$, $p < .001$) and the United States ($b = -.74$, $SE = .16$, $t = 4.6$, $p < .001$). As our sample from Mexico does not include 10- to 12-year-olds in the DI condition, we repeated the above analysis without children from Mexico to permit comparisons between evaluative AI aversion and DI aversion. This analysis produced the same pattern of results. These findings directly support the existence of cross-cultural variation in the developmental trajectory and emergence of evaluative preferences for equity over AI.

Children's verbal justifications for AI rejections suggest that several considerations factor into AI aversion and that these considerations vary by country (see the online supplemental materials). Namely, both considerations of equality (e.g., "we should both have the same amount") and of comparison (e.g., "I didn't want them to get more") appear in children's verbal responses with differing rates across societies, suggesting that the evaluative preference for equality is influenced by multiple considerations and that the relative weight of these considerations is culturally sensitive.

DI Aversion

Next, we explored cross-cultural and developmental effects on the evaluative preference for DI (i.e., v for unequal offers in the DI condition minus v for equal offers in the DI condition, denoted v[DI]). In contrast to evaluative preferences for equity over AI, which emerged as children aged in some, but not all societies, evaluative preferences for equity over DI eventually emerged in every society (Figure 4A and B). Among 4- to 6-year-olds, v(DI) was credibly lower than zero only in the United States and Mexico, but among 10- to 12-year-olds, v(DI) was credibly lower than zero in every country (with the exception of Mexico, where data were not collected among 10- to 12-year-olds in the DI condition).

