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Age Trends in Cooperative and Competitive Decision-Making During Adolescence: A Computational Approach

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Abstract

Adolescence is marked by significant developmental changes in social decision-making, particularly in contexts requiring cooperation and competition. The present thesis investigates the computational mechanisms underlying developmental shifts in cooperative and competitive tacit coordination across adolescence. A total of 827 participants (526 females, 295 males; age range 9–48 years) completed dyadic coordination tasks with anonymous peers and no feedback: a cooperative coordination (stag-hunt game), a competitive coordination (entry game), as well as non-social lottery task. In each game, participants chose between a safe option yielding a guaranteed payoff and a risky option whose outcome depended on context. Behavioural analyses demonstrate age-related increases in risky choices and payoffs specific to cooperation, reflecting increasing propensity for cooperation. In contrast, competition shows age-related increases in switching between the risky and safe options and longer response times relative to cooperation and lottery, suggesting increasing competitive caution. Random-effects Bayesian model comparison identifies a model incorporating recursive reasoning levels (k), decision consistency (β), beliefs about others' choices (*k0 bias*), and risk preference (ρ) as the best account of behaviour. All four parameters show significant developmental associations: *k0 bias* exhibits the strongest positive association with age (ρ = .20), followed by recursive reasoning (ρ = .19) and decision consistency (ρ = .18), whereas risk aversion declines with age (ρ = −.13). Optimistic beliefs about others' choices are strongly associated with cooperative risk-taking, while greater recursive reasoning is associated with increased switching and longer response times in competition. Furthermore, recursive reasoning and decision consistency are positively associated with non-verbal reasoning abilities, while greater decision consistency is associated with greater centrality in social network. Overall, developmental shifts in recursive reasoning, decision consistency, and beliefs about others' choices contribute to distinct age trends in cooperative and competitive decision-making, providing insights into normative social development and implications for atypical social functioning.

Keywords: adolescence, tacit coordination, computational modelling, recursive reasoning, social decision-making

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Chapter 1 – Overview

Social decision-making problems arise when the outcomes of one's decisions depend on others' choices. Such interdependent decisions are ubiquitous in everyday life, encompassing both cooperative situations, in which individuals benefit from making the same choices as others, and competitive situations, in which success depends on choosing differently. These forms of social interaction have been studied across evolutionary biology, economics, and psychology (Camerer, 2003; Nowak, 2006; Sutter et al., 2018). However, how these social decisions develop with age has been investigated less. Furthermore, attempts to computationally model this development, that is, to formally characterise how multiple psychological processes contribute to those even less so.

Adolescence is a developmental period marked by profound changes in the social domain, often described as a social re-orientation (Nelson et al., 2016; Cheng et al., 2024), spanning ages 10 to 24 (Sawyer et al., 2018). During this period, individuals become more sensitive to peers, exhibit sophisticated perspective-taking abilities, and navigate increasingly complex social environments (Blakemore & Mills, 2014; Dumontheil et al., 2010; Towner et al., 2023). These changes occur alongside the continued brain maturation supporting reward processing, cognitive control, and social cognition (Crone & Dahl, 2012; Fuhrmann et al., 2015; Larsen & Luna, 2018). Consequently, adolescence is an important period for understanding how strategic social decision-making emerges and develops, and previous work from our lab has documented distinct age trends in this domain.

Previous research from our lab demonstrated distinct age trends in cooperative and competitive tacit coordination, reviewed in detail here using an expanded sample. Cooperation increased across adolescence, whereas competition was characterised by increased switching between risky and safe options across payoff structures and longer response times (Kurtisi et al., in prep.). Although these behavioural patterns are informative, they leave an open question: which underlying psychological processes produce them, as similar behaviours may arise from different latent algorithms, including recursive reasoning, decision consistency, beliefs about others' choices, and risk preferences.

Thus, the primary aim of this thesis is to computationally characterise age trends in cooperative and competitive decision-making. The main paradigms are two tacit coordination paradigms: cooperative coordination (stag-hunt game) and competitive coordination (entry game; Chierchia et al., 2020a). Although both require decisions under uncertainty, they differ in strategic structure: cooperation rewards mutual coordination, whereas competition rewards anti-coordination. To establish whether age-related changes in these paradigms reflect condition-specific developmental signatures rather than a general age effect on decision-making under uncertainty, participants also completed a non-social lottery task, where the risky outcome depended on chance rather than another player's behaviour. Both coordination paradigms are one-shot dyadic problems played with anonymous peers and without feedback, providing a framework for understanding how participants infer others' choices from commonly known incentives. This thesis examines four computational parameters implicated in strategic decision-making: recursive reasoning levels (*k*), decision consistency (β), beliefs about others' choices (*k0 bias*), and risk preferences (ρ), as computational models provide access to latent algorithms not directly observable from behaviour and allow competing algorithmic accounts to be compared (van den Bos et al., 2018; Wilson & Collins, 2019).

Beyond characterising age-related trajectories, the thesis examines associations with behavioural measures. It also investigates links between computational parameters and non-verbal reasoning abilities, assessed using the Matrix Reasoning Item Bank (MaRs-IB; Zorowitz et al., 2023), as well as social integration, assessed using sociometric networks of peer connectedness. These associations position computational parameters within a broader picture of socio-cognitive development.

Although computational approaches have increasingly been applied to strategic decision-making (Buergi et al., 2026; Yoshida et al., 2010), few studies have examined developmental change using these methods (e.g., Liu et al., 2024; Rosenblau et al., 2018; Xia et al., 2021), and to my knowledge, no study has investigated the computational bases of age-related differences in cooperative and competitive tacit coordination without feedback-based learning. This distinction matters because previous developmental computational research has focused on learning and belief updating from feedback (e.g., Westhoff et al., 2020), whereas the present thesis investigates strategic reasoning under uncertainty in one-shot interactions, mapping the latent algorithms that could drive behaviour across development.

Overall, this thesis aims to contribute to a more mechanistic understanding of adolescent social development by identifying the latent processes underlying cooperation and competition across age. More broadly, it highlights the value of integrating developmental psychology, behavioural economics, computational modelling, and sociometrics to explain adolescent strategic social behaviour, with implications for normative and atypical social development.

Chapter 2 – Introduction

2. 1. Cooperative and competitive decision-making in adolescence

Cooperation and competition are two forms of social interaction. In everyday social life, individuals must coordinate with others to achieve shared goals while also navigating situations where their interests conflict with those of others. Although both forms of interaction require anticipating and responding to the behaviour of other people, they differ in their underlying strategic structure. Cooperative situations reward individuals for making the same choice as others, whereas competitive situations reward choosing differently.

Understanding the development of these types of strategic social behaviour is crucial, therefore, during adolescence, as this period is marked by social re-orientation (Blakemore & Mills, 2014; Cheng et al., 2024). Recent work from our laboratory suggests that cooperation and competition follow distinct developmental trajectories across adolescence (Kurtisi et al., in prep.). Using two tacit coordination games, the stag-hunt game (cooperation condition) and the entry game (competition condition), participants, age 9 to 48, made choices between a safe option across a value range and a fixed risky option while coordinating with an anonymous peer. Behavioural results showed that cooperation increased with age; participants were more likely to choose the risky option in cooperation. They became increasingly likely to coordinate on mutually beneficial outcomes across all ages relative to the competitive condition, with this propensity for cooperation increasing during adolescence. In the competitive condition, however, age-related changes were reflected not in greater risk-taking but in more variable choice patterns (i.e., switching) and longer response times, observed in adults, and only partially in adolescents, suggesting that increased competitive caution implying more complex reasoning about others' behaviour is a feature that emerges during adolescence (Kurtisi et al., in prep.).

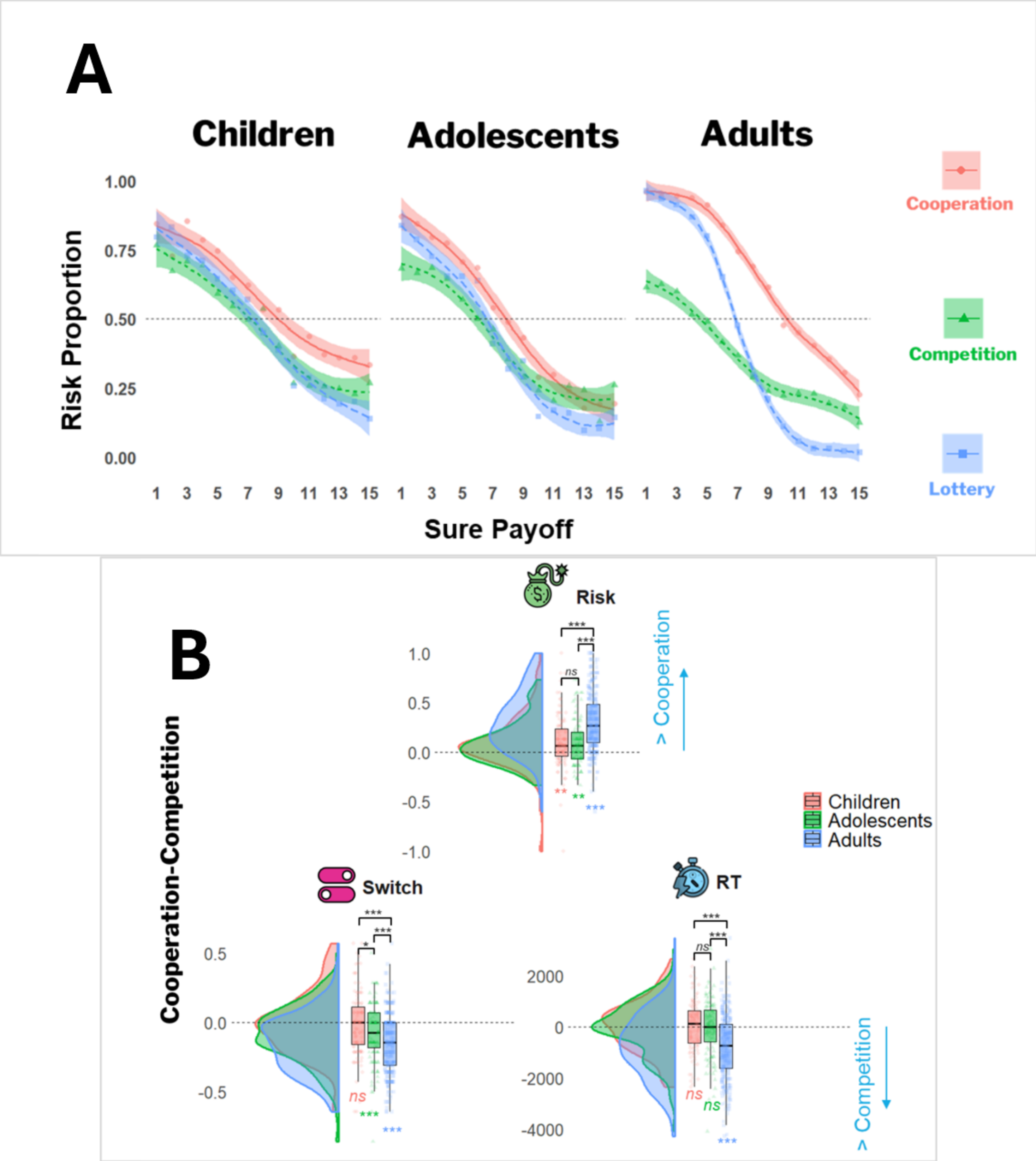

Figure 1. Cooperation and competition follow distinct developmental trajectories. **(A) Differentiation between decision contexts increases with age.** Each point represents the average proportion of risky choices across participants. The line represents estimated fixed effects from a mixed-effects model, and the shaded ribbons represent 95% confidence intervals. **(B) Adults display heightened risk-taking in cooperation compared to competition, and**

heightened switching and response times in competition compared to cooperation. Raincloud plots showing cooperation–competition difference scores (y-axis) for risk proportion, switching, and response time (RT) across age groups (children = red, adolescents = green, adults = blue). Each point represents one participant. Coloured asterisks reflect estimated marginal means-based deviations from zero; bracketed asterisks reflect age-group contrasts. Note: ****p* < .001, ***p* < .01, **p* < .05, ns: *p* > .05. Reprinted with permission from Kurtisi et al., in prep.[1]

Why do cooperation and competition develop differently? One possibility is that age-related changes reflect developmental improvements in social cognition and strategic reasoning. Another possibility is that they reflect changes in decision consistency, beliefs about other people's behaviour, or risk preferences. Observed behaviour alone cannot distinguish between these alternatives. Different underlying psychological processes may produce similar behavioural patterns, necessitating a move beyond descriptive analyses to examine the algorithms that could drive strategic choices, such as through computational modelling (Bolenz et al., 2017; Lockwood et al., 2020)

The present thesis focuses on two classic forms of tacit coordination: cooperative coordination and competitive coordination. Tacit coordination refers to situations in which individuals must coordinate their actions without communication (Chierchia & Coricelli, 2015). Such situations are common in everyday life, ranging from collaborative problem-solving and team activities to competitive environments in which success depends on anticipating others' behaviour. The two forms used throughout this thesis capture contrasting forms of social interaction while maintaining a highly comparable task structure, along with the lottery serving as a non-social baseline to isolate condition-specific effects.

Two games, the stag-hunt and entry game, which will be further referred to as cooperation and competition, respectively, for simplicity, provide a powerful comparative framework for studying strategic reasoning: they share binary choices under uncertainty with fixed and variable payoffs, while differing in the computations participants must perform to succeed in the game. In cooperation, the primary source of uncertainty is whether the other player will cooperate; in competition, it is whether they will deviate (Chierchia et al., 2020a). These distinct types of uncertainty produce systematically different patterns of behaviour even when the underlying payoffs are matched (Nagel et al., 2018), and they interact with social context and individual differences in ways that cannot be captured by observed choices alone (Yoshida et al., 2010).

[1] Note that the colour scheme of the figures here matches the original source, whereas later figures in this thesis use a different scheme for consistency within the present analyses.

In cooperation, each player chooses between a safe option yielding a small but guaranteed payoff and a risky option yielding a larger payoff only if the other player also chooses it, otherwise zero. This structure creates two Nash equilibria, that is, a set of strategies in which no individual decision-maker can unilaterally deviate without lowering their utility (Houser & McCabe, 2009): one in which both players choose the risky option, yielding the highest joint payoff, and one in which both choose the safe option, which protects against coordination failure (Chierchia et al., 2020a; Chierchia & Coricelli, 2015; Nagel et al., 2018; Yoshida et al., 2010).

Competition imposes a different strategic structure. Here, the risky option yields a reward only if the other player does not choose it. If both players choose the risky option, neither receives the reward. Consequently, success requires anti-coordination rather than coordination. This difference, as noted above, creates distinct forms of strategic uncertainty and places different demands on reasoning about other people's choices (Chierchia et al., 2020a; Krueger et al., 2016; Nagel et al., 2018).

It is worth noting that previous research suggests that social factors influence cooperation and competition differently. Friendship and social distance facilitate coordination in cooperation by reducing uncertainty about others' behaviour, whereas the same factors may hinder performance in competition by increasing uncertainty about what others will choose (Chierchia et al., 2020a; Krueger et al., 2016). The same observation was demonstrated using perceived similarity: similarity to a counterpart increases risk-taking in the cooperation but decreases it in the competition (Chierchia & Coricelli, 2015). These findings suggest that cooperation and competition rely on overlapping but partially distinct socio-cognitive mechanisms.

Neuroimaging evidence further supports this distinction. Cooperative and competitive coordination recruit regions associated with Theory of Mind, including the temporoparietal junction (TPJ), dorsomedial prefrontal cortex (dmPFC), and precuneus (Tsoi et al., 2016). However, competition additionally recruits the dorsolateral prefrontal cortex (dlPFC), which is associated with higher-level strategic reasoning, and shows greater overall neural activity within the risk network, consistent with more complex belief formation in anti-coordination (Nagel et al., 2018).

Previous findings like these also posit adolescence as a particularly interesting period. Adolescence is characterised by profound changes in social cognition, reward processing, risk preferences, and sensitivity to social information. As these systems mature, they may shape how individuals approach cooperation and competition in different ways. Indeed, developmental findings from our laboratory suggest that cooperation and competition do not simply improve with age along a common trajectory (Kurtisi et al., in prep.). Rather, they appear to reflect distinct developmental processes, raising the possibility that different latent socio-cognitive mechanisms support strategic thinking and consequently behaviour in cooperative and competitive contexts. Thus, cooperative and competitive paradigms previously employed with the developmental population in our lab motivated the computational approach adopted in the present thesis, which aims to capture "latent" processes that govern these patterns in two tacit coordination games.

2. 2. Development of strategic decision-making

The previous chapter outlined that cooperation and competition exhibit distinct developmental trajectories and possibly rely on partially different socio-cognitive processes. To understand why these developmental differences are observed, it is necessary to examine adolescence as a phase of heightened plasticity, when cognitive, neural, and social aspects are actively reorganised, rather than viewing adolescence as a mere transition between childhood and adulthood. Strategic interactions require individuals to reason about others, evaluate uncertain outcomes, and adapt their behaviour to dynamic social environments. Consequently, developmental changes occurring during adolescence may substantially shape cooperative and competitive coordination.

2. 2. 1. Adolescence as a sensitive period for social development

Adolescence is typically defined as spanning ages 10 to 24 (Sawyer et al., 2018). Its beginning is largely determined by biological events (i.e., the onset of puberty), while its end is more socially defined (Blakemore & Mills, 2014). This period is marked not only by pubertal maturation but also by profound changes in social behaviour, identity formation, and decision-making processes. Furthermore, recognising it as a period of intense growth, learning, adaptation, and neurobiological development has many practical implications, as for targeted interventions, especially given that many mental illnesses have their onset during adolescence and early adulthood (Andrews et al., 2020; Blakemore & Mills, 2014; Dahl et al., 2018; Fuhrmann et al., 2015).

Contemporary developmental theories conceptualise adolescence as a sensitive period for social and affective learning (Blakemore & Mills, 2014; Crone & Dahl, 2012; Fuhrmann et al., 2015; Towner et al., 2023). Sensitive periods are windows of heightened plasticity during which environmental experiences can exert particularly strong influences, a phenomenon known as experience-dependent plasticity (Blakemore & Mills, 2014; Cheng et al., 2024). During adolescence, individuals experience increasing autonomy, expanding social networks, and growing reliance on peers, all of which contribute to the emergence of increasingly sophisticated social behaviour.