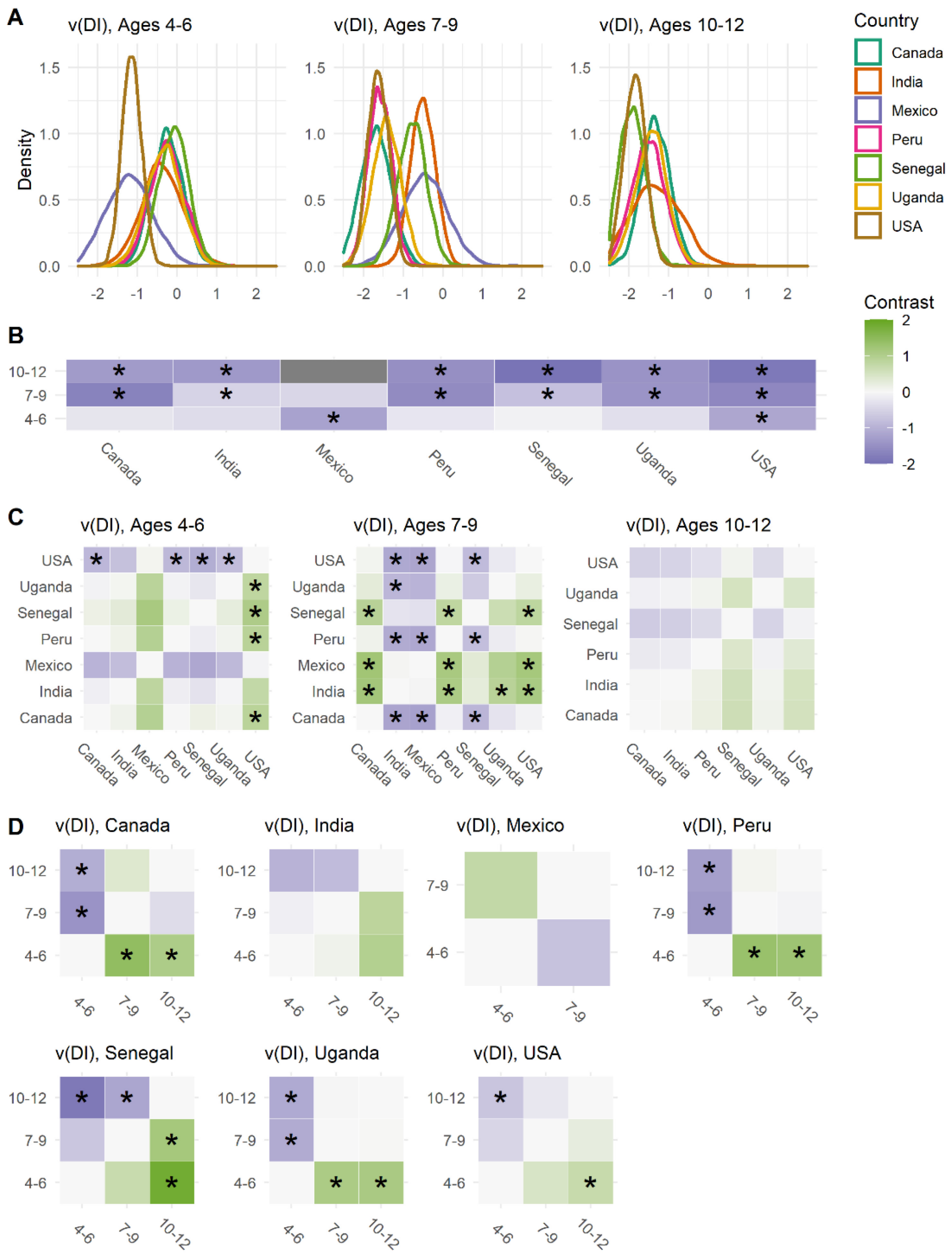
The cross-cultural consistency in the development of evaluative preferences for equity over DI was also reflected in effects of age on v(DI) across countries (Figure 4D). We found that v(DI) decreased with age in every country besides India and Mexico. Relative to 4- to 6-year-olds, 7- to 9-year-olds had lower values of v(DI) in Peru (90% HDI = −2.16 to −.44), Canada (90% HDI = −2.47 to −.61), and Uganda (90% HDI = −1.97 to −.12), and 10- to 12-year-olds had lower values of v(DI) in Peru (90% HDI = −2.19 to −.24), United States (90% HDI = −1.34 to −.10), Senegal (90% HDI = −2.68 to −1.03), and Uganda (90% HDI = −2.13 to −.23). Relative to 7- to 9-year-olds, 10- to 12-year-olds had lower values of v(DI) in Senegal (90% HDI = −2.03 to −.41) and Canada (90% HDI = −1.96 to −.22). These results suggest that, in most of the societies sampled, children converged on an evaluative preference for equity over DI with age. Indeed, we observed more cross-cultural differences in v(DI) among younger children relative to older children (Figure 4C). Among 4- to 6-year-olds, v(DI) was lower in the United States than Senegal (90% HDI = −1.78 to −.32), Canada (90% HDI = −1.67 to −.17), Uganda (90% HDI = −1.7 to −.04), and Peru (90% HDI = −1.75 to −.07). Among 7- to 9-year-olds, Peru and Canada joined the United States among the countries with the lowest values of v(DI); all three had lower values of v(DI) than 7- to 9-year-olds in Senegal (Peru vs. Senegal: 90% HDI = −1.58 to −.04; Canada vs. Senegal: 90% HDI = −1.76 to −.002; United States vs. Senegal: 90% HDI = −1.59 to −.15), Mexico (Peru vs. Mexico: 90% HDI = −2.14 to −.09; Canada vs. Mexico: 90% HDI = −2.44 to −.16; United States vs. Mexico: 90% HDI = −2.14 to −.1), and India (Peru vs. India: 90% HDI = −1.79 to −.44; Canada: 90% HDI = −2.02 to −.41; United States: 90% HDI = −1.8 to −.46). However, among 10- to 12-year-olds, v(DI) did not differ across countries.

The developmental trajectory of v(DI) stands in contrast to that of v(AI). Whereas evaluative preferences for equity over AI emerged among a subset of societies, evaluative preferences for equity over DI emerged among all societies. In other words, the developmental trajectory of v(DI) appears cross-culturally consistent. We tested this hypothesis directly using the same OLS regression approach employed in our analysis of v(AI). Specifically, we regressed subject-level estimates of v(DI) on country (excluding Mexico, due to a lack of data from 10- to 12-year-olds), age group (4- to 6-year-olds vs. 10- to 12-year-olds), and their interaction term. The interaction was not significant, $F(5) = 1.49$, $p = .194$, such that, regardless of country, 10- to 12-year-olds had lower values of v(DI) than 4- to 6-year-olds ($b = -1.11$, $SE = .14$, $t = 7.67$, $p < .001$). Moreover, among 10- to 12-year-olds, v(DI) was significantly lower than zero in every country (Canada: $b = -1.33$, $SE = .25$, $t = 5.39$, $p < .001$; India: $b = -1.39$, $SE = .43$, $t = 3.26$, $p = .001$; Peru: $b = -1.53$, $SE = .28$, $t = 5.54$, $p < .001$; Senegal: $b = -1.95$, $SE = .24$, $t = 8.18$, $p < .001$; Uganda: $b = -1.44$, $SE = .27$, $t = 5.45$, $p < .001$; United States: $b = -1.87$, $SE = .18$, $t = 10.53$, $p < .001$), whereas, among 4- to 6-year-olds, v(DI) was significantly lower than zero only in the United States ($b = -1.15$, $SE = .17$, $t = 6.92$, $p < .001$). Finally, we directly compared the developmental trajectory of v(DI) to that of v(AI) by estimating the three-way interaction between country (excluding Mexico), age group (4- to 6-year-olds vs. 10- to 12-year-olds), and inequity type (AI vs. DI). The three-way interaction was significant, $F(5) = 4.18$, $p = .001$, consistent with the idea that the development of v(DI), but not v(AI), is cross-culturally consistent.

Children's verbal justifications for DI rejections closely mirrored those for AI rejections (see the online supplemental materials), revealing cross-societal differences in the degree to which considerations of equality and/or comparison influenced evaluative preferences.

Figure 4

Model-Based Analyses of Disadvantageous Inequity Aversion



Note. Panel A represents posterior distributions over v(DI) by age group and country. Negative values correspond to an evaluative preference for equal offers over DI offers, and positive values correspond to an evaluative preference for DI offers over equal offers. Panel B represents distance of v(DI) from zero by age group and country. Negative values (purple) denote evaluative DI aversion, and positive scores (green) denote an attraction to DI. Credible differences are denoted by an asterisk. Panel C represents effects of country on v(DI). Cell values denote the difference in v(DI) between countries such that positive values indicate that v(DI) is greater in the country on the y-axis. Credible differences are denoted by an asterisk. Panel D represents effects of age on v(DI) by country. Cell values denote the difference in v(DI) between age groups such that positive values indicate that v(DI) is greater in the age group on the y-axis. Credible differences are denoted by an asterisk. The more opaque the color, the greater the magnitude of the contrast. AI = advantageous inequity. See the online article for the color version of the figure.

Response Strategies and Nondecision Time

We next turned to responses strategies (which include z, the starting point or bias, and a, the threshold of the boundaries) in addition to nondecision time (t, which captures the time it takes children to start the decision-making process and to act on their decisions). We observed significant cultural variation in a such that the decision threshold was lowest in the United States, consistent with greater emphasis on speed versus deliberation, and highest in Senegal and Canada, consistent with greater emphasis on deliberation versus speed. Specifically, in the United States, a was lower than in Peru (90% HDI = −.21 to −.004), Senegal (90% HDI = −.46 to −.25), Canada (90% HDI = −.46 to −.23), Uganda (90% HDI = −.22 to −.03), and India (90% HDI = −.27 to −.04). Conversely, in Senegal and Canada, a was higher than in Peru (Canada vs. Peru: 90% HDI = .11 to .38; Senegal vs. Peru: 90% HDI = .13 to .38), India (Canada vs. India: 90% HDI = .07 to .35; Senegal vs. India: 90% HDI = .08 to .34), Uganda (Canada vs. Uganda: 90% HDI = .09 to .35; Senegal vs. Uganda: 90% HDI = .12 to .37), and Mexico (Canada vs. Mexico: 90% HDI = .05 to .47; Senegal vs. Mexico: 90% HDI = .06 to .47).