One of the defining characteristics of adolescence is social re-orientation (Cheng et al., 2024). As individuals transition from childhood into adolescence, peers become increasingly influential, while parental influence gradually decreases (Nelson et al., 2016). Adolescents spend progressively more time interacting with peers, navigating increasingly large and complex social networks, and forming stable social relationships. These changes create new opportunities and challenges for strategic social interactions, including coordinating cooperation and competition when interacting with others.

The developmental changes observed during adolescence are paralleled by extensive neural development (Goddings et al., 2014; Grydeland et al., 2019; Mills et al., 2016; Tamnes et al., 2017). Brain maturation continues well into early adulthood and is characterised by ongoing structural and functional changes in regions involved in cognitive control, reward processing, and social cognition (Crone & Dahl, 2012; Crone et al., 2022; Fuhrmann et al., 2015; Larsen & Luna, 2018). Importantly, these systems do not mature simultaneously. Socio-affective and reward-related systems often exhibit earlier developmental changes, whereas prefrontal regions supporting executive functions and cognitive control continue to mature throughout adolescence and into young adulthood (Blakemore & Robbins, 2012; Icenogle & Cauffman, 2021; Shulman et al., 2016).

This developmental imbalance has been proposed to contribute to characteristic adolescent behaviour, including heightened sensitivity to rewards, increased peer influence, and changes in decision-making under uncertainty (Figner et al., 2009; Steinberg et al., 2016). However, recent perspectives emphasise that adolescent behaviour should not be understood solely in terms of risk-taking. Rather, adolescence may represent a period of adaptive learning during which individuals become increasingly skilled at navigating complex social environments (Ciranka & van den Bos, 2021; Crone & Dahl, 2012; Nussenbaum & Hartley, 2019; Wilbrecht & Davidow, 2024).

From the perspective of strategic social behaviour, adolescence is particularly important because successful cooperation and competition require integrating multiple cognitive and social processes (Camerer, 2003). Individuals must represent others' intentions, predict future behaviour, evaluate uncertain outcomes, and adjust their decisions accordingly. Consequently, age-related changes in strategic coordination may emerge from developmental improvements across several interacting domains rather than from a single underlying mechanism.

Thus, understanding developmental changes in cooperation and competition requires examining the cognitive and social systems that support strategic behaviour. The next section, therefore, focuses on the development of cognition and strategic reasoning across adolescence, with particular emphasis on recursive reasoning and decision-making under uncertainty.

2. 2. 2. Cognitive development and strategic reasoning

Strategic interactions require more than choosing between alternatives with different payoffs. They require individuals to anticipate the behaviour of others, evaluate uncertain outcomes, and adapt their choices accordingly. Consequently, strategic social behaviour depends on a range of socio-cognitive abilities that continue to develop throughout adolescence, including executive functions, learning, cognitive control, and recursive reasoning.

Executive functions refer to a set of higher-order cognitive processes that support goal-directed behaviour, including working memory, inhibitory control, and cognitive flexibility (Tervo-Clemmens et al., 2023). These abilities undergo prolonged development throughout adolescence (Tervo-Clemmens et al., 2023) and are closely linked to the maturation of prefrontal brain regions (Fuhrmann et al., 2015; Larsen & Luna, 2018). Developmental improvements in executive functions have been associated with more adaptive decision-making, better learning from feedback, and greater behavioural flexibility in social contexts (Crone & Dahl, 2012; Gopnik, 2020; Hofmans & van den Bos, 2022; Romer et al., 2017).

From a behavioural economics perspective, human decision-making departs systematically from the assumptions of perfect rationality (Camerer, 2003). Classical economic models assume that individuals behave as rational agents who maximize expected utility (Fehr & Rangel, 2011; Lee & Seo, 2015). However, Simon (1955) proposed the concept of bounded rationality, arguing that cognitive limitations constrain decision-making. Rather than optimizing, individuals often satisfice, selecting options that are sufficiently good given limited information and computational resources. This perspective has been highly influential in behavioural economics and also provides a useful framework for understanding strategic reasoning across development. Similarly, empirical findings have demonstrated that individuals frequently deviate from normative models of decision-making (e.g., Henrich et al., 2005). Moreover, prospect theory proposes that people evaluate gains and losses relative to a reference point rather than in absolute terms, with nonlinear probability weighting, and often exhibit loss aversion (Kahneman & Tversky, 1979; Camerer et al., 2011).

Strategic interactions introduce an additional layer of complexity because outcomes depend not only on one's own decisions but also on others' choices. This requires recursive reasoning: reasoning about what another person believes, what they think one will do, and what they think one thinks they will do, potentially ad infinitum (Camerer et al., 2004; Nagel et al., 2018). The ability to engage in such higher-order reasoning is central to strategic decision-making and may be especially important in social environments characterised by uncertainty.

The p-beauty contest game is one of the most widely used paradigms for studying recursive reasoning. In this game, participants choose a number between 0 and 100, and the winner is the individual whose choice is closest to two-thirds of the group average (Camerer, 2003; Nagel, 1995). The Nash equilibrium of the game is zero because infinitely recursive reasoning eventually converges on this value. However, empirical findings consistently show that individuals rarely reach equilibrium, with the average number in the range of 20 – 40, and instead perform only a limited number of reasoning steps (Camerer, 2003; Nagel, 1995). Most participants choose values corresponding to one or two iterations of strategic thinking, suggesting that recursive reasoning is bounded rather than infinite.

These findings motivated the development of behavioural game theory and computational models of strategic thinking (Bhatt & Camerer, 2005; Camerer et al., 2004; Nagel et al., 2018; Nagel, 1995; Yoshida et al., 2008; Yoshida et al., 2010). In level k and cognitive hierarchy models, individuals differ in the depth of their recursive reasoning (Bhatt & Camerer, 2005; Camerer et al., 2004). A level 0 player behaves non-strategically or randomly, a level 1 player best-responds to level 0 behaviour, and higher-level players recursively respond to lower-level agents. Across a wide range of experiments, it has been shown that individuals typically engage in one or two levels of recursive reasoning, with considerable variation among participants (Camerer et al., 2004; Nagel et al., 2018). At the neural level, the medial prefrontal cortex (mPFC) specifically dissociates higher- from lower-level strategic reasoning, with level 2 players showing increased mPFC activity, consistent with the recursive reasoning processes they employ (Coricelli & Nagel, 2009).

Integrating behavioural game theory with developmental psychology benefits both fields: developmental psychology provides insights into the emergence of social competencies, while game theory equips developmental psychologists with formal methods and tools

(Gummerum et al., 2008). Moreover, strategic reasoning itself appears to develop throughout childhood and adolescence. Young children already demonstrate considerable strategic competencies, including sensitivity to incentives and basic forms of recursive reasoning (Sutter et al., 2018). However, the ability to integrate information about others' beliefs, adapt to dynamic social environments, and engage in more sophisticated strategic planning continues to improve across adolescence (Brocas et al., 2017; Gonzalez-Cabrera, 2018; Liu et al., 2024). These developmental improvements may be supported by the ongoing maturation of executive functions, working memory, and cognitive control.

Learning processes also play a critical role in strategic behaviour. Individuals continuously update their expectations about others and adjust their decisions based on past outcomes. Reinforcement learning frameworks propose that behaviour is shaped through prediction errors, whereby outcomes that are better or worse than expected modify future choices (Palminteri et al., 2016). Developmental changes in learning and adaptation may therefore contribute to age-related differences in cooperation and competition.

Together, these findings suggest that strategic social behaviour depends on multiple interacting socio-cognitive processes that continue to mature throughout adolescence. Developmental improvements in executive functions, learning, and recursive reasoning may contribute to increasingly sophisticated coordination with others and may help explain why cooperation and competition follow distinct developmental trajectories. Because strategic interactions fundamentally require representing and predicting other people's mental states, understanding these developmental changes also requires examining the development of social cognition and Theory of Mind.

2. 2. 3. Development of social cognition and Theory of Mind

Humans are inherently social beings, and many decisions are not made in isolation but in interaction with others. Strategic social behaviour therefore requires more than evaluating rewards and risks; it also depends on the ability to represent and predict the mental states of other individuals. This capacity, commonly referred to as Theory of Mind (ToM) or mentalising, enables individuals to infer the beliefs, intentions, desires, and emotions of others and use this information to guide their own behaviour (Frith & Frith, 2012; Van Overwalle & Baetens, 2009).

ToM plays a central role in strategic interactions because successful coordination often depends on anticipating how another person is likely to behave (Bhatt & Camerer, 2005; Bolenz et al., 2017; Buergi et al, 2026; Camerer et al, 2004; Camerer, 2003; Nagel et al., 2018;

Yoshida et al., 2008). In many social situations, individuals must reason not only about what others believe, but also about what others believe about them. Such higher-order recursive reasoning has been proposed as a key component of strategic decision-making and may therefore be central to both cooperative and competitive social interactions (Frith & Frith, 2021).

Neuroimaging research has identified a distributed mentalising network supporting ToM. Core regions include TPJ, mPFC, posterior superior temporal sulcus (pSTS), and precuneus (Schurz et al., 2014; Van Overwalle & Baetens, 2009). These regions are consistently activated when individuals reason about others' beliefs, intentions, and perspectives and appear to support distinct components of social cognition. The mPFC and the bilateral posterior TPJ were identified as activated during reasoning about mental states, irrespective of the task or stimulus format (Schurz et al., 2014). Additionally, the right TPJ has been shown to be causally involved in strategic choices, and when disrupted by transcranial magnetic theta-burst stimulation, it led to a deficit in the ability to integrate the consequences of one's own actions on the opponent's behaviour (Hill et al., 2017). One meta-analysis found that the mPFC, TPJ, and precuneus are recruited in adults, adolescents, and children, suggesting that the mentalising system is at least partially established in childhood (Fehlbaum et al., 2022). Within the broader distributed social brain network, neural circuits for face perception, embodied cognition, and mentalising interact to produce complete social cognition (Wang et al., 2018).

Notably, the mentalising network continues to develop throughout adolescence. Structural and functional changes have been observed across this period, accompanied by improvements in perspective-taking, social understanding, and social decision-making (Blakemore & Mills, 2014). A longitudinal study of children aged 9 to 11 found that ToM improved over time along a non-linear trajectory (Manzi et al., 2026). Perspective-taking (i.e., understanding what another person can or cannot see) continues to develop into adulthood, even after working memory and response inhibition reach adult levels (Dumontheil et al., 2010; Tamnes et al., 2018). Adolescence is therefore increasingly viewed as a sensitive period for social-cognitive development, during which individuals become more adept at navigating complex social environments (Cheng et al., 2024).

The development of ToM includes increasingly sophisticated forms of strategic mentalising. Strategic interactions often require individuals to represent beliefs like: "I think that you think that I will choose option X". Computational models of social cognition suggest that recursive reasoning can be conceptualised as a process of modelling another person's mind while simultaneously considering how they model one's own behaviour (Yoshida et al., 2010). Such recursive representations may place substantial demands on cognitive resources (Coricelli & Nagel, 2009). Findings further support the importance of mentalising in strategic coordination. Using a competition paradigm combined with functional magnetic resonance imaging (fMRI) and transcranial magnetic stimulation, as noted above, Hill et al. (2017) demonstrated that the right TPJ plays a causal role in strategic decision-making. Disrupting this region impaired participants' ability to incorporate second-order beliefs into their choices, suggesting that the TPJ is crucial for integrating information about how one's actions influence an opponent's future behaviour. Similarly, Coricelli and Nagel (2009) reported that increasing levels of recursive reasoning recruit both mentalising and executive networks, highlighting the close relationship between social cognition and strategic thinking.

Cooperative and competitive coordination also appear to recruit the mentalising network differently. Tsoi et al. (2016) examined neural activity during cooperative and competitive tacit coordination and found that regions including the TPJ, dmPFC, and precuneus encoded the distinction between cooperation and competition only when participants believed they were interacting with another person rather than a computer. These findings suggest that strategic coordination in genuinely social contexts selectively engages mentalising processes. Moreover, competitive interactions may place greater demands on recursive reasoning and belief formation, consistent with the greater behavioural complexity observed in anti-coordination games (Nagel et al., 2018).

Developmental changes in ToM may therefore provide an important explanation for age-related differences in cooperation and competition. As adolescents become increasingly capable of representing others' mental states and integrating social information into their decisions, they may exhibit more sophisticated strategic behaviour. Improvements in mentalising could facilitate successful coordination in cooperative contexts while simultaneously enabling more complex reasoning in competitive environments. Such developmental changes are particularly relevant for understanding the divergent trajectories observed in previous work from our laboratory, where cooperation increased across adolescence whereas competition was characterised by increased competitive caution (Kurtisi et al., in prep.).

However, ToM alone is unlikely to fully explain developmental changes in strategic behaviour. Social decisions are also shaped by reward sensitivity, risk preferences, fairness concerns, and social motivations, all of which undergo substantial developmental changes during adolescence. Consequently, understanding cooperation and competition requires considering not only how individuals reason about others but also how they evaluate outcomes and social rewards. The next section, therefore, examines the development of reward processing, risk-taking, and social preferences across adolescence.

2. 2. 4. Development of reward processing, risk-taking, and social preferences

Strategic social behaviour depends not only on the ability to reason about others but also on how individuals evaluate outcomes, process rewards, and respond to uncertainty. Decisions made in cooperative and competitive environments often involve balancing potential gains against risks while considering the social consequences of one's actions. Consequently, developmental changes in reward processing, risk-taking, and social preferences may substantially shape strategic behaviour across adolescence.

Neuroeconomics, an interdisciplinary field integrating neuroscience, psychology, and economics, seeks to understand the neural and cognitive mechanisms underlying decision-making (Camerer et al., 2011; Fehr & Rangel, 2011). Research in neuroeconomics has demonstrated that decision-making relies on distributed neural systems involved in valuation, reward processing, and learning. Central to these processes is reinforcement learning, whereby individuals update expectations based on prediction errors: the discrepancy between expected and obtained outcomes (Schultz, 1998; Coricelli & Nagel, 2015). Midbrain dopaminergic neurons have been shown to encode such reward prediction errors, providing a mechanism through which individuals learn from experience and adapt future behaviour (Schultz, 1998).

Reward valuation involves a network of brain regions, including the ventral striatum, orbitofrontal cortex (OFC), and ventromedial prefrontal cortex (vmPFC) (Clithero & Rangel, 2014). These regions contribute to the representation of subjective value and to the integration of information about rewards and costs. Interestingly, social rewards recruit many of the same neural systems as non-social rewards. When monetary value is held constant, fair offers activate reward regions more strongly than unfair offers of equivalent worth, suggesting the brain encodes fairness itself as rewarding, independently of material gain (Tabibnia & Lieberman, 2007). Overall, experiences such as prosociality, fairness, and cooperation activate reward-related regions, highlighting the intrinsically rewarding nature of social behaviour (Morelli et al., 2015; Tabibnia & Lieberman, 2007).

Developmental changes in reward processing are particularly pronounced during adolescence. Epidemiological data show that risk behaviours are a leading cause of adolescent morbidity and mortality globally, and laboratory studies suggest a peak in risky behaviour during this period (Duell et al., 2018). Risk-taking follows an inverted-U developmental pattern, peaking earlier on laboratory measures than on real-world measures, with late adolescents showing the highest propensity for risk across diverse cultural settings (Duell et al., 2018; Steinberg et al., 2016).

Peers significantly modulate adolescent risk-taking. Social isolation during adolescence harms exploratory behaviour in rodent models, and experimental ostracism produces significantly greater affective consequences in adolescents than in adults (Fuhrmann et al., 2015; Sebastian et al., 2010). This suggests adolescents' heightened sensitivity to peer rejection and desire to be accepted by peers (Blakemore, 2018; Blakemore & Mills, 2014), which may guide risky behaviour. In a simulated driving fMRI study, adolescents engaged in riskier behaviour when peers were present (Chein et al., 2011). Adolescents also shift toward safer choices when peers model safe behaviour, with the strongest such effects observed in late adolescence (Braams et al., 2018). This suggests that peer influence during adolescence is bidirectional and context-dependent, rather than uniformly risk-inducing. Susceptibility to social influence declines between early adolescence and adulthood regardless of whether the influence is prosocial or selfish, reflecting a domain-general developmental factor in social information use (Chierchia et al., 2020b; Knoll et al., 2017; Molleman et al., 2022; Reiter et al., 2021). These observed changes may influence how individuals approach cooperation and competition, particularly when outcomes depend on others' actions.

Risk-taking has long been considered a defining feature of adolescence. Traditional dual-systems and imbalance models propose that socio-affective systems involved in reward processing mature earlier than cognitive control systems, thereby increasing risk-taking during adolescence (Icenogle & Cauffman, 2021; Shulman et al., 2016). However, recent perspectives have challenged the view of adolescence as a period of generalized risk-taking. Meta-analytic evidence suggests that developmental changes in risky behaviour depend strongly on task characteristics and context, with many forms of risk-taking showing modest or inconsistent age effects (Defoe et al., 2015). These findings oppose simple dual-systems accounts and point toward a more complex picture: adolescent risk-taking may be adaptive, serving the developmental goal of becoming an independent adult in a complex and changing social environment (Blakemore, 2018; Ciranka & van den Bos, 2021; Romer et al., 2017; Slagter et al., 2023; Tymula et al., 2012).

However, risk-taking in social contexts may differ fundamentally from risk-taking in non-social settings. In strategic interactions, uncertainty often arises not from chance but from the behaviour of other people. Consequently, social decisions involve strategic uncertainty in addition to risk. Choosing the risky option in cooperation is beneficial only if one expects the other player to cooperate. Similarly, choosing the risky option in competition requires anticipating whether the other player will deviate. Thus, social expectations and beliefs about others may play a more important role in strategic decision-making than risk preferences alone.

Beyond reward processing and risk-taking, social preferences shape how individuals evaluate outcomes involving others. Classical economic models assume that individuals maximize their own utility. However, behavioural research demonstrates that people frequently care about fairness, reciprocity, and the welfare of others (Fehr & Schmidt, 1999). Social preferences are preferences over outcomes that depend not only on one's own payoff but also on others' payoffs. Such preferences can motivate cooperation even when selfish behaviour would maximize immediate gains.