We observed no effect of country or age group on z, consistent with an absence of developmental or cross-cultural effects on prepotent biases toward accepting versus rejecting various offers. Overall, z was not credibly different from 0 (90% HDI = .497 to .517), which suggests that participants were unbiased. In other words, we did not find evidence that children in some societies have a stronger prepotent bias towards accepting or rejecting all offers as compared to children in other societies (follow-up analyses confirmed that neither the lack of variance over z nor the absence of evidence for a starting point bias can be attributed to the fact that z was estimated only at the group level; when v, a, and t were estimated at the group level instead of z, the best fitting model still held z constant across conditions, and z still was not credibly different from zero). Finally, we found that t varied as a function of condition and distribution such that nondecision time on equal offers was greater in the AI condition versus the DI condition (90% HDI = .006 to .074). Conversely, condition was unrelated to nondecision time on unequal offers (90% HDI = −.014 to .059). In other words, relative to the DI condition, children in the AI condition spent more time looking at the stimuli and/or pulling the lever when equal offers were given.

Discussion

Previous work on the ontogeny of inequity aversion across cultures has documented the developmental emergence of DI aversion in children's decisions in all seven societies studied, but only found evidence for the emergence of AI aversion in a subset of those societies (Blake et al., 2015; Blake & McAuliffe, 2011). However, as this past research focused exclusively on variation in raw decision-making data (i.e., choices and response times), it is unclear whether and how this variation extends to the computational mechanisms underlying the decision-making process. Here, using video-recorded sessions of more than 800 children's behavior in the Inequity Game from Blake et al. (2015), we fit DDMs to explore the computational mechanisms underlying cross-cultural variation in the development of inequity aversion. Specifically, we examined whether, and to what extent, behavioral differences in the Inequity Game across ages and cultures reflect three distinct components of the decision-making process: *evaluative processing, response strategies,* and *nondecision time.*

The results of our novel approach suggest that differences in evaluative processing—specifically, evaluative preferences for equity over inequity—account for the bulk of the developmental and cultural variation in the behavioral expression of inequity aversion. This rules out several alternative hypotheses that could not have been eliminated with traditional analytic techniques. Specifically, our findings rule out accounts of behavioral variation in the Inequity Game that appeal solely to nonevaluative components of the decision-making process. On these alternative accounts, response strategies and nondecision time are what drive developmental and cultural differences in Inequity Game performance, not evaluative preferences for equity. In ruling out these alternative hypotheses, and revealing evaluative processing as the primary driver of cross-cultural variation in the development of inequity aversion, our findings shed light on the psychological origins of human fairness and cooperation.

Importantly, the specific pattern of variation in evaluative processing that we observed aligns with the results of Blake et al. (2015), who found greater cross-societal variation in the emergence and trajectory of aversion to AI versus DI. Specifically, we found that the evaluative preference for equity over AI emerges later and in fewer societies than the evaluative preference for equity over DI. Therefore, in addition to revealing a primary role for evaluation in the development of inequity aversion across cultures, our findings corroborate the theory that DI aversion is distinct from—and more foundational than—AI aversion, and grounds this distinction in the computational mechanism of evaluative processing.

Focusing on evaluative preferences for AI, we first find that, among most age groups in most societies, children do not have an evaluative preference for equitable relative to AI offers. This makes sense given that rejecting AI offers would mean losing out on four candies, which children value. When taking age into account, we find evidence of evaluative preferences for equity over AI among older children, but only in a subset of countries. That is, the emergence of an evaluative preference for equity over AI is culturally constrained. Specifically, we find no evidence of such a preference among 4- to 6-year-olds in any society. In Uganda, an evaluative preference for equity over AI is observed between the ages of 7 and 9, and by the ages 10–12, this preference appears in the United States and Canada. Our results also suggest that the United States was the only country in which an evaluative preference for equity over AI *increased* with age. We do not find strong evidence for age-related changes in evaluative preferences for AI in any other country, with the slight exception of Uganda in which 7- to 9-year-olds have a stronger preference for equity over AI than 4- to 6-year-olds, but this trend does not continue into the later age group. In sum, there are substantial cultural differences in the trajectory and emergence of evaluative preferences of equity over AI.