One influential theory is the inequity aversion theory, which proposes that individuals experience disutility from unequal outcomes (Fehr & Schmidt, 1999). People may dislike both disadvantageous inequity, in which others receive more than they do, and advantageous inequity, in which they receive more than others. Fairness preferences have been observed across a wide range of social decision-making tasks and appear to emerge early in development, although their expression continues to change across childhood and adolescence (Fett et al., 2014; McAuliffe et al., 2017; Sutter et al., 2018). Neuroimaging studies further suggest that fair and cooperative outcomes are intrinsically rewarding. Receiving fair offers activates reward-related brain regions, including the ventral striatum and vmPFC (Tabibnia & Lieberman, 2007). These findings indicate that social preferences are closely intertwined with reward processing and may contribute to strategic behaviour.

Developmental changes in social preferences may also shape cooperation and competition. An asymmetric developmental pattern was observed: adjustment requiring uncooperative behaviour remains constant across adolescence, whereas adjustment requiring cooperative behaviour improves markedly, driven by age-related differences in inequality aversion and belief updating about others (Westhoff et al., 2020). From childhood to young adulthood, there is a shift in age-related reciprocity toward more nuanced, intention-based reciprocity. This shift is linked to cortical thinning in the dmPFC and posterior temporal cortex, both of which are involved in social inference (Sul et al., 2017). Adolescents increasingly integrate information about others' intentions and outcomes into their decisions, which may facilitate successful cooperation while also influencing behaviour in competitive environments. At the same time, increasing social sensitivity during adolescence may amplify the importance of peer relationships and social reputation.

To conclude, these findings suggest that strategic social behaviour emerges from the interaction of multiple systems, including reward processing, risk evaluation, and social preferences. These systems continue to develop throughout adolescence and may contribute to the divergent developmental trajectories observed in cooperation and competition. The following chapter turns to the two paradigms through which these processes are examined in the present thesis.

2. 3. Cooperative and competitive tacit coordination

The previous chapter highlighted several developmental processes that may contribute to age-related changes in strategic social behaviour. To investigate how these processes shape behaviour in different social environments, the present thesis employs two paradigmatic tacit coordination games introduced in section 2. 1: the stag-hunt and the entry game (referred to as cooperation and competition throughout). Although both require strategic reasoning under uncertainty, they differ in the type of coordination they reward and the computations they require, distinctions that are now examined in detail.

Strategic reasoning is often studied using one-shot (non-iterated), non-zero-sum normal-form games requiring tacit coordination, that is, games in which players must coordinate their choices without communication. Such games provide a useful framework for studying how individuals form expectations about others and adjust their own behaviour accordingly, with distinct social demands captured by the stag-hunt and entry game paradigms, respectively.

Developmental evidence suggests that cooperative coordination improves across adolescence, though the mechanisms remain debated. Early adolescence represents a key period for strategic decision-making, with age-related improvements in information sampling, adaptiveness to others' behaviour, and coordination ability (Liu et al., 2024). Coordination success increases across childhood and adolescence, with improvements particularly pronounced in cooperative games (Brocas & Carrillo, 2021). However, Czermak et al. (2010) found that the probability of exhibiting strategic behaviour did not vary significantly with age among 10 to 17 year olds, suggesting that basic strategic reasoning may already be present by late childhood. Consistent with this, Glätzle-Rützler et al. (2024) found no consistent age effects on equilibrium selection in a large sample of participants age from 9 to 18, with social expectations, rather than age per se, strongly predicting cooperative choices. Together, these findings suggest that developmental increases in cooperation may reflect increasingly accurate belief formation about others rather than changes in risk preferences or the emergence of entirely new reasoning capacities.

The stag-hunt is a paradigmatic cooperative coordination game in which each player chooses between a safe option yielding a guaranteed payoff and a risky option yielding a payoff only if the other player also chooses the risky option. The game contains two Nash equilibria: the payoff-dominant equilibrium, in which both choose the risky option and maximize joint rewards, and the risk-dominant equilibrium, in which both choose safe and avoid coordination failure (Chierchia et al., 2020a; Nagel et al., 2018). Because each player's incentive to choose the risky option increases with their expectation that the other will do the same, the stag-hunt is a game of strategic complements (Chierchia et al., 2020a). Behaviourally, the stag-hunt produces remarkably stable choice patterns. Most participants adopt threshold strategies, choosing the risky option up to a particular safe payoff value and switching to the safe option beyond it (Nagel et al., 2018). Crucially, this pattern is robust across levels of recursive reasoning: even simple strategic thinking converges on threshold behaviour, meaning behavioural variability is driven more strongly by beliefs about others and risk preferences than by differences in strategic sophistication.

On the other hand, developmentally, competitive coordination appears to follow a distinct trajectory. Previous work from our laboratory found that switching behaviour increases across adolescence in the entry game despite no corresponding increase in competitive risk-taking (i.e., emergent competitive caution; Kurtisi et al., in prep.). This suggests that older adolescents engage in increasingly complex reasoning about others' potential actions rather than simply taking greater risks, and that this development may rely on the prolonged development of prefrontal cognitive control and mentalising as described in section 2. 2. 2 and section 2. 2. 3.

The entry game shares the binary choice structure of the stag-hunt but reverses the coordination logic: the risky option yields a reward only if the other player does not choose it (Chierchia et al., 2020a; Nagel et al., 2018). Success, therefore, requires anti-coordination. Because each player's incentive to choose the risky option decreases as they expect the other to do the same, the entry game is a game of strategic substitutes (Chierchia et al., 2020a), creating a fundamentally different strategic environment. This asymmetry places greater demands on recursive reasoning. In the stag-hunt, initial beliefs generally promote convergence behaviour, and increased strategic sophistication produces little behavioural change. In the entry game, each additional level of reasoning can shift the optimal choice, potentially generating non-threshold strategies and elevated switching between risky and safe options across payoff structures (Camerer et al., 2004; Nagel et al., 2018). Empirically, adults exhibit substantially more switching, also referred to as "trembling" (Chierchia et al., 2020a), in entry games than in stag-hunt games (Chierchia et al., 2018; Nagel et al., 2018).

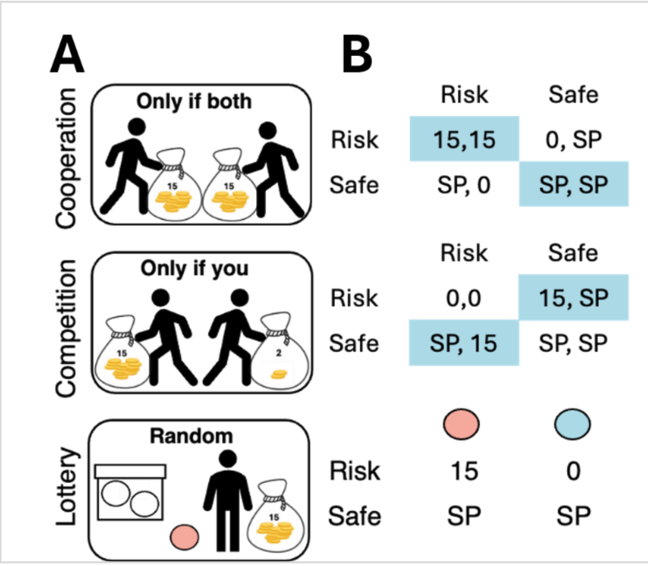

Figure 2. Tacit coordination games. **(A) Task conditions.** Three conditions share identical choice structures but differ in the icon above the risky option and corresponding rules. In the cooperative condition, two mutually anonymous players can each earn 15 by both choosing the risky option together ("only if both"), while choosing it alone yields 0. In the competitive condition, a single player earns 15 by choosing the risky option alone, while mutual risky choices yield 0 for both players ("only if you"). In the non-social control condition, the maximum payoff is obtained if a red ball is randomly drawn from a box containing two balls, whose color composition is itself randomly determined (both red, both blue, or one of each; "random draw"). **(B) Payoff matrices.** The three games are illustrated in matrix notation, where one player chooses a row, the other a column, and each cell shows the resulting payoffs, with the row player's payoff listed first. Reprinted with permission from Stagnitto et al., in prep.

Essential to note, switching behaviour is methodologically ambiguous: it may reflect deeper recursive reasoning, but it may equally arise from decision inconsistency. Behavioural observations alone cannot determine which latent mechanisms drive these differences, making computational modelling essential for decomposing switching into its constituent processes. Developmental changes in cooperation may reflect improvements in belief formation or increased risk-taking; those in competition may reflect deeper recursive reasoning, changes in decision consistency, or both. The present thesis, therefore, applies computational modelling to decompose observed choices into underlying algorithms, and further examines whether the resulting parameters relate to individual differences in fluid non-verbal reasoning abilities (MaRs-IB; Zorowitz et al., 2023) and peer social integration, testing whether strategic development is embedded within broader cognitive and social development.

2. 4. Computational modelling of strategic decision-making

The previous chapters highlighted that cooperation and competition exhibit distinct developmental trajectories and rely on multiple interacting socio-cognitive processes, including social cognition, strategic reasoning, reward processing, and social preferences, but these accounts remain largely descriptive. Similar behavioural patterns may arise from fundamentally different processes. For example, increased switching behaviour in competitive contexts may reflect deeper recursive reasoning, or increased decision inconsistency. Distinguishing among these alternatives requires computational approaches capable of decomposing observed behaviour into its underlying components, i.e., algorithms. Thus, computational models provide a complementary perspective by explaining how behaviour emerges, translating theoretical assumptions into quantitative predictions, and making latent socio-cognitive processes empirically accessible.

Computational modelling has gained considerable momentum in psychology and cognitive neuroscience over recent years. Unlike descriptive or verbal theories, in silico models explicitly formalise processes, enabling precise numerical predictions about how experimental manipulations affect behavioural outcomes, a level of specificity that verbal theories alone cannot achieve (Bolenz et al., 2017). Computational models serve two related functions: parameter estimation and model comparison. Parameter estimation identifies the best-fit values of model parameters, while also characterising differences in socio-cognitive processes across individuals or groups. Model comparison evaluates multiple models, each embodying different assumptions about how processes interact, to identify the model that best explains observed behaviour, typically using fit indices that penalise model complexity such as Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC; Nussenbaum & Hartley, 2019).

The organising framework for computational models is Marr's three levels of analysis: the computational level (what problem is being solved and why), the algorithmic level (how it is solved, including the representations and processes involved), and the implementational level (how the algorithm is physically realised in the brain). Most models operate at the algorithmic level and are particularly suited for capturing individual differences and developmental changes (van den Bos et al., 2018). A further distinction can be drawn between statistical models, which describe patterns in data, and generative models, which specify the algorithm (i.e., parameter estimates) by which behaviour is produced and can also simulate new data (McElreath, 2020; Palminteri et al., 2017). For developmental researchers, generative models are especially valuable: they reveal how developmental changes influence decision-making in ways that statistical analyses alone cannot (Bolenz et al., 2017; Wilbrecht & Davidow, 2024). In the present thesis, developmental differences in cooperation and competition may thus reflect changes in recursive reasoning levels, decision consistency, initial expectations/beliefs, risk preferences, or combinations thereof, distinctions that only computational modelling can make.

The emergence of reinforcement learning (RL) models has enabled the study of developmental change in value-based learning (i.e., associating actions with outcomes that guide future decisions). RL models assume that individuals learn from experience by updating expectations based on prediction errors: discrepancies between expected and obtained outcomes, via a Rescorla-Wagner rule, with a learning rate governing how strongly new information updates expected value (Hofmans & van den Bos, 2022). A core developmental question has been whether change is better explained by differences in how individuals adapt their learning to environmental statistics or by more stable learning biases that manifest across diverse contexts (Nussenbaum & Hartley, 2019). From childhood to adulthood, individuals become better at optimally weighing recent outcomes and less exploratory in value-based decision-making.

However, classic RL models cannot incorporate uncertainty about others. Bayesian models address this by assigning probability distributions to beliefs about outcomes, updating priors via Bayes' rule as new evidence arrives. Crucially, the influence of new data on belief change depends on prior strength: when uncertainty is high, new information carries greater weight (Hofmans & van den Bos, 2022). Developmental differences in learning algorithms are well documented. Unlike adults, adolescents do not incorporate counterfactual information even when complete feedback is available and tend to focus more on seeking rewards than avoiding punishments, whereas adults learn equally from both (Palminteri et al., 2016). In social learning specifically, adolescents display more conservative belief updating and lower learning rates than adults when predicting peers' preferences, with these differences reflected in activity in the mPFC and fusiform cortex (Rosenblau et al., 2018). Bayesian modelling of conformity has further shown that as preference uncertainty decreases with age, susceptibility to peer influence decreases accordingly (Reiter et al., 2021).

Multi-agent frameworks extend these approaches to interactive settings. Strategic interactions require models capable of representing other agents, individuals who are themselves reasoning and deciding. Yoshida et al. (2008) proposed a computational framework in which individuals recursively model one another's beliefs and intentions, and Devaine et al. (2014) developed Bayesian models of social learning capturing how people infer and adapt to others' strategies. More recently, participant behaviour has been modelled as an interactive partially observable Markov decision process (I-POMDP), capturing the depth of thinking in multi-agent interactions by specifying beliefs about others' beliefs, possible actions, and transition probabilities (Reiter et al., 2023). Reiter et al. (2021, 2023) and Buergi et al. (2026) proposed models capable of disentangling multiple latent mechanisms underlying strategic behaviour, decomposing choices into interpretable parameters reflecting recursive reasoning levels, decision consistency, beliefs about others, and risk preferences, making it possible to distinguish between behavioural patterns that appear similar at the surface but arise from different underlying processes.

Understanding when and how individuals develop their capacity to infer others' mental states has long been central to developmental psychology and has recently been extended to lifespan research on social cognition. One influential idea is that humans use and continuously update models to simulate and predict others' behaviour (Bhatt & Camerer, 2005; Bolenz et al., 2017; Buergi et al, 2026; Camerer et al, 2004; Nagel et al., 2018; Yoshida et al., 2008). The sophistication of this process is often measured by the level/depth of recursive reasoning — "I think that you think that I think" — and is the defining cognitive demand of strategic coordination games, which are central to both cooperative and competitive social interactions (Frith & Frith, 2021). Computationally, the level of recursive reasoning is encoded as parameter level k, sometimes called ToM level (Reiter et al., 2023) or mentalising depth (Buergi et al., 2026; Griessinger & Coricelli, 2015). A level 0 agent holds static, non-learning models of their partners and does not engage in iterated reasoning. A level 1 agent models the partner as level 0 and updates beliefs accordingly. In general, a level k agent models its partner as level $(k - 1)$ and updates beliefs based on a set of level $(k - 1)$ (Buergi et al., 2026; Reiter et al., 2023). Empirically, ToM sophistication varies across people and is likely upper-bounded at around two levels of recursive reasoning (Devaine et al., 2014). At the neural level, the mPFC, TPJ, and precuneus form the core mentalising network recruited during strategic reasoning about others, with mPFC activation specifically dissociating higher- from lower-level strategic reasoning in p-beauty contest games (Coricelli & Nagel, 2009; Hill et al., 2017). Behaviourally, strategic sophistication increases across childhood and adolescence, with earlier development in cooperation than in competition (Kurtisi et al., in prep.), and recursive reasoning depth improves progressively with age (Westhoff et al., 2020). Critically, recursive reasoning serves different strategic functions across the two conditions: in cooperation, reasoning about others' likely coordination supports convergence on the payoff-dominant equilibrium; in competition, reasoning about others' likely decisions determines whether to enter or stay out. The present thesis models recursive reasoning levels, enabling estimation and comparison of developmental changes in reasoning levels (i.e., mentalising depth) across cooperative and competitive contexts.

Decision consistency refers to the degree to which differences in estimated value translate into differences in the choice probability of agents. In RL and game-theoretic models, this is formalised via the inverse temperature parameter of a softmax choice function: low values imply near-random choices regardless of value differences in outcomes, while high values produce deterministic choices in favour of the highest-valued option (Bolenz et al., 2017; Gopnik, 2020; Nussenbaum & Hartley, 2019). Decision consistency consistently increases with age across development, reflecting a shift from exploratory, high-temperature search in childhood toward more exploitative behaviour in adulthood, i.e., decisions become consistent (Chierchia et al., 2023; Gopnik, 2020; Nussenbaum & Hartley, 2019; Xia et al., 2021). The developmental analogy of simulated annealing is instructive here: beginning with a high-temperature search and gradually cooling allows the learner to both escape local optima and settle on stable solutions (Gopnik, 2020). Young children are more exploratory, inconsistent, and flexible, traits that facilitate broad learning but impair focused, goal-directed action. Adolescence represents an intermediate state: teens increasingly reject unlikely physical hypotheses, as adults do, but remain more open to unlikely social hypotheses than children or adults, thereby maintaining a form of social cognitive flexibility (Gopnik, 2020). In RL studies, age-related improvements in learning are explained in part by increased decision consistency rather than by changes in the magnitude of learning biases, such as confirmation bias (Chierchia et al., 2023). In the present modelling framework, decision consistency is estimated as a separate parameter representing noisy implementation of strategic reasoning, distinct from the level/depth of that reasoning itself.

Beliefs about others' choices refer to the degree to which an agent fails/succeeds to account for others' strategic reasoning: the extent to which they behave as a level 0 player, choosing without considering what others might do (Buergi et al., 2026; Camerer et al., 2004; Coricelli & Nagel, 2009). As established previously, behavioural evidence from the p-beauty contest and related paradigms consistently shows that human players do not fully equilibrate; instead, they engage in a limited number of steps of iterated reasoning, distributed according to a Poisson-distributed cognitive hierarchy with a mean reasoning depth of 1–2 (Camerer et al., 2004). A naïve player who does not engage in iterated reasoning at all provides a baseline against which more sophisticated reasoning can be measured. In developmental contexts, strategic naiveness is expected to decrease with age as adolescents develop a greater capacity for recursive reasoning. However, because naiveness and decision inconsistency can both produce apparently random behaviour, separating them empirically requires computational modelling that estimates these parameters independently (Buergi et al., 2026).

Mathematical modelling of utility functions dates back to Bernoulli (1738/1954), who proposed a concave utility function implying risk aversion. The modern successors in economics are the constant absolute risk aversion (CARA) and constant relative risk aversion (CRRA) utility families, capturing the relationship between objective outcomes and their subjective value (Phelps, 2024). As noted previously, prospect theory extends this framework by introducing loss aversion: the subjective disutility of a loss exceeds the utility of an equivalent gain, producing characteristic asymmetries in risky decision-making (Tom et al., 2007; Kahneman & Tversky, 1979). In the context of cooperation and competition used in the present thesis, risk preference governs the degree to which an agent weighs the higher-payoff but more uncertain option against the safer option. Developmentally, risk preference is expected to interact with strategic reasoning rather than acting independently. Computational modelling of risk-taking with agent-based simulations shows that an inverted-U pattern can emerge without adolescent sensation-seeking, simply from the increased availability of options during adolescence and the adaptive value of exploration for long-term learning (Ciranka & van den Bos, 2021). Risk contagion from peers is stronger among male adolescents than adults and is associated with social motives and deliberate consideration rather than impulsivity, suggesting that social context modulates the expression of risk tolerance in ways that pure utility models do not capture (Reiter et al., 2019). Adolescents with greater risk preferences may be more willing to attempt cooperative coordination or to deviate from safe strategies in competition, regardless of their level of recursive reasoning. In the present thesis modelling framework, risk preference is estimated as a parameter of the utility function applied to payoff outcomes, separately from decision consistency, allowing developmental changes in risk preference to be disentangled from changes in decision consistency. The following section outlines the specific aims and hypotheses that have guided the thesis.

2. 5. Research aims and hypotheses

Previous work from our laboratory demonstrated distinct developmental trajectories in cooperative and competitive tacit coordination, with cooperation increasing across adolescence and competition characterised by increasing switching behaviour and longer response times (Kurtisi et al., in prep.). However, behavioural observations alone cannot determine which latent algorithms give rise to these developmental patterns. Similar behaviours may emerge from different underlying mechanisms, including recursive reasoning, decision consistency, beliefs about others' behaviour, and risk preferences.

The primary aim of the present thesis was therefore to provide a computational characterisation of developmental changes in strategic decision-making across cooperation and competition. Specifically, this study employed computational modelling to decompose behaviour in cooperation and competition into latent parameters reflecting recursive reasoning levels (k), decision consistency (β), beliefs about others' choices (*k0 bias*), and risk preferences (ρ). A second aim was to investigate whether these computational parameters exhibit change with age. Given previous evidence linking strategic decision-making to social cognition and executive functions, age-related changes were expected in several latent parameters. A third aim was to examine the associations of the computational parameters by relating them to behavioural measures, non-verbal reasoning abilities, and social integration. Specifically, non-verbal reasoning was assessed using the MaRs-IB (Zorowitz et al., 2023), and social integration was assessed via sociometric networks. These aims sought to bridge developmental psychology, behavioural economics, sociometrics, and computational modelling to provide a more mechanistic account of how individuals navigate cooperative and competitive social environments across development.

Based on previous behavioural findings and theoretical accounts of strategic social decision-making, several behavioural and computational hypotheses were formulated.

A) <u>Behavioural hypotheses</u>

H1: Age-trends in cooperation and competition during adolescence: extending previous findings to a larger sample (Kurtisi et al., in prep.), cooperation was expected to increase with age, as reflected in predictions of higher rates of risky choices and greater payoffs compared to competition and lottery. In contrast, switching and response times in competition were expected to increase with age during adolescence compared to cooperation and lottery.

B) Computational hypotheses

H2: Development of recursive reasoning: Recursive reasoning level (k) was expected to be positively associated with age, reflecting developmental improvements in strategic thinking and mentalising abilities, and to be positively associated with switching behaviour in competition but not cooperation.

H3: Development of decision consistency: Decision consistency (β) was expected to be positively associated with age, reflecting increasingly consistent decision-making.

H4: Development of cooperative expectations: Beliefs about others' choices (*k0 bias*) were expected to be positively associated with age, leading to greater cooperation and, in turn, with the probability of risk-taking in the cooperation condition.

H5: Development of risk preferences: Risk preference (ρ) was expected to be negatively associated with age, although the effect was anticipated to be weaker than that for recursive reasoning and beliefs about others.

H6: Associations with non-verbal reasoning and social integration: Recursive reasoning level (k) and decision consistency (β) were expected to be positively associated with non-verbal reasoning abilities, while associations between computational parameters and the most-liked (ML) and least-liked (LL) peer network centrality measures were examined on an exploratory basis.

These hypotheses were tested using the methods and computational models described in the following chapter.

Chapter 3 – Method

3. 1. Participants

The sample consisted of N = 827 participants (526 females, and 295 males), including 209 children aged 9 to 12 (of which 44% were females and 56% were males), 332 adolescents aged 13 to 19 (of which 65% were females and 34% were males), and 285 adults aged 20 to 48 (of which 76% were females and 22% were males), and one participant who did not indicate age. Gender data were missing for 6 participants (1 adolescent, 4 adults, and 1 participant who did not indicate age). All participants were native Italians. The developmental part of the sample was recruited through the official school principal's office, while adults were recruited through university announcements and included psychology students. All sessions took place in school or university classrooms, with 2 to 4 experimenters, and informed consent was obtained before the experiment began. The University of Pavia's ethics committee approved the experiment (approval number 113/22), and all participants were treated in accordance with the Declaration of Helsinki. Demographic characteristics of participants are reported in Table 1.

	Children	**Adolescents**	**Adults**
N	209 (92F, 117M)	332 (217F, 114M, 1NS)	285 (217F, 64M, 4NS)
Age range	9–12	13–19	20–48
M (SD)	10.89 (.88)	16.20 (2.34)	22.35 (3.00)

Table 1. Demographic characteristics of participants across age groups.
Note: F – females, M – males, NS – not assigned.

3. 2. Design and procedure

The design, procedure, and data collection are an extension of previous lab research that uses the same methodology, and the additional data were collected afterward by the experimenters (Kurtisi et al., in prep.). I use these datasets in my thesis, extending behavioural analyses to computational modelling and analyses.

The design comprised three conditions, each with 15 trials. Each player played the cooperative and competitive coordination condition (respectively, a stag-hunt and an entry game) with an anonymous peer-paired player randomly matched (social environment), as well as the lottery condition (i.e., a non-social environment).

In the social environment, each trial involved one bag containing a variable number of gold coins, ranging from 1 to 15. Choosing this bag guaranteed this reward amount, making it the "safe payoff" option. The other bag, in contrast, always contained either 0 or 15 coins across all trials, making it a "risky payoff" option. In the cooperative condition, selecting the risky payoff yielded 15 gold coins only if the matched partner also chose it; otherwise, the payoff was 0. In contrast, in the competitive condition, the risky payoff granted 15 gold coins only if the matched partner did not pick the same option; if both participants chose the risky payoff, neither earned any coins (the task structure of the three conditions is illustrated in Figure 2, section 2. 3).

In the non-social lottery environment, if one chose the risky option, they obtained 15 gold coins only if a red ball was randomly drawn from a lottery with an unknown probability, and 0 otherwise. The chances of winning in the lottery condition were intentionally made ambiguous to reflect real social environments, where the likelihood that a social partner would choose either option was unknown. To illustrate this ambiguity to participants of various ages, they were shown four balls being placed into an opaque box, two blue and two red. After sealing and shaking the box to produce random movement, the experimenter secretly removed two balls without revealing their colours, then resealed the box. Participants knew that selecting the risky payoff option in the lottery meant winning 15 gold coins if a red ball was drawn and nothing if a blue ball was drawn. They also knew the box contained only two balls, but did not know the colours inside. If they chose the risky payoff option, they were unaware of the chances of winning. All environments were visually similar in terms of instructions and the coins likely to be obtained, and the player indicated their choice by clicking the preferred bag in each trial.

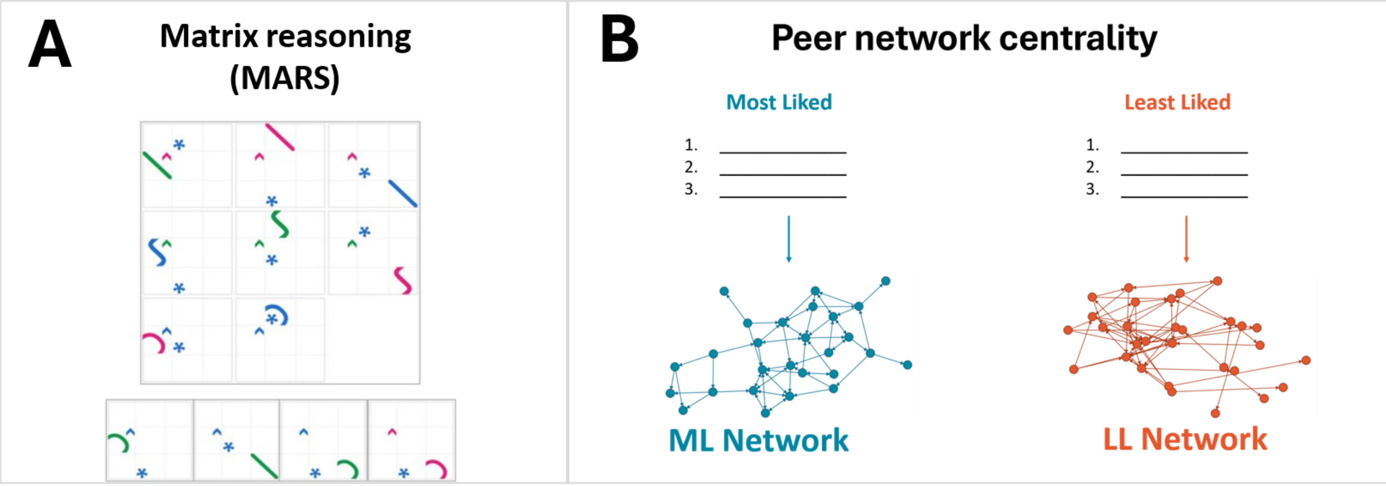

Figure 3. Additional measures. **(A) Example item from the Matrix Reasoning Item Bank (**MaRs-IB; Zorowitz et al., 2023). Participants selected the missing square to complete the pattern from four options. **(B) Peer nomination networks.** Each participant nominated classmates they liked most (Most-Liked, ML) and least (Least-Liked, LL). Reprinted with permission from Kurtisi et al., in prep.

All tasks were performed using electronic devices, primarily laptops, with a few PCs and tablets, and the procedure lasted from 30 to 40 minutes. The experimenters utilized Gorilla Experiment Builder (www.gorilla.sc; Anwyl-Irvine et al., 2020), and tasks were previously developed in the lab (Kurtisi et al., in prep.). After the instructions, participants completed a questionnaire to confirm their understanding of the rules before starting the task. They answered true/false and multiple-choice questions for general rules, cooperation, competition, and lottery trials. The general rules section contained 5 true/false questions related to instructions common to all three conditions. There were 10 multiple-choice questions about the coordination conditions (5 focused on cooperation and 5 on competition). The lottery also had 3 multiple-choice questions, like those for the coordination conditions. During this process, participants were encouraged to ask the experimenters questions about play. To clarify any doubts, they received immediate feedback on each answer (a green tick for correct responses and a red cross for incorrect ones). They could not proceed or access the games until they correctly answered all questions.

Participants also completed the Matrix Reasoning Item Bank (MaRs-IB; Zorowitz et al., 2023), a computer-based matrix reasoning task designed to measure fluid/non-verbal reasoning abilities. This open-access, non-verbal abstract reasoning test involves incomplete matrices (Figure 3, panel A). Similar to Raven's Progressive Matrices, participants needed to identify relationships among matrices of varying complexity and select the correct missing square from four options across 16 trials. They received no feedback during the task and were instructed to complete each puzzle as quickly and accurately as possible. Each matrix had a 30-second time limit, and if participants hesitated, they were given a 5-second countdown before moving on to the next image. Recently validated in adults (Zorowitz et al., 2023), the MaRs-IB shows good reliability and convergent validity. Furthermore, this task has been used to confirm that non-verbal reasoning abilities tend to increase during adolescence (Chierchia et al., 2019), illustrating the MaRs-IB's sensitivity to age-related improvements in non-verbal reasoning.

Peer network measures were also collected via a peer nomination procedure. Each participant nominated classmates they liked most (Most-Liked, ML) and least (Least-Liked, LL), yielding two directed nomination networks (Figure 3, panel B).

3. 3. Behavioural measures and parameter estimates

3. 3. 1. Behavioural measures

Switching was constructed so that, for each game, trials were ordered by ascending safe payoff value. Each trial was coded as 1 if the participant changed their choice relative to the previous trial and 0 otherwise. Switching, therefore, indexed alternations between risky payoff and safe payoff choices across trials, also referred to as "trembling" in the literature (Chierchia et al., 2020a).

Response times (RTs) were measured in milliseconds and reflected the time required for a participant to make a choice.

Risky payoff choices were coded as 1 if participants selected the risky payoff, and 0 if they selected the safe payoff.

Payoff: In all conditions, the payoff following a safe payoff choice corresponded directly to safe payoff value, since it was always guaranteed when selected. In contrast, the payoff associated with a risky payoff choice depended on the condition. In the ambiguous lottery condition, the payoff assigned to risky choices was fixed at 7.5, corresponding to the expected value of a 50% probability of obtaining the maximum reward of 15 coins (i.e., $15 \cdot .50 = 7.5$). Although the actual probability of winning was unknown to participants, the task structure implied a second-order probability of .5. In the cooperation condition, the expected value of the risky payoff was computed by multiplying the maximum potential winning (15) by the average probability that other participants selected the risky option on the same trial. Importantly, the specific participant was excluded from the expected value calculation for the risky payoff. Thus, considering the total number of participants minus one each time, for example, if the average probability of choosing the risky payoff on the trial with safe payoff =

3 was .70 among all participants excluding that specific participant, the expected value of selecting the risky payoff for that participant in the trial was 15 · .70 = 10.5. In competition, the expected value of the risky payoff was computed as the inverse of the average probability that other participants selected the risky payoff on the same trial, reflecting the competitive payoff structure in which choosing the same option as others was disadvantageous. Thus, the expected value of risky payoff = 15 · (1 − mean probability of risky choices by all other participants on that trial).

Matrix reasoning (MARS): The MaRs-IB (Zorowitz et al., 2023) yielded a mean score (mean MARS) across 16 trials, which was used to examine associations between winning model parameters and individual differences in fluid reasoning abilities, to test whether age trends in certain variables are consistent also with non-verbal reasoning abilities.

Peer network centrality: Participants nominated classmates they liked most (ML) and least (LL), yielding two directed nomination networks that were used as proxy measures of social integration. The centrality measure computed for each network was harmonic. Harmonic centrality not only indicates the most accessible nodes (peers) but also the most influential and those who can reach others with the fewest hops (fastest spreaders), implying the participant's position and the positions of their peer friends/preferred ones in the network. These indices were used to examine associations between computational model parameters and individual differences in peer social connectedness.

3. 3. 2. Parameter estimates

Parameter	Description	Range	*Mdn*	*M*	*SD*
k	Reasoning level	0–5*	1.00	1.92	1.35
β	Decision consistency	.00–10.00	.91	1.93	2.68
k0 bias	Beliefs about others' choices	.00–1.00	.67	.67	.25
ρ	Risk preference (CRRA)	−2.00–10.00	.37	.51	1.57

Table 2. Descriptive statistics for winning model parameter estimates (N = 827). Ranges are parameter bounds defined during model fitting; *Mdn*, *M*, and *SD* are the distributions of individual-level estimates across participants. *k is a discrete integer parameter, β, *k0 bias*, and ρ are continuous. $\rho = 0$ indicates risk neutrality, $\rho > 0$ risk aversion, $\rho < 0$ risk seeking.

Reasoning level (k) is a discrete integer parameter representing the depth of strategic/recursive thinking, ranging from 0 to 5.

Decision consistency (β) is a continuous parameter bounded between 0 and 10, capturing consistency in the participant's own final choice via the softmax rule. Candidate models differed in β, following a softmax or an argmax rule (see Candidate models, section 3. 4. 2.), and model comparison favoured the argmax specification: lower-level agents were better characterised as reasoning without noise, and β is therefore restricted to the subject's final action selection.

Beliefs about others' choices (k0 bias) is a continuous parameter bounded between 0 and 1, reflecting the participant's assumed probability that their partner would choose the risky payoff.

Risk preference (ρ) is a continuous parameter estimated using the CRRA utility function, bounded between −2.00 and 10.00, where $\rho = 0$ indicates risk neutrality, $\rho > 0$ risk aversion, and $\rho < 0$ risk seeking.

Descriptive statistics for all four parameters are reported in Table 2, while histograms of the parameter distributions are presented in the Appendices, Figure 13.

3. 4. Statistical and computational analyses

Previous research from the lab was conducted on a smaller sample ($N = 596$; Kurtisi et al., in prep.); here, we included a larger number of participants across all ages in all analyses ($N = 827$), enabling a more robust examination of age-related changes in behaviour and computational model parameters. Statistical analyses, theoretical model simulations, computational model fitting, and model validation were conducted using R and MATLAB.

3. 4. 1. Statistical analyses of behavioural measures

Behavioural differences across the three conditions (cooperation, competition, lottery) were examined using one-way repeated-measures ANOVAs for each of four aggregate behavioural measures: switching behaviour, RTs, probability of choosing the risky payoff, and payoff. Mauchly's test was used to assess violations of sphericity, and Greenhouse-Geisser-corrected degrees of freedom and p-values were reported where appropriate. Significant effects were followed up with pairwise paired-samples t-tests (Holm-corrected across the three condition pairs), together with Cohen's d effect sizes with 95% confidence intervals. Age-related trajectories were examined in the developmental subsample (age ≤ 28 years) using polynomial regression models. Age × Condition (cooperation, competition, lottery) interactions were tested by comparing cubic models with and without the interaction terms to examine whether developmental trajectories differed across the three environments. Where the interaction was significant, pairwise contrasts of agre-related slopes between condition pairs were computed at representative ages across the developmental range (10, 15, 20, and 25 years) using estimated marginal trends, Holm-corrected across the three pairwise comparisons at each age. Locally Estimated Scatterplot Smoothing (i.e., LOESS) with 95% confidence intervals was used for visualisation only; all inferential statistics are based on the polynomial regression models described above. These analyses were conducted in R.

3. 4. 2. Model simulations, fitting, and validation

Theoretical model simulations

Theoretical simulations were conducted in R to evaluate whether the proposed computational models generated behaviour consistent with the structure of the experimental tasks and to establish the behavioural signatures associated with different parameter values. Simulations were conducted separately for the lottery condition and for the two coordination conditions.