When considering evaluative preferences for DI, we find a different pattern: The developmental trajectory and emergence of evaluative preferences for equity over DI are consistent across societies. Among 4- to 6-year-olds, an evaluative preference for equity over DI is observed only in the United States, but by the time children are between the ages of 10 and 12, this preference appears in every society. Moreover, the evaluative preference for equity over DI increased with age in every country besides India (and Mexico, where data in the DI condition was missing).

The contrasting patterns of variation in evaluative preferences for AI and DI by age and country are striking. It corroborates the idea that aversion to AI may be more sensitive to cultural and normative influence than DI, which is more foundational and less sensitive to input across developmental time (Blake et al., 2015; Corbit et al., 2017; McAuliffe et al., 2017). It is also consistent with work suggesting that culturally variable prosocial behavior develops hand-in-hand with increased responsiveness to norms in later childhood (House et al., 2020). Additionally, the variation in evaluative preferences for AI and DI lends further support to the notion that responses to these two forms of inequity are psychologically and developmentally distinct.

One hypothesis we ruled out was that behavioral variation in the Inequity Game primarily reflects variation in response strategies—specifically, variation in the emphasis children place on speed versus accuracy, and decision biases characterized by a preference for one response option over the other regardless of the specific offer on hand. Our results provide little evidence of developmental or cultural effects on decision biases. We did find cross-societal differences in the speed-deliberation tradeoff—speed was favored in the United States, deliberation was favorited in Senegal and Canada, and children in India, Uganda, and Peru struck more of a balance between these two factors—but these effects were not qualified by age. We also did not find evidence that *nondecision time*—the time it takes individuals to start the decision-making process and to act on those decisions—varies significantly across societies.

Critically, our results do not challenge the results described in Blake et al. (2015), which highlighted substantial cross-cultural and developmental variation in the behavioral expression of inequity aversion. Rather, our results offer additional insight into the computational mechanisms that produced those behavioral patterns, revealing that the behavioral expression of AI aversion emerges from a heterogeneous set of mechanisms, but is largely accounted for by variation in evaluative preferences.

Limitations and Future Directions

There are a number of limitations to this work that warrant discussion and point to avenues for future research. By focusing on inequity aversion, the present study sheds light on the more general phenomenon of human fairness. However, the psychology of fairness encompasses more than just inequity aversion: Developmental and cross-cultural differences in reasoning, judgment, attention, and other aspects of human performance contribute to the overall picture of how the psychology of fairness varies across societies and age. Accordingly, by taking a more holistic approach, future work can build on the insights presented here.

Though our results reveal which decision-making parameters underlie variation in Inequity Game performance, they do not explain why these parameters vary. Our results do, however, serve to guide and constrain future inquiry. Specifically, future efforts to identify the cultural factors underlying variation in Inequity Game performance can restrict their search to factors that might plausibly alter evaluative preferences; factors more likely to influence response bias or speed-deliberation tradeoff are poor candidates. Examples of factors that may drive cultural variation in evaluative preferences for equity over inequity include social norms (House & Tomasello, 2018; Tropp et al., 2014), and the subjective value of reward.

The results we present here on children's verbal responses also suggest that different considerations, such as those related to fairness and social comparison, may also exert influence on evaluative preferences. To distinguish between these competing possibilities, we believe that future work should model drift rate in terms of psychological variables (e.g., competitiveness, selfishness, preferences for fairness, etc.) and cultural variables (e.g., norms, values, income inequality, familiarity, etc.) to more closely examine the sources of cross-cultural variation in evaluative preferences for equity over AI and DI.