Lottery model simulations: The first model simulated the behaviour in a binary lottery task, with safe payoffs ranging from 1 to 15 across trials and a risky payoff of either 0 or 15. Although the lottery condition involved ambiguous probabilities in the actual task, simulations were conducted assuming fixed probability p = .5, which corresponds to the second-order probability given the box's design (i.e., two remaining balls, each equally likely to be red or blue). Risk preferences were modelled using a power utility function: $U(x) = x^{\alpha}$, where α is the risk-preference exponent and x is the outcome value. The 3 risk-preference profiles simulated are risk aversion, risk neutrality, and risk tolerance. Note that theoretical simulations employed the power utility parameter α because it provides an intuitive representation of risk preferences and facilitates visualisation of risk-averse, neutral, and risk-tolerant profiles. Later model fitting compared the power utility α and CRRA utility ρ specifications. Because the CRRA provided superior model fit, the final candidate model operationalised risk preference using the CRRA parameter ρ.

Rather than selecting equidistant values of α around neutrality, which produced asymmetric deviations in utility space, risk preference values were chosen to be symmetric with respect to their certainty equivalents[2] (CE). The CE is the guaranteed payoff that yields the same expected utility[3] as the risky payoff option, formally $CE(\alpha) = [p \cdot win^{\alpha}]^{1/\alpha}$. For risk neutrality $(\alpha = 1)$, $CE(1) = p \cdot win = 7.5$, since with p = .5 and a maximum win of 15 coins is $CE(1) = .5 \cdot 15 = 7.5$. A risk-averse value of α = .7 was selected, yielding $\delta = CE(1) -$

[2] Certainty equivalent is defined as the guaranteed payoff value at which a participant would be indifferent between selecting the safe and risky payoff options.

[3] Utility is the subjective value assigned to an outcome. Expected utility is the value of an option with uncertain outcome computed by weighting the utility of each possible outcome by its probability of occurrence, and then summing across outcomes, that is, $EU = \Sigma\, p(x) \cdot U(x)$.

$CE(.7) = 7.50 - 5.57 = 1.93$, a fixed deviation of $\delta = 1.93$ below neutrality. The risk-tolerant α was then determined numerically as the value greater than 1 satisfying $CE(\alpha) = CE(1) + \delta = 7.50 + 1.93 = 9.43$, using a root-finding procedure (yielding $\alpha = 1.49$), ensuring the three simulated risk profiles are equidistant from risk neutrality in CE terms (CE = 5.57, 7.50, 9.43).

The expected utility of the risky payoff was computed as $EU(risky\ payoff) = p \cdot U(win, \alpha)$, and the utility of each safe payoff as $U(safe\ payoff, \alpha) = safe\ payoff^{\alpha}$. Choices were simulated using a softmax decision rule, $p(risky\ payoff) = \frac{1}{1+exp\left(-\beta\left(EU_{risky\ payoff} - U_{safe\ payoff}\right)\right)}$, where β is the decision consistency parameter (often referred to as inverse temperature in the literature). Smaller β values introduce greater noise – choice variability, while larger values approach deterministic utility maximisation. A full parameter grid crossing all 3 α levels with 5 β values (.1, .5, 1, 5, 10) was constructed. Each parameter combination was assigned a unique simulated agent. For each agent, 50 simulations were run across all 15 safe payoffs, and choices were sampled from a Bernoulli distribution with probability *p(risky payoff)*. Choice entropy was computed in natural logarithms (nats) as $H = -p \cdot ln(p) - (1-p) \cdot ln(1-p)$, with probabilities clipped to a small epsilon neighbourhood away from 0 and 1 to avoid numerical instability. This procedure yielded a simulated dataset of 15 · 50 · 15 = 11,250 observations across all parameter combinations.

Cooperation and competition model simulations: The second set of simulations extended the framework to the two social coordination conditions, cooperation and competition. As in the lottery simulations, safe payoffs ranged from 1 to 15 across trials, whereas the risky payoff yielded either 0 or 15. To model how agents strategically reason about their opponents, a level k framework was adopted. In this framework, agents differ in their depth of strategic recursive reasoning: a level 0 agent ($k = 0$) does not model the opponent at all and instead selects the risky payoff according to a fixed prior probability, referred to as the *k0 bias*. A level 1 agent ($k = 1$) best responds to a level 0 opponent. Higher-level agents ($k = 2$, 3) form beliefs over the distribution of lower-level opponents. These beliefs were modelled using a Poisson distribution with mean $\tau = 1.2575$, selected based on prior findings (e.g., Camerer et al., 2004). The resulting Poisson-weighted mixture determined each agent's belief regarding the probability that the opponent would select the risky payoff, denoted *p(other risky payoff)*.

The same power utility function and softmax decision rule used in the lottery simulations were applied. In the cooperation, the expected utility of the risky payoff was computed as: $EU(risky\ payoff) = U(win, \alpha) \cdot p(other\ risky\ payoff)$, reflecting the cooperative payoff matrix in which the risky reward is obtained only if the opponent also selects the risky payoff. In competition, the expected utility was $EU(risky\,payoff) = U(win, \alpha) \cdot (1 - p\ (other\ risky\ payoff))$, reflecting the rule that the risky reward is obtained only if the opponent chooses differently. The utility of the safe option remained $U(safepayoff, \alpha) = safepayoff^{\alpha}$. Choices were generated using the same softmax decision rule and β values as in the lottery model. The *k0 bias* was varied across 3 levels (.3, .5, .7), representing pessimistic, neutral, and optimistic beliefs, respectively, about the opponent's propensity to choose the risky payoff. For each parameter combination, 50 simulations were run across all 15 safe payoffs, yielding 750 observations per combination. The full parameter grid comprised combinations of α (3 levels), β (5 levels), k (4 levels), game (2 levels), and *k0 bias* (3 levels), yielding 270,000 simulated observations. Choice entropy was computed using the same procedure as in the lottery simulations.

Computational model fitting

To characterise individual differences in reasoning levels, decision consistency, beliefs about others' choices, and risk preference, a series of computational modelling procedures was implemented. These analyses consisted of preliminary models fitting in R, followed by the estimation and comparison of candidate models, jointly fitted across 3 conditions, in MATLAB.

Preliminary lottery model fitting: Prior to the main modelling analyses, maximum likelihood estimation (MLE) was applied to participants' trial-level lottery choices to evaluate utility functions and inform the subsequent model-fitting procedure. Participants with missing age data or flagged response slopes were excluded prior to fitting. Two utilities were compared. The first was the power utility model: $U(x) = x^{\alpha}$, where α represents the risk-preference parameter. The second was the constant relative risk aversion (CRRA) utility model: $U(x) = \frac{x^{1-\rho}}{1-\rho}$ for $\rho \neq 1$ and $U(x) = ln(x)$ otherwise, where ρ represents risk preference. In both models, β was a second parameter, i.e., decision consistency. For each participant and utility model, the negative log-likelihood of the observed binary choice sequence was minimised using the Limited-memory Broyden-Fletcher-Goldfarb-Shanno (L-BFGS-B) algorithm with constraints. Parameter bounds were set to [.05, 5] for α, and [.05, 50] for β, initialised from 3 starting points to reduce sensitivity to local minima. Model comparison was conducted separately for each participant using the AIC and the BIC. To examine overall risk preferences in the sample, a one-sample Wilcoxon signed-rank test was used to test whether the median α differed significantly from 1 (risk neutral value). Associations between fitted parameters and age were assessed using Spearman's rank correlations in both the full sample and the developmental subsample (age ≤ 28 years).

Preliminary cooperation and competition model fitting: A second preliminary fitting procedure was applied jointly to participants' trial-level choices in the cooperation and competition. Here, the cognitive hierarchy model was fitted by estimating three continuous parameters: risk preference (α), decision consistency (β), and beliefs about others' choices (*k0 bias*) while selecting the discrete reasoning level (k = 0–3) through model comparison. Parameter estimation was performed using an L-BFGS-B optimisation with 10 random starting points for each reasoning level. Parameter bounds were set to [.05, 5] for α, [.01, 30] for β, and [.01, .99] for *k0 bias*. For each participant, the k value yielding the lowest negative log-likelihood was retained as the best-fitting solution. Model fitting was parallelised across central processing unit cores to reduce computation time. Participants with fewer than 10 trials or no response variability were excluded from fitting. Model fit was evaluated using AIC and BIC, assuming 3 continuous parameters, while k was treated as a model selection index. Associations between fitted parameters and age were examined using Spearman rank correlations within the developmental subsample (age ≤ 28 years).

Candidate models: 12 candidate models were specified. Models varied across 4 dimensions. First, the reasoning level was represented either as a discrete level k or a continuous Poisson mean parameter τ. Second, models differed in their decision consistency (β) rule, using either a softmax function or argmax. The use of argmax at intermediate reasoning levels meant that lower-level agents were assumed to reason without noise, whereas β captured only the consistency of the subject's own final choice via the softmax rule. Third, models either included or omitted a *k0 bias* parameter that represents prior beliefs about opponents' propensity to choose the risky option. Finally, models either included or omitted a CRRA risk preference parameter (ρ). Two additional models were included, each with a separate cooperative beliefs about others' choices parameter (*k0 bias coop*), using the same range of values as the general parameter *k0 bias*. Additionally, two further models included a lottery-specific decision consistency parameter (β *lottery*), using the same range of values as the general decision consistency parameter, thereby decoupling decision consistency in the non-social environment from that in the social environment. For parameter value bounds, see Method section 3. 3. 2. and for descriptive statistics of parameter estimates, see Results section 4. 4. All candidate models were fitted simultaneously to trial-level choices across conditions.

Parameter estimation: Parameter estimation was implemented using the MERLIN toolbox (Buergi, pre-release version). For each participant and candidate model, parameters were estimated using MLE by minimising the negative log-likelihood of the observed binary choices. Optimisation proceeded in two stages. First, a coarse grid search was conducted across the parameter space to identify promising regions. Second, parameter estimates were refined using Nelder-Mead simplex optimisation with 4 independent restarts from the best performing grid points. Parameters estimated in transformed space were subsequently converted back to their natural scales for interpretation. In models using discrete reasoning levels, k was treated as an integer parameter while the Poisson mean was fixed at $\tau = 1.5$. In cognitive hierarchy models with continuous τ, the Poisson mean was estimated, while the reasoning level was fixed at $k = 10$. It should be noted that the $\tau = 1.5$ fixed in the MATLAB models differs slightly from the $\tau = 1.2575$ used in the R simulations; the latter was selected based on prior empirical findings (Camerer et al., 2004) while the former was a rounded working value adopted for computational efficiency during parameter estimation.

Psychometric curve fitting: In addition, a separate psychometric curve-fitting procedure was subsequently implemented to estimate condition-specific β and *k0 bias* independently in each condition. In the primary analysis, β was constrained to positive values [0, 10]. A secondary analysis allowed β to vary between −10 and 10 in order to identify participants exhibiting inverted psychometric functions, that is, a systematic tendency to select options with lower expected utility. In both versions, *k0 bias* was constrained to [0, 1]. This disaggregated fitting procedure allowed examination of whether decision consistency and prior beliefs about opponent risk-taking varied systematically across task contexts.

<u>Model validation</u>

Model validation proceeded in two stages: model comparison to identify the model that best accounted for observed data, and parameter recovery to assess the identifiability of the winning model's parameters. Model validation is a necessary step prior to interpreting individual and developmental differences in fitted parameters, as inadequate model specification can introduce spurious differences in parameter estimates that do not reflect genuine variation in the underlying cognitive processes (Schaaf et al., 2025; Wilson & Collins, 2019).

Model selection: Model comparison was conducted using random effects Bayesian model selection (RFX-BMS) via the VBA toolbox (Daunizeau et al., 2014). RFX-BMS estimates both the expected model frequency and the protected exceedance probability (PXP), quantifying the likelihood that a model is more frequent than all other candidates, while accounting for chance differences. RFX-BMS is particularly appropriate for developmental samples because it accommodates genuine individual heterogeneity in the data-generating process, rather than assuming all participants are best described by the same model. AIC scores were additionally computed to account for differences in the number of parameters. For participants with an estimated $k > 1$, β was treated as undefined and set to missing, because level 0 agents respond probabilistically according to the *k0 bias* directly rather than through iterative utility-based reasoning. Similarly, the τ parameter only influenced behaviour from $k \geq 2$ onwards, when agents form beliefs over multiple lower-level reasoning types and Poisson weights determine the contribution of each lower-level strategy. The model achieving the highest expected model frequency and PXP was selected as the winning model and used in all subsequent analyses.

Parameter recovery: Analyses were conducted to assess whether the fitting procedure could reliably recover the generating parameter values from simulated data. Trial-level choices were generated across a broad range of the winning model parameter combinations, and the same fitting procedure used for behavioural data was then applied to the simulated datasets. Recovery performance was evaluated by correlating the generated and recovered values for each parameter of the winning model. Strong positive correlations indicate that the fitting procedure can distinguish between parameter values and recover them with reasonable accuracy, supporting the identifiability of the estimated parameters.

Posterior predictive checks (PPCs): To evaluate the extent to which the winning model reproduced the behavioural patterns observed in the empirical data, PPCs were conducted in the developmental subsample (age ≤ 28). Posterior parameter estimates obtained from the winning model were used to generate trial-level predictions for each participant across all task conditions. Observed and simulated choices were summarised at the participant level using three behavioural measures: the proportion of risky choices, the proportion of switching responses across ordered safe-payoff trials, and mean choice entropy. To examine developmental trajectories, observed and simulated behavioural indices were entered into generalised additive mixed models (GAMMs) implemented using the *gamm4* package in R (Wood & Scheipl, 2025). Separate smooth functions of age were estimated for each combination of task condition and data (observed vs. simulated), while participant identity was included as a random intercept. Binomial distributions were used for risky-choice and switching proportions, whereas entropy was modelled using a Gaussian distribution.

In addition, difference-score analyses (i.e., deltas) were computed by contrasting each social condition against the lottery condition as a baseline. These difference scores were analysed using the same GAMM framework to assess whether the model successfully captured developmental changes specific to social decision-making beyond those observed in the non-social lottery condition.

3. 4. 3. Associations with non-verbal reasoning and social integration

All subsequent analyses were conducted in R, using parameter estimates from the winning model to examine age-related trajectories and intercorrelations among parameters, as well as associations with behavioral measures, non-verbal reasoning abilities, and social integration. Models with psychometric curves (condition-specific estimation of β and *k0 bias*) were additionally examined for age-related trajectories and intercorrelations.

Age-related associations: Age-related associations with model parameters were examined in the developmental subsample (age $\leq$ 28 years). Posterior parameter estimates from the winning model, namely reasoning level (k), decision consistency (β), beliefs about others' choices (*k0 bias*), and risk preference (ρ), were extracted for each participant. Associations between parameter estimates and age were assessed using Spearman's rank correlation. To visualise age-related trajectories, LOESS with 95% confidence intervals was applied across the age range. In addition, mean parameter estimates and bootstrapped 95% confidence intervals (2,000 iterations; percentile method) were computed to help the interpretation of age-related trends and condition-specific differences.

Parameter estimates intercorrelations: Relationships among the winning model parameters were examined using Spearman rank correlations with pairwise correlation matrices. To examine the extent to which individual differences generalised across tasks, analyses were conducted using parameter estimates obtained from the psychometric curve-fitting procedure. Spearman rank correlations were computed between cooperation, competition, and lottery conditions for both decision consistency (β) and beliefs about others' choices (*k0 bias*). Correlations were calculated for all game pairs (cooperation–competition, cooperation–lottery, and competition–lottery). These analyses allowed assessment of whether participants who exhibited high levels of a given parameter in one context tended to show similar parameter values in other contexts.

Associations with behavioural measures: To examine the associations of the computational parameters, Spearman rank correlations were computed between winning model parameter estimates and observed behavioural measures. Behavioural measures included switching behaviour, RTs, probability of choosing the risky payoff, and mean payoff. Associations were examined separately for the cooperation and competition conditions to determine whether the same computational parameters predicted different behavioural outcomes across social environments. LOESS smoothing with 95% confidence intervals was used for visualisation.

Associations with MARS and peer network centrality: Spearman rank correlations were computed between MaRs-IB scores and each winning model parameter. These analyses were intended to evaluate whether computational parameters, particularly reasoning level k, were associated with individual differences in non-verbal reasoning abilities. Finally, associations between model parameters and social network position were examined in the subsample for whom peer nomination data were available. Two directed peer networks were constructed from ML and LL nominations and used as proxy measures of social integration. Harmonic centrality was selected as the primary network measure. Spearman rank correlations were computed separately for the ML and LL networks between harmonic centrality and each winning model parameter. To formally test whether parameter-centrality associations differed between networks, linear regression models were fitted with harmonic centrality as the dependent variable and network type, parameter estimates, and their interaction as predictors. These analyses allowed assessment of whether parameter estimates were associated with position among peers, and whether such associations differed between positive and negative peer nomination networks.

Chapter 4 – Results

4. 1. Behavioural results

Behavioural differences between the cooperation, competition, and lottery conditions were examined across four aggregate behavioural measures: probability of choosing risky payoff, payoff, switching behaviour[4], and response times (RTs)[5] of the full sample ($N = 827$). One-way repeated-measures ANOVAs were conducted for each behavioural measure. Mauchly's test indicated violations of sphericity in all cases (all *p*s < .001); therefore, Greenhouse-Geisser-corrected values are reported.

Probability of choosing the risky payoff differed significantly across conditions, $F(1.62, 1341.94) = 279.56$, $p < .001$, $\eta G^2 = .13$. Participants chose the risky payoff more frequently in cooperation ($M = .61$, $SD = .25$) than in competition ($M = .41$, $SD = .21$, $t(826) = 18.94$, $p < .001$, $d = .66$, 95% *CI* [.58, .73]) or the lottery ($M = .45$, $SD = .19$, $t(826) = 17.50$, $p < .001$, $d = .61$, 95% *CI* [.53, .68]). Choosing the risky payoff was also slightly lower in competition than in the lottery ($t(826) = −5.93$, $p < .001$, $d = −.21$, 95% *CI* [−.28, −.14]). Similarly, payoff differed significantly across conditions, $F(1.47, 1212.75) = 1081.27$, $p < .001$, $\eta G^2 = .35$. Participants achieved substantially higher payoffs in cooperation ($M = 10.41$, $SD = 1.57$) than in competition ($M = 8.59$, $SD = .66$, $t(826) = 36.46$, $p < .001$, $d = 1.27$, 95% *CI* [1.18, 1.36]) or the lottery ($M = 8.93$, $SD = .74$, $t(826) = 33.44$, $p < .001$, $d = 1.16$, 95% *CI* [1.07, 1.25]). Competition also yielded slightly lower payoffs than the lottery ($t(826) = −12.53$, $p < .001$, $d = −.43$, 95% *CI* [−.50, −.36]).

Switching behaviour differed significantly across conditions, $F(1.89, 1560.40) = 112.67$, $p < .001$, $\eta G^2 = .05$. Switching was higher in competition ($M = .31$, $SD = .19$) than in cooperation ($M = .20$, $SD = .18$, $t(826) = −13.51$, $p < .001$, $d = −.47$, 95% *CI* [−.54, −.40]) or the lottery ($M = .23$, $SD = .18$, $t(826) = 10.19$, $p < .001$, $d = .36$, 95% *CI* [.29, .43]). Also, in cooperation, participants showed slightly lower switching than in the lottery ($t(826) = −4.29$, $p < .001$, $d = −.15$, 95% *CI* [−.22, −.08]). RTs differed significantly across conditions, $F(1.92, 1589.73) = 99.28$, $p < .001$, $\eta G^2 = .05$. RTs were slower in competition ($M = 2773.61$, $SD = 1277.64$) than in cooperation ($M = 2272.60$, $SD = 999.48$, $t(826) = −11.68$, $p < .001$, $d = −.41$, 95% *CI* [−.48, −.34]) or the lottery ($M = 2257.35$, $SD = 903.51$, $t(826) = 11.55$, $p < .001$, $d =$

[4] Note that switching and entropy measure correlate strongly (Spearman ρ (rho) = .93, $p < .001$), as expected, confirming the same underlying construct of choice variability, and justifying the use of entropy as an analog in subsequent analyses.

[5] Measures are reported in a different order here than in Method, because comparisons lead with whichever condition shows the higher value: cooperation versus competition and lottery for choosing the risky payoff and payoff, but competition versus cooperation and lottery for switching and RTs.

.40, 95% *CI* [.33, .48]). Cooperation and the lottery did not differ significantly in RTs ($t(826) = 0.41$, $p = .68$, $d = .01$, 95% *CI* [−.05, .08]).

Importantly, adding Age × Condition interaction to cubic models containing main effects of age and condition significantly improved model fit for all four behavioural measures, indicating that age-related trajectories differed across conditions: probability of choosing the risky payoff, $F(6, 2448) = 16.76$, $p < .001$; payoff, $F(6, 2448) = 56.79$, $p < .001$; switching, $F(6, 2448) = 9.07$, $p < .001$; and RTs, $F(6, 2448) = 13.25$, $p < .001$. The resulting full interaction models explained substantial proportions of variance in each measure (probability of choosing the risky payoff $R^2 = .17$; payoff $R^2 = .57$; switching $R^2 = .18$; RTs $R^2 = .11$).

To characterise these interactions further, pairwise contrasts of age-related slopes were computed at a representative developmental range (10, 15, 20, and 25 years). These contrasts confirmed that cooperation differed primarily from the other two conditions for risky choice and payoff, whereas competition differed primarily for switching and response times. The reported results further below correspond to age 15 and provide a representative illustration. Cooperation's age trend differed significantly from both competition ($t(2448) = 8.72$, $p < .0001$ for choosing the risky payoff; $t(2448) = 14.41$, $p < .0001$ for payoff) and the lottery ($t(2448) = 6.23$, $p < .0001$ for choosing the risky payoff; $t(2448) = 13.13$, $p < .0001$ for payoff), while competition and the lottery did not differ from one another (choosing the risky payoff: $t(2448) = -2.49$, $p = .013$; payoff: $t(2448) = -1.28$, $p = .20$). Thus, probability of choosing the risky payoff and payoff increased substantially with age specifically in cooperation, while competition and the lottery followed comparatively flat, similar trajectories. For switching and RTs, the pattern reversed. For switching, competition's age trend differed significantly from both cooperation ($t(2448) = -4.82$, $p < .0001$) and the lottery ($t(2448) = 4.31$, $p < .0001$), while cooperation and the lottery did not differ from one another ($t(2448) = -.51$, $p = .61$). Competition showed comparatively elevated switching throughout development, while both cooperation and the lottery showed declining switching. RTs showed the same structure (competition–cooperation: $t(2448) = -3.91$, $p < .001$; competition–lottery: $t(2448) = 5.43$, $p < .0001$; cooperation–lottery: $t(2448) = 1.52$, $p = .13$), with RTs showing a stronger age-related increase in competition than in cooperation or lottery.

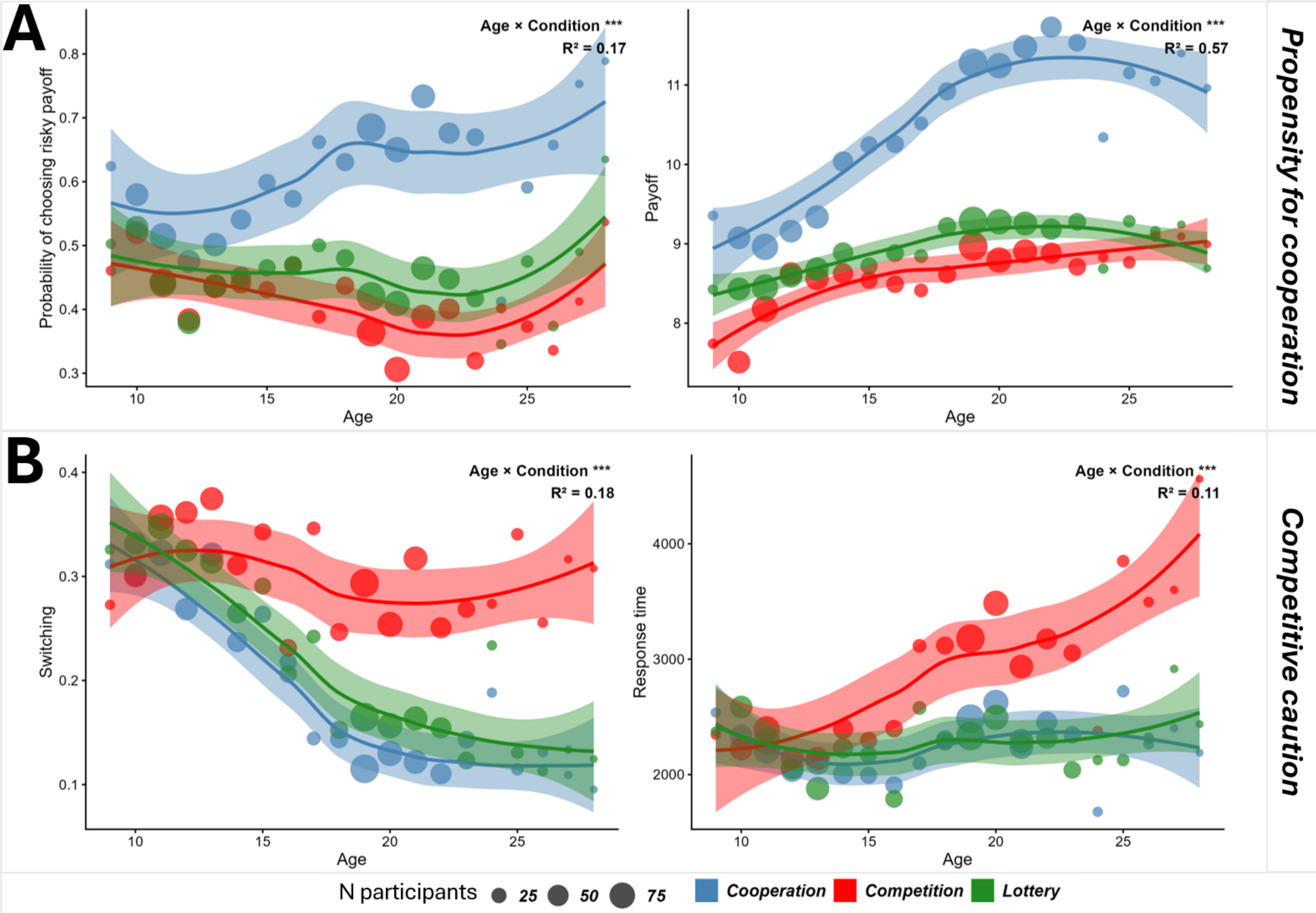

Figure 4. Age-related trajectories of behavioural measures in cooperation, competition, and lottery, age ≤ 28. Each panel shows age-related trajectories for cooperation (blue), competition (red), and the lottery (green), fitted with LOESS and 95% confidence intervals. Point size reflects the number of participants at each age. LOESS curves are shown for visualisation purposes; inferential statistics are based on interactive cubic regression models. **(A) Propensity for cooperation**. **Left:** probability of choosing the risky payoff increased more strongly with age in cooperation than in competition or lottery (cubic model, $R^2 = .17$). **Right:** mean payoff increased substantially with age in cooperation, whereas competition and lottery followed comparatively flatter trajectories (cubic model, $R^2 = .57$). **(B) Competitive caution. Left:** switching probability declined with age in cooperation and lottery, whereas competition maintained comparatively elevated switching across age (cubic model, $R^2 = .18$). **Right:** response time showed a stronger age-related increase in competition than in cooperation or lottery (cubic model, $R^2 = .11$). Note: ***$p < .001$, **$p < .01$, *$p < .05$, ns: $p > .05$.

Overall, the lottery condition served as an informative baseline, confirming that the age-related divergence between cooperation and competition reflects genuine, condition-specific developmental signatures. Age-related increases in risky choice and payoff were stronger in cooperation compared to the two other conditions – propensity for cooperation signature; while competition was characterised by elevated switching and slower RTs compared to the two other conditions – competitive caution signature. Initial behavioural analyses provided preliminary confirmation for further computational analyses: theoretical model simulations, model comparison and selection, model fitting procedures, and parameter estimates and their correlations with behavioural data.

4. 2. Model simulations

Simulation results for the lottery are reported in the Appendices, together with accompanying figures, as this analysis served primarily to validate baseline model behaviour prior to the main cooperation and competition simulations described below.

Cooperation and competition model simulations

First, at the trial-level, reasoning levels above $k = 1$ increased switching behaviour in the competition but not in the cooperation. This pattern held across all combinations of risk preferences (i.e., α) and beliefs about others' choices (i.e., *k0 bias*) (Figure 5; see Figure 11. in the Appendices for full trial-level plots across all combinations). Second, the *k0 bias* exerted opposite directional effects in the two games: a higher k0 bias linearly increased risk-taking in cooperation, consistent with the cooperative payoff structure, whereas its effect in competition was less systematic. This is because a higher *k0 bias* increases risk-taking among $k = 1$ agents but may reduce it among $k = 2$ and $k = 3$ agents, who anticipate that risk-taking can be disadvantageous in the competitive context. Third, α shifted the indifference thresholds across both games, with higher α moving the thresholds to the right, that is, to risk tolerance, and vice versa, lower α moving the thresholds to the left. Together, these simulations confirm that the level k model captures the structure of each strategic environment.

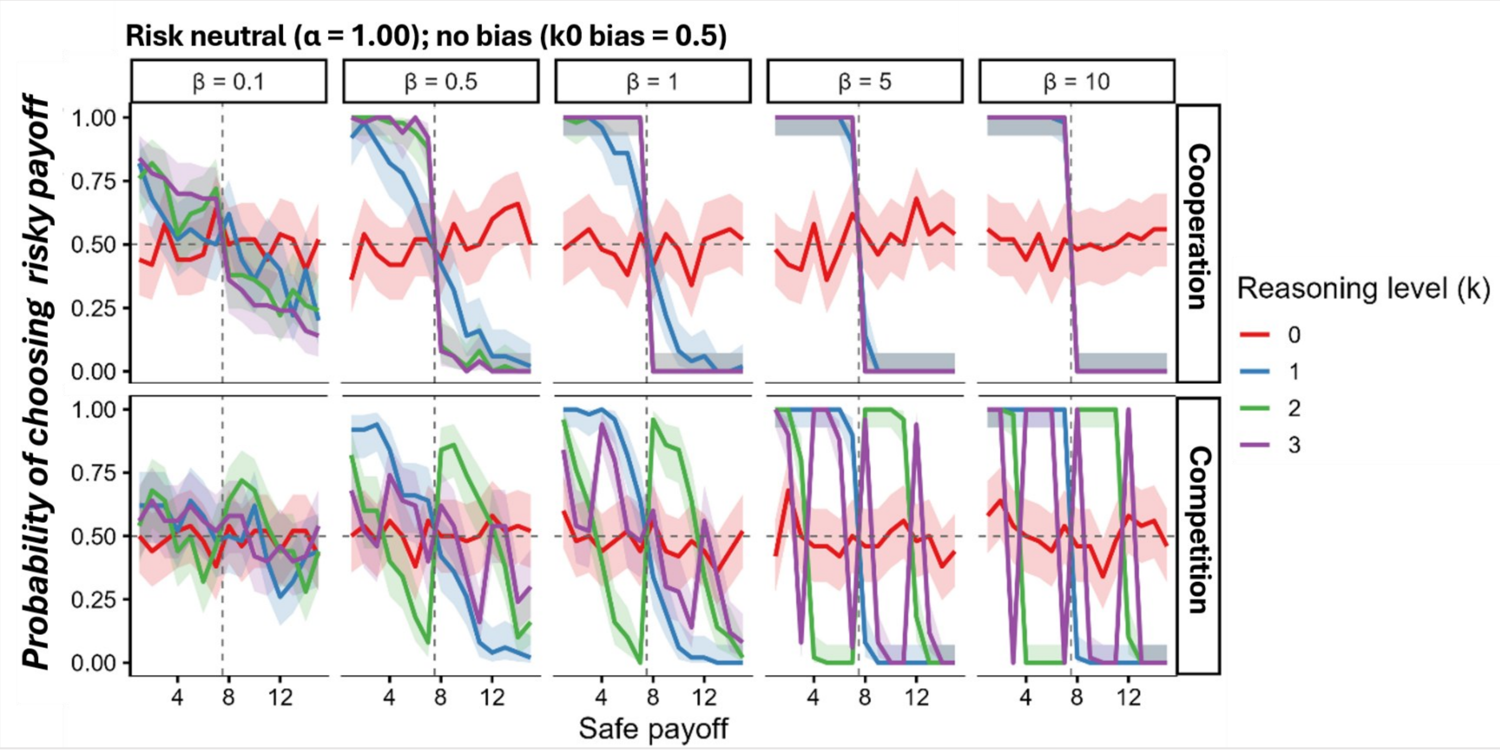

Figure 5. Probability of choosing the risky payoff as a function of reasoning level, decision consistency, and safe payoff, under risk neutrality and unbiased beliefs of others' choices. Simulated choice probabilities are shown for two tacit-coordination games: cooperation (**top**) and competition (**bottom**) across five levels of decision consistency (β = .1, .5, 1, 5, 10; columns) and four reasoning levels (k = 0–3; colours). The risky option yields a fixed payoff of 15 if the opponent does choose it (cooperation) or does not (competition). The dashed vertical line marks the indifference point (safe payoff = 7.5). Risk preference is fixed at α = 1.00 (risk-neutral), and *k0 bias* is fixed at .5 (unbiased beliefs about others' choices). Shaded regions represent variability across safe payoff values within each level.

The probability of choosing the risky payoff and the choice entropy were examined at the aggregate-game level. A particularly notable finding was choice entropy as a function of reasoning level. $k = 1$ reduced entropy in both games. However, from $k = 1$ onward, entropy diverged sharply between conditions: it continued to decline in cooperation but rebounded in competition for $k \geq 2$ (Figure 6). This asymmetry arises because higher-level reasoners in competition switch repeatedly between risky and safe options as they iteratively best-respond to their beliefs about lower-level opponents. This switching behaviour increases entropy[6], not because participants make less consistent choices, which is separately controlled by the beta parameters, but because of strategic reasoning. Crucially, if entropy is only related to decision consistency, it should be comparable between cooperation and competition. In contrast, uniquely high levels of entropy in competition compared to cooperation are most parsimoniously explained by recursive reasoning, since this is the only parameter that oppositely modulates entropy in the two conditions. Similarly, β reduced entropy in both games, confirming its role as a decision consistency parameter. Neither k nor β consistently

[6] Note that switching and entropy are highly correlated; the strong correlation between switch probability and entropy was replicated in simulated data (Spearman ρ = .94, p < .001), closely mirroring the pattern observed in real participant data (ρ = .93, p < .001), confirming that the two measures capture the same underlying dimension of choice variability.

modulated mean risk-taking averaged across all parameter combinations (see Figure 12. in the [Appendices](#) for k and β on choosing risky payoff).

Risk preference (α) increased overall risk-taking across games, while the effect of *k0 bias* (i.e., the belief that naïve others would choose the risky option, expressed in probability) was clear in cooperation, where it increased risk-taking, but was weaker and less consistent in competition (Figure 6), confirming the directional asymmetry observed at the trial level. α continued to show the inverse relationship with entropy previously observed for the lottery condition noted above. *k0 bias* had no meaningful effect on average entropy in either game (see Figure 12. in the Appendices for α and *k0 bias* on entropy).