Methodologically, children in our study always saw the rewards on the recipients' tray first and the task involved an experimenter physically doling out resources onto the trays, all of which occurred before the stick was removed and RT was coded. Future iterations of this task can minimize the potential impacts this protocol may have on nondecision time by occluding the offers before presenting them to children, thus more systematically and rigorously controlling the beginning of the RT window. While we view this as a useful methodological change, we do not believe this feature of our design can fully account for our results, which largely relied on comparisons between distributions and inequity trials, all of which were administered the same way. Additionally, despite the inclusion of a fairly large age range, we do not know how these patterns extend into adolescence and adulthood. Further ethnographic and quantitative work exploring inequity aversion among adults, for instance, can help us better understand the nuances of these behaviors across cultures and provide clearer insight into when children's evaluations converge with those of adults. Furthermore, our samples are largely restricted to one group or community within each country and should not be taken as wholly representative samples of each country. Given the importance of within-country variation, future work should also attempt to incorporate more communities and focus on the forces shaping variation within countries (Amir et al., 2019; Amir & McAuliffe, 2020). And lastly, the cross-cultural variation we observe in the speed-deliberation tradeoff merits additional attention. It is possible that this tradeoff itself reflects slightly different cultural values, or perhaps reflects a different process or stage of acquiring AI aversion. If, for instance, AI aversion is internalized earlier in the United States, that could result in weighing speed over deliberation. Or it may be the case that children in the United States are more familiar with these types of decisions. A closer investigation of the speed-deliberation tradeoff might allow for an avenue through which we can interrogate whether children in different societies experience the task itself in different ways.

Summary

Previous work on cross-cultural variation in inequity aversion has demonstrated that children show more variation in their willingness to reject AI offers than DI offers, suggesting that AI aversion is more sensitive to cultural input than DI aversion. However, as past work has primarily used traditional analytic approaches to study children's decisions to either accept or reject an offer, it is unclear how this variation extends to the underlying components of the decision-making process itself. Here, we use an analytic approach centered on drift-diffusion modeling to examine—for the first time—the computational signatures of inequity aversion across diverse societies. Through DDM, we formally dissociate three factors—nondecision time, response strategies, and evaluative preferences—to investigate which factors account for the behavioral variation observed across age and society. Our results suggest that this variation is best explained by variation in evaluative processing—specifically, evaluative preferences for equity over different types of inequity.

We believe that the computational approach used here could be used to advance research at the intersection of culture and development in general. DDMs are applicable to a wide range of research questions—not just those focused on fairness. Experimental paradigms centered on choice or RT in binary forced choices lend themselves well to DDM analyses, which can offer greater precision and inferential power without massive constraints on the experimental paradigm. The parameterization of decision-making processes can also lend itself to integrative work with neuroscience, more directly linking neural and behavioral data. Furthermore, DDMs open the door to new research questions. In the case of inequity aversion, we can ask follow-up questions like how the amount of noise in the evidence accumulation process changes with age or culture, and how and when children learn to strategically control different DDM parameters when making equity-based decisions (if they do at all). In sum, we believe the approach we have championed in this manuscript—that is, the coupling of systematic behavioral experiments across diverse societies with analytical techniques such as DDMs—can provide greater resolution into decision-making, continuing to proffer novel insights into cognitive development across cultures.

Context

Previous work suggests that DI aversion is common across cultures while AI aversion appears to be more culture-specific, manifesting at the decision level in only some of the societies surveyed (Blake et al., 2015). However, as previous research has relied almost solely on explicit decision data, it is unclear if this variation also exists in the underlying computational processes that produce these decisions. Teaming up with anthropologists and cognitive psychologists, we set out to formally analyze what features in the underlying decision-making process varied across societies, using DDM to analyze the intersection of children's decisions and RTs. These models allowed us to formally disentangle and assess distinct computational components (e.g., evaluative processing or nondecision time) in the decision-making process. Our findings enrich our understanding of how social behaviors relating to inequity aversion develop across diverse cultural contexts.

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