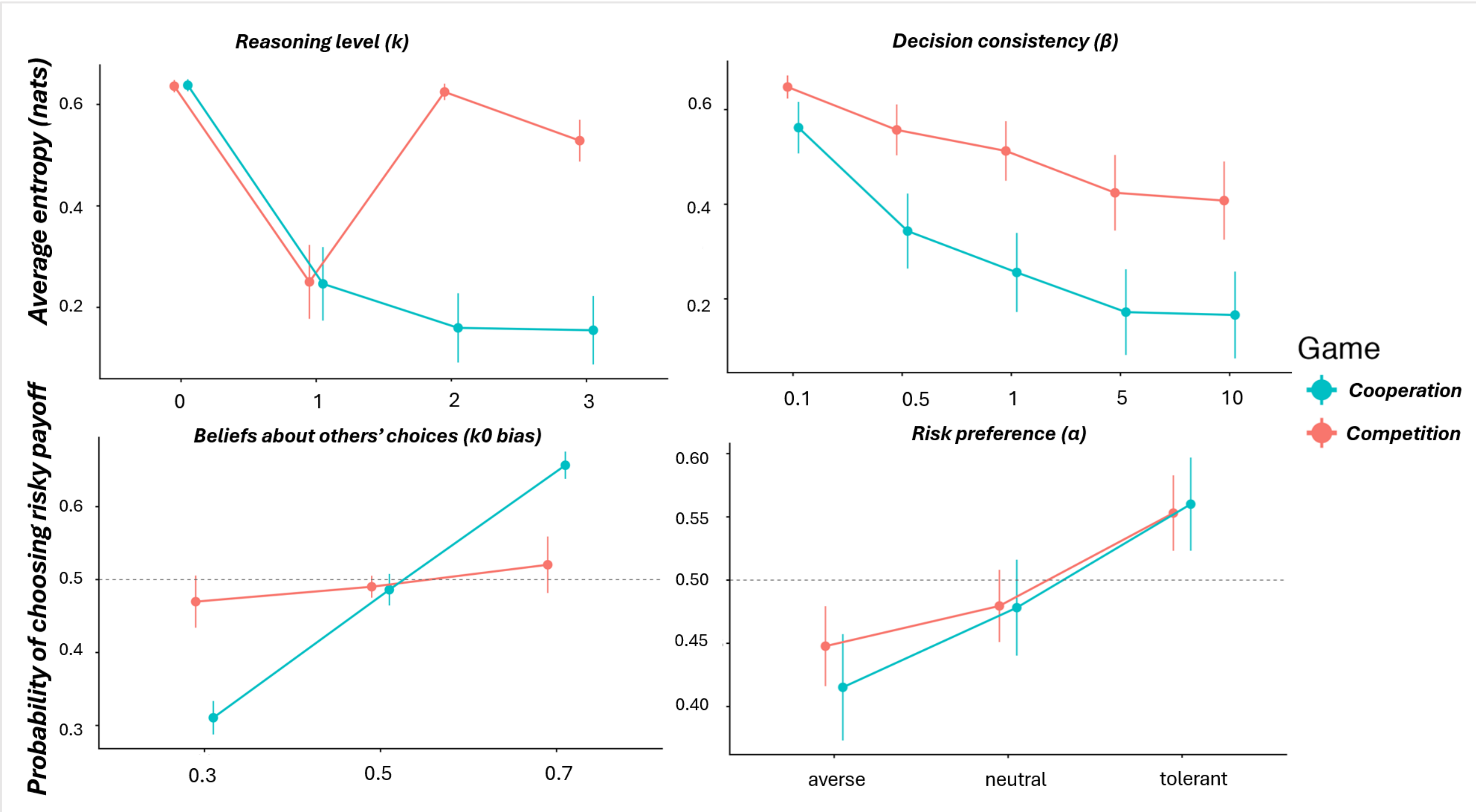

Figure 6. Social game simulations: predicted choice behaviour as a function of model parameters. Each panel shows game-level means with 95% confidence intervals averaged across all safe payoff values. **Top left:** average entropy (natural logs – nats) as a function of reasoning level (k = 0–3). **Top right:** average entropy as a function of decision consistency (β = .1, .5, 1, 5, 10). **Bottom left:** average probability of choosing the risky option as a function of *k0 bias* (.3, .5, .7), reflecting beliefs about others' choices. **Bottom right:** average probability of choosing the risky option as a function of risk preference (α; averse, neutral, tolerant).

4. 3. Model validity: model selection, posterior predictive checks, and model fitting

Model selection

Random effects Bayesian model selection (RFX-BMS) across the twelve candidate models identified TC_k_k0_bias_riskpref_CRRA_argmax as the winning model, achieving the highest posterior model frequency (approximately .22) and a PXP ≈ 1. This winning model combines a discrete integer reasoning level k; decision consistency, i.e., β, as the argmax choice rule; a belief about others' choices *k0 bias*; and risk preference (ρ) (operationalised a CRRA) utility function across cooperation, competition, and lottery. All subsequent analyses are based on this model, with additional analyses using a psychometric curve-fitting procedure that allowed for the distinction between β and *k0 bias* across conditions, rather than using the parameters across all conditions together as in the winning model (see below).

Parameter recovery analyses confirmed that the fitting procedure reliably recovered the generating parameters from simulated data. Correlations between true and recovered parameters were r = .67 for reasoning level k, r = .85 for decision consistency β, r = .83 for *k0 bias*, and r = .89 for risk preference ρ. Recovery was strong for decision consistency, *k0 bias*, and risk preference. Recovery for k was somewhat lower, with recovered values showing clustering around k = 1. Nonetheless, all four parameters showed recovery correlations in the moderate-to-strong range, supporting the validity of the estimation procedure.

Posterior predictive checks

Posterior predictive checks (PPCs) were conducted by comparing observed and model-simulated trial-level choices as a function of age across all three game conditions. GAMMs were fitted separately for each game condition and data source (observed vs. simulated), with separate smooth terms for age and a random intercept for participant. Difference-score analyses contrasting each social game against the lottery baseline were also conducted (i.e., delta levels; see Figure 15. in Appendices).

The model reproduced the observed age-related trajectory in risky choice proportions moderately well across all three conditions, with an overall Spearman ρ = .55 between observed and simulated age-related trajectories at the winning model level; this moderate correlation, as detailed below, reflects a stronger recovery of the cooperation trajectory relative to competition and the lottery.

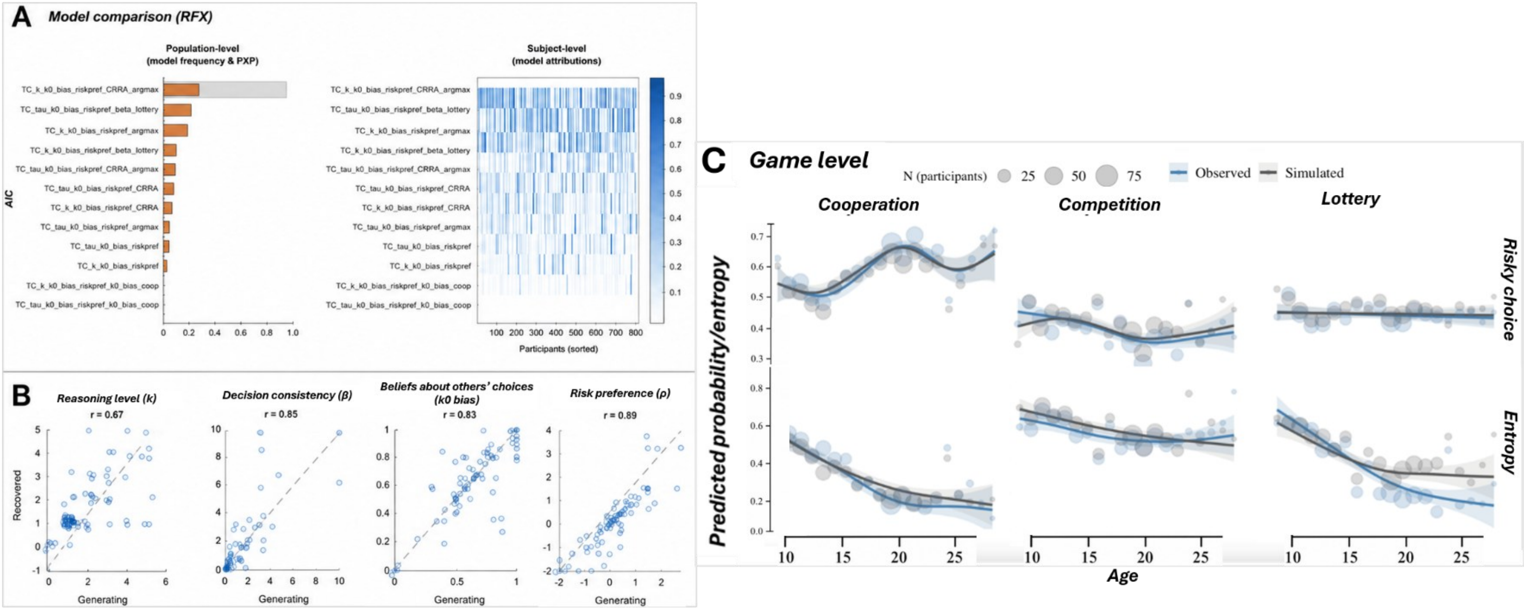

Figure 7. Model selection, parameter recovery, and model fit across age. **(A) Random effects Bayesian model selection (RFX-BMS). Left:** Population-level model frequency (orange bars) and protected exceedance probability (gray bars) across twelve candidate models, ordered by AIC. **Right:** Subject-level model attributions across participants (sorted by participant index), with colour intensity reflecting the posterior probability assigned to each model per individual. **(B) Parameter recovery.** Scatter plots of generating versus recovered parameter values for 4 parameters of the winning model. Recovery was moderate for *k*, and strong for *β*, *k0 bias*, and risk preference. **(C) Model fit across development.** Choices were summarised per participant as the proportion of risky choices, and mean choice entropy. Average predicted probability of choosing risky choice (i.e., payoff) (**top row**), and entropy (**bottom row**) as a function of age, shown separately for cooperation, competition, and lottery. Blue lines and shading represent observed data (LOESS smooth with 95% CI); black lines represent model simulations from the winning model. Point size reflects the number of participants at each age.

Entropy was less well recovered than risky choices, with the model tending to overestimate entropy, particularly for participants age 15 and above in the lottery condition. A disaggregated psychometric model allowing game-specific *β* estimation showed improved overall fit (*ρ* = .62), though this specification underestimated entropy at older ages instead (Appendices, Figure 14). Difference-score analyses contrasting each social game against the lottery baseline revealed a positive age trend in the cooperation–lottery contrast for risky choice, indicating increasing cooperation relative to the lottery baseline across age. The competition–lottery contrast was smaller and more variable in the observed data, with model simulations following this pattern. For entropy, the cooperation–lottery contrast remained close to zero across age, whereas the competition–lottery contrast increased with age in the observed data, though this increase was more underestimated by the simulated data at older ages (see Figure 15. in the Appendices).

4. 4. Parameter estimates and age associations

Prior to fitting the candidate model jointly across three conditions, preliminary per-game model fitting was conducted separately for the lottery (N = 748, after excluding participants with missing age data or flagged response slopes) and for cooperation and competition jointly (N = 827); these analyses served as sanity checks and are reported in full in the Appendices. Briefly here, a power utility specification α fit lottery choices marginally better than CRRA ρ at the individual level, though the subsequent joint model comparison across all three conditions favoured the CRRA ρ, which was retained in the winning model reported below. Additionally, preliminary parameter-age associations in cooperation and competition were broadly consistent with, though weaker than, those later obtained from the winning model reported below.

Parameter estimates from the winning model were extracted and examined across the full sample (N = 827). The distribution of estimated reasoning level k was concentrated at lower values (Mdn = 1, M = 1.92, SD = 1.35), with the majority of participants reasoning at $k = 1$ (N = 355, 43.0%), followed by $k = 2$ (N = 199, 24.1%), $k = 3$ (N = 80, 9.7%), $k = 4$ (N = 69, 8.3%), $k = 5$ (N = 63, 7.6%), and $k = 0$ (N = 61, 7.4%). These mean estimates are slightly higher than typically reported in adult samples (i.e., between 1.0 and 1.5; Camerer et al., 2004; Nagel et al., 2018). The decision consistency β had a median of .91 (M = 1.93, SD = 2.68, range: .00–10.00). The *k0 bias* had a median of .67 (M = .67, SD = .25, range: .00–1.00), suggesting that participants, on average, held optimistic prior beliefs about the opponent's propensity to choose the risky payoff. The CRRA risk preference parameter (ρ) had a median of .37 (M = .51, SD = 1.57, range: −2.00–10.00), indicating a general tendency toward risk aversion. Full parameter distributions are shown in the Appendices Figure 13.

Spearman rank correlations between winning model parameters and age were computed in the developmental subsample (age ≤ 28). All four parameters showed significant associations with age. Reasoning level k increased significantly with age (ρ = .19, p < .001), supporting the main hypothesis that strategic depth/recursive reasoning develops across childhood and adolescence. β also showed a positive association (ρ = .18, p < .001), consistent, again, with the known age-related increase in decision consistency and replicating the pattern observed in the preliminary fitting. *k0 bias* showed the strongest positive association among the four parameters (ρ = .20, p < .001), indicating that older participants held increasingly optimistic prior beliefs about opponents' propensity to take risks. This association is theoretically coherent: in the stag-hunt, higher *k0 bias* incentivises cooperative risk-taking, and the age-related increase in *k0 bias* maps onto the observed age-related increase in cooperation previously found in our lab (Kurtisi et al., in prep.) and corroborated here. Risk preference ρ showed a small but significant negative association with age ($\rho = -.13$, $p < .001$), indicating a slight decrease in risk aversion across age (see section 3. 3. 2. for parameter interpretation); this association is further discussed in section 5. 3.

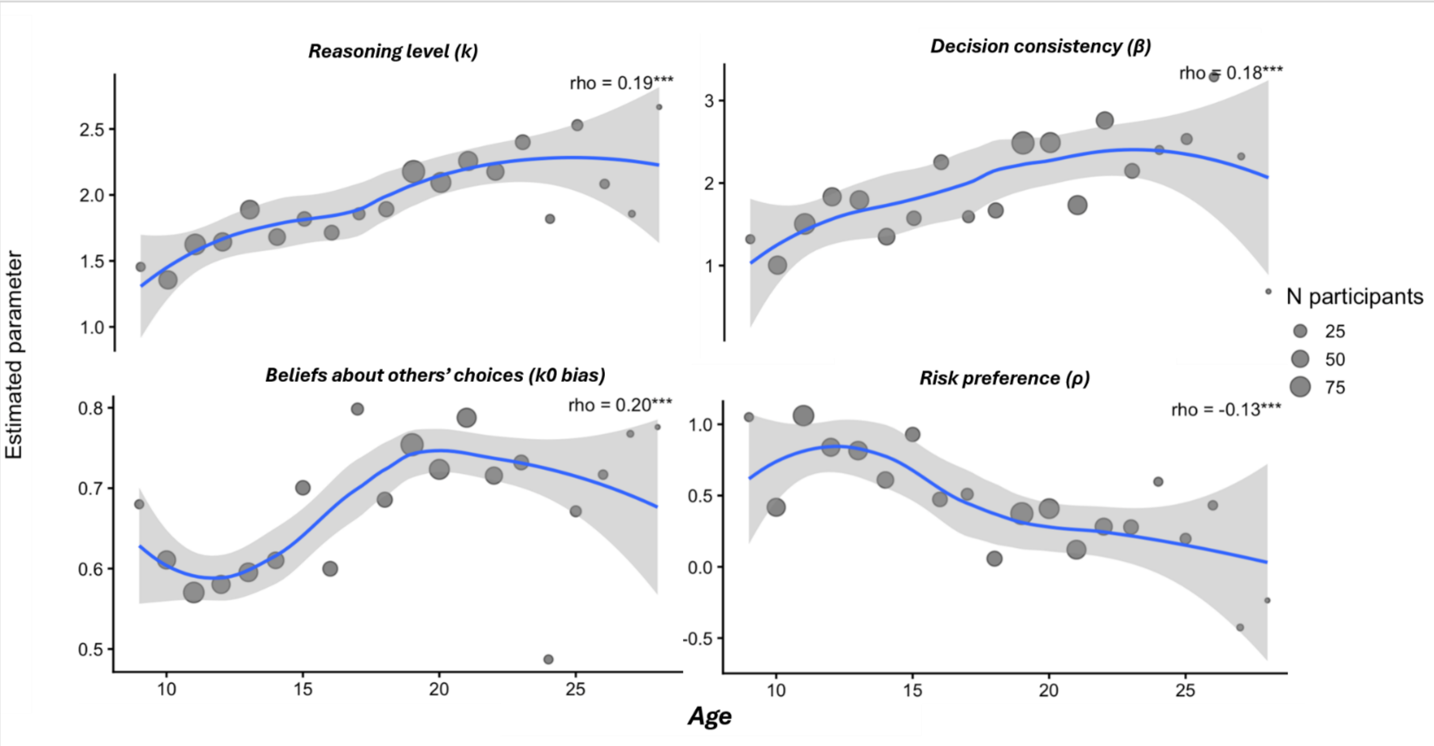

Figure 8. Age-related associations between winning model parameter estimates and age ≤ 28. Each panel shows the LOESS smooth (blue line) with 95% confidence interval (shaded region) fitted to participant-level parameter estimates as a function of age. Point size reflects the number of participants of each age. Spearman rank correlations (i.e., rho) with associated significance levels are displayed in each panel. Reasoning level k (**top left**) and decision consistency β (**top right**) showed a positive association with age. *k0 bias* (**bottom left**) showed positive associations with age. Risk preference ρ (**bottom right**) showed a small negative association with age. Note: ***$p < .001$, **$p < .01$, *$p < .05$, ns: $p > .05$.

Parameter intercorrelations were generally low (see Figure 16. in the Appendices). The strongest association was a moderate positive association between β and risk preference ρ: higher risk aversion was associated with a larger β. Descriptive statistics, intercorrelations, and age associations for the disaggregated psychometric models are also reported in the Appendices.

4. 5. Computational bases of cooperation and competition

To examine how winning model parameters related to observed behavioural data, Spearman rank correlations were computed between each winning model parameter and switching, RTs, probability of choosing the risky payoff, and mean payoff separately for the cooperation and competition in the full sample ($N = 827$).

Reasoning level k showed a significant positive association with switching in competition ($\rho = .40$, $p < .001$), but a small negative association with switching in cooperation ($\rho = -.08$, $p < .05$). The competition–cooperation dissociation is plausible: in the competition, higher-level reasoning players engage in choice alternation across the safe payoff range, producing more switching, whereas in the cooperation, higher-level thinking is not contributing any longer to choice, producing less switching. RTs increased with k in both competition ($\rho = .34$, $p < .001$) and cooperation ($\rho = .16$, $p < .001$) (Figure 9, panel A), consistent with the interpretation that strategic reasoning requires more time regardless of context. Associations with the probability of choosing the risky payoff were non-significant in both games ($\rho = .04$, $p = .25$ in competition; $\rho = -.02$, $p = .53$ in cooperation). Associations with payoff were non-significant in competition ($\rho = .02$, $p = .59$) but positive in cooperation ($\rho = .36$, $p < .001$) (see Appendices, Figure 17, panel A). Decision consistency β showed negative associations with switching in both competition ($\rho = -.19$, $p < .001$) and cooperation ($\rho = -.09$, $p < .01$), suggesting that participants with more consistent choices switched less frequently in general. RTs showed no significant association with β in competition ($\rho = .06$, $p = .07$), but a positive association in cooperation ($\rho = .16$, $p < .001$) (Figure 9, panel A), suggesting that players with more consistent choices were also slower to respond in that context. β showed negative associations with probability of choosing the risky payoff in both games ($\rho = -.47$, $p < .001$ in competition; $\rho = -.30$, $p < .001$ in cooperation), indicating that participants with more consistent choices chose the risky payoff less frequently on average. Associations with payoff were positive in both games, in competition ($\rho = .09$, $p < .01$) and in cooperation ($\rho = .27$, $p < .001$) (see Appendices, Figure 17, panel A), suggesting that higher choice consistency is associated with higher earnings, particularly in cooperation.

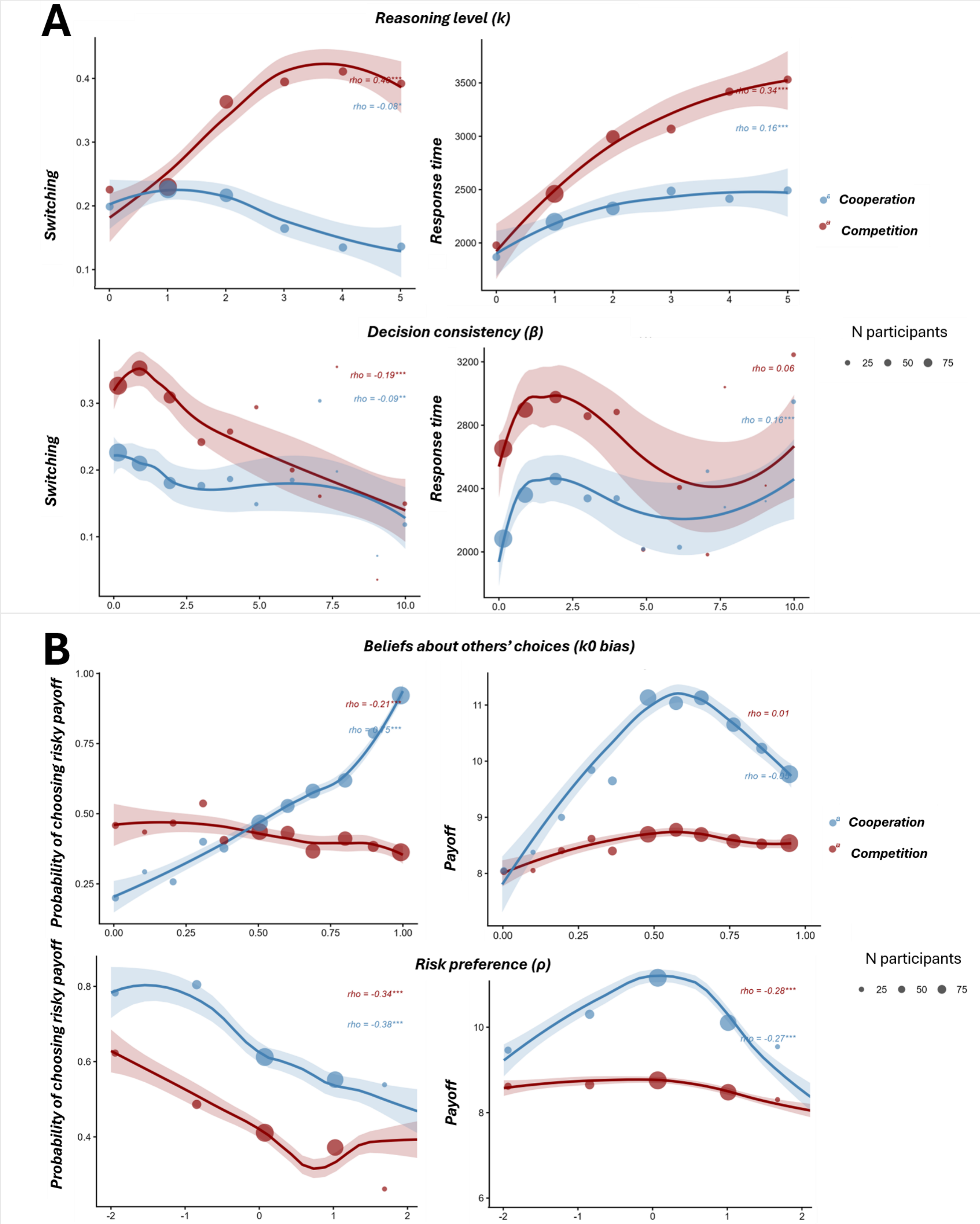
A
Reasoning level (k)
Switching
Response time
rho = -0.08*
rho = 0.16***
Cooperation
Competition
Decision consistency (β)
N participants
25
50
75
rho = -0.19***
rho = -0.09**
rho = 0.06
B
Beliefs about others' choices (k0 bias)
Probability of choosing risky payoff
Payoff
rho = 0.01
Risk preference (ρ)
rho = -0.34***
rho = -0.38***
rho = -0.28***

Figure 9. Associations between winning model parameter estimates and behavioural outcomes. Each panel shows LOESS with 95% confidence intervals fitted to participant-level data as a function of each model parameter. Point size reflects the number of participants at each parameter value. Spearman rank correlations (rho) with significance levels are displayed separately for each condition. **(A) Reasoning level (*k*) and decision consistency (*β*). Top left**: switching probability increased substantially with k in competition but showed a small negative association in cooperation. **Top right:** response time increased with k in both competition and cooperation. **Bottom left:** switching decreased with β in both competition and cooperation. **Bottom right:** response time showed no significant association with β in competition but a positive association in cooperation. **(B) Beliefs about others' choices (*k0 bias*) and risk preference (*ρ*). Top left:** the probability of choosing the risky payoff showed a strong positive association in cooperation and a moderate negative association in competition, with *k0 bias*. **Top right:** payoff showed no significant association in competition and a small negative association in cooperation with *k0 bias*. **Bottom left:** the probability of choosing the risky payoff showed a strong negative association with risk preference in both competition and cooperation; note that ρ with larger values, indicates increased risk aversion, suggesting that risky choices were more likely to be exhibited by less risk-averse participants. **Bottom right:** payoff showed negative associations with risk preference in both competition and cooperation, indicating that more risk-averse participants earned less across both games. Note: for visual clarity, the x-axis for risk preference is truncated to [−2, 2] in the panels, and Spearman rank correlations were computed over the full parameter range [−2, 10] as estimated by the winning model. ***$p < .001$, **$p < .01$, *$p < .05$, ns: $p > .05$.

Belief about others' choices (*k0 bias*) showed a strong positive association with probability of choosing the risky payoff in cooperation ($\rho = .75$, $p < .001$) and a moderate negative association in competition ($\rho = -.21$, $p < .001$), confirming the predictions from simulations: participants who believe opponents to risk frequently choose the risky payoff more in the cooperation (where this expectation incentivises cooperation) and less in the competition (where the same expectation incentivises deviation). Associations with payoff were not significant ($\rho = .01$, $p = .82$ in competition; $\rho = -.05$, $p = .16$ in cooperation) (Figure 9, panel B). Associations with switching were negative and significant only in cooperation ($\rho = -.29$, $p < .001$), suggesting that higher *k0 bias* is associated with more consistent choices in cooperation and thus less switching (non-significant in competition, $\rho = -.04$, $p = .21$). RTs showed a small positive association in competition ($\rho = .12$, $p < .001$) and a negative association in cooperation ($\rho = -.10$, $p < .01$) (see Appendices, Figure 17, panel B), suggesting that participants with stronger prior beliefs about opponents respond faster in cooperation but slower in competition. Risk preference (ρ) associations with probability of choosing the risky payoff were negative in both games ($\rho = -.34$, $p < .001$ in competition; $\rho = -.38$, $p < .001$ in cooperation), meaning higher risk-averse participants were less likely to choose the risky option and confirming that the CRRA risk preference parameter is meaningfully associated with overall risk-taking behaviour, as expected, and ρ captures a relatively domain-general risk dispositions. Associations with payoff were negative and significant in both games ($\rho = -.28$, $p < .001$ in competition; $\rho = -.27$, $p < .001$ in cooperation) (Figure 9, panel B), indicating that higher risk aversion was associated with lower earnings. ρ showed a small positive association only in cooperation with switching ($\rho = .14$, $p < .001$; $\rho = -.02$, $p = .52$ in competition). RTs showed a negative association in competition ($\rho = -.13$, $p < .001$) and a small positive association in cooperation ($\rho = .07$, p < .05) (see Appendices, Figure 17, panel B).

4. 6. Correlates of parameter estimates: non-verbal reasoning ability and social integration

Associations between winning model parameters and matrix reasoning scores (MaRs-IB; Zorowitz et al., 2023) were examined using Spearman rank correlations with LOESS (N = 755). Reasoning level k showed a small positive association with MARS ($\rho = .16$, $p < .001$), suggesting that participants with higher levels of strategic reasoning also showed higher non-verbal reasoning abilities. β was also positively associated with MARS ($\rho = .20$, $p < .001$), indicating that more consistent, deterministic players performed better on matrix reasoning. *k0 bias* similarly showed a small positive association ($\rho = .13$, $p < .001$). Risk preference (ρ) showed a small negative association with MARS ($\rho = -.13$, $p < .001$), indicating that more risk-averse participants scored slightly lower on the matrix reasoning measure (see Figure 18. in Appendices).

Associations between winning model parameters and peer network harmonic centrality were examined on an exploratory basis in the subsample with network data (ML: $N = 408$; LL: $N = 380$; age range: 9−20). Of the four parameters, only decision consistency β showed a significant positive association with ML harmonic centrality ($\rho = .18$, $p < .001$), suggesting that participants who make more consistent, deterministic choices tend to occupy more central positions in the most-liked network (see Figure 19, panel A in Appendices). No significant association was found between β and LL harmonic centrality ($\rho = -.03$, $p = .56$), and no other parameters showed significant associations with either network (all ps > .10).

To formally test whether associations with harmonic centrality differed between ML and LL networks, linear models were fitted with harmonic centrality as the outcome and network type, each parameter, and their interaction as predictors. The Network × β interaction was the only significant effect ($B = .012$, $p = .043$), indicating that the positive association between β and centrality was significantly stronger in the ML than in the LL network (see Figure 19, panel B in Appendices). No significant Network × Parameter interactions were found for k, *k0 bias*, or ρ (all ps > .10).

Chapter 5 – Discussion

The primary aim of the present thesis was to provide a computational characterisation of developmental changes in strategic social decision-making across age. Beyond this developmental focus, the present findings also provide, to my knowledge, the first demonstration that cooperation and competition rest on distinct computational mechanisms in the first place, independent of any developmental question. Previous work from our laboratory identified unique behavioural signatures in competitive coordination and speculated that these might arise from recursive reasoning (Kurtisi et al., in prep.); the present simulations and model-fitting results directly confirm this account, showing that elevated switching in competition is related to higher-level recursive reasoning rather than decision inconsistency. Building on the behavioural findings, I then examined how developmental changes in recursive reasoning, decision consistency, beliefs about others' choices, and risk preferences[7] contribute to observed developmental shifts in cooperative and competitive coordination in two tacit coordination games: the stag-hunt (cooperation) and the entry game (competition), henceforth referred to as cooperation and competition.

Several key findings emerged. First, behavioural analyses replicated and extended previous findings to a larger sample by demonstrating that cooperation, and competition follow distinct developmental trajectories. Across the sample, participants achieved higher payoffs and selected the risky option more frequently in cooperation than in either competition or the lottery: a signature named propensity for cooperation. Age-related increases in payoff and risky choice were also stronger in cooperation than in the competition or lottery, which followed comparatively flat trajectories. Conversely, competition was characterised by elevated switching behaviour and slower response times relative to both cooperation and the lottery: the competitive caution signature. Switching remained comparatively elevated, and response times became increasingly prolonged in competition across age, while cooperation and the lottery showed converging, declining trajectories on both measures.

Second, theoretical simulations demonstrated that these adolescent-developing behavioural signatures could emerge from different underlying mechanisms rather than a single common process. Higher beliefs about others' choices increased risk-taking specifically in cooperation, consistent with the cooperative payoff structure, providing a candidate mechanism

[7] Parameters are listed either in the order above or, where only three are listed, as recursive reasoning, decision consistency, and beliefs about others' choices. This ordering is used for consistency throughout the following chapters and is not intended to indicate relative effect magnitude, except where explicitly stated (e.g., via "respectively", "strongest", etc.).

for the propensity for cooperation signature identified above. On the other hand, higher reasoning levels generated significantly more switching behaviour in the competition but not in the cooperation, thereby accounting for the competitive caution signature. This latter finding is important because switching behaviour is often interpreted as decision inconsistency. The simulations instead suggested that elevated switching in competition may emerge from increasingly sophisticated recursive reasoning.

Third, random-effects Bayesian model selection identified a model incorporating recursive reasoning level (k), decision consistency (β), beliefs about others' choices (*k0 bias*), and risk preference (ρ) as the best account of behaviour. Parameter recovery analyses indicated that all four parameters were recovered with acceptable reliability, supporting the model's validity.

Fourth, all four winning model parameters showed significant associations with age. Recursive reasoning increased across development, supporting the hypothesis that strategic depth continues to mature throughout adolescence. Decision consistency also increased with age, consistent with developmental findings proposing a gradual reduction in decision-making inconsistency. Beliefs about others' choices showed the strongest positive age association, indicating that older participants increasingly expected others to choose the risky option. Risk aversion showed a modest decline with age, although this finding should be interpreted with caution, given inconsistencies with previous findings in the developmental risk-taking literature.

Finally, analyses demonstrated that model parameters were meaningfully associated with observed behaviour and broader individual differences. Recursive reasoning was strongly associated with switching behaviour in competition but not cooperation, whereas beliefs about others' choices showed opposite associations with choosing the risky option in cooperation and competition, as predicted by the simulations. Furthermore, recursive reasoning and decision consistency were positively associated with non-verbal reasoning abilities, while decision consistency was positively associated with centrality within the most-liked peer network.

All together, these findings suggest that developmental improvements in strategic social decision-making cannot be explained solely by increased risk-taking or reduced decision inconsistency. Instead, it appears to reflect developmental changes in recursive reasoning, the consistency with which strategic decisions are implemented, and social expectations/beliefs.

5. 1. Age trends in cooperative and competitive decision-making

A central finding of the present thesis is that cooperation and competition followed distinct developmental trajectories. Although two conditions shared a highly similar structure, involving repeated choices between a safe and a risky option under uncertainty, age-related changes differed substantially across contexts. Cooperation was characterised by increasing risky choices and increasing payoffs across age relative to both competition and lottery, whereas competition was characterised by elevated switching behaviour and increasing response times relative to both cooperation and lottery. These findings replicate and extend previous behavioural observations from our laboratory (Kurtisi et al., in prep.) and provide new insight into the likely cognitive mechanisms underlying developmental changes in strategic social decision-making.

At the behavioural level, participants achieved higher payoffs and selected the risky option more frequently in the cooperative than in either competition or the lottery. This finding is consistent with the strategic structure of the cooperation. In cooperative coordination, selecting the risky option can produce the highest possible outcome if both players coordinate successfully. Consequently, increasingly optimistic expectations about others' behaviour should promote cooperation and improve collective outcomes. The observed age-related increase in cooperative risk-taking, therefore, suggests that older participants became increasingly willing to rely on expectations that others would also cooperate. It is worth noting, however, that this willingness was not always optimal: the association between beliefs about others' choices (*k0 bias*) and payoff in cooperation followed an inverted-U pattern, indicating that some participants held more optimistic beliefs than the actual behaviour of their partners justified, resulting in sub-optimal outcomes. This finding indicates that there may be an optimal level of optimism, beyond which further increases in risk-taking no longer improve performance.

Notably, the developmental increase in cooperation was not accompanied by a corresponding increase in competitive risk-taking, which remained comparable to the lottery. Instead, competition was characterised by elevated switching behaviour and longer response times relative to both other conditions. This asymmetry is theoretically meaningful because the two social games differ in the strategic computations required for successful performance. In the cooperation, strategic complements create convergence toward threshold-like behaviour: once a player expects the other person to cooperate, choosing the risky option becomes increasingly attractive. In the competition, however, strategic substitutes generate a fundamentally different problem. Success depends not on matching the behaviour of others but on differentiating from it (Chierchia et al., 2020a; Krueger et al., 2016; Nagel et al., 2018). Consequently, reasoning about another person's likely behaviour becomes more computationally demanding because the optimal choice depends on anticipating how others may themselves be reasoning about the situation.

The computational simulations support this interpretation. Simulated agents with higher reasoning levels exhibited more switching behaviour in the competition but not in the cooperation. This switching emerged despite decision consistency remaining constant. In other words, elevated switching was generated by recursive reasoning itself rather than by reduced decision consistency. This distinction is crucial because switching behaviour is often interpreted as an index of decision inconsistency. The present findings suggest that, at least within competitive coordination, switching may instead reflect increasingly sophisticated strategic reasoning. As higher-level reasoners iteratively best respond to their beliefs about lower-level opponents, they alternate between risky and safe choices across the payoff range, generating more variable choice patterns despite behaving strategically.

This interpretation is reinforced by the observed age-related trajectories. Switching declined in both cooperation and the lottery but remained relatively elevated in competition. If switching merely reflected reduced decision consistency, one would expect it to decrease across contexts as participants matured, which is consistent with previous findings showing that decision consistency increases with age (Bolenz et al., 2019; Chierchia et al., 2023; Towner et al., 2023). Instead, competition alone maintained elevated switching across development, while response times simultaneously increased. Together, these findings suggest that older participants may have engaged in increasingly deliberative reasoning specifically within the competitive environment. Rather than becoming more random, they may have been considering a broader range of possible opponent responses before making a decision.

The response time findings further support this interpretation. Across age, response times remained relatively stable in cooperation and lottery but increased in competition. This pattern stands in notable contrast to the broader developmental literature on executive functioning, where age is typically associated with simultaneous improvements in both accuracy and speed (Tervo-Clemmens et al., 2023); the present findings show an exception to this trend, with the age-related increase in response times in competition unaccompanied by a corresponding decline in switching or an increase in payoff in this condition. If anything, older participants took longer to respond and appeared to struggle more than younger participants in this strategic environment. The pattern is consistent with the possibility that competitive coordination increasingly recruits higher-order strategic reasoning processes. Previous neuroimaging work has similarly suggested that competitive coordination imposes greater demands on belief formation and recursive reasoning than cooperative coordination, recruiting additional prefrontal regions associated with strategic thinking (Coricelli & Nagel, 2009; Hill et al., 2017; Nagel et al., 2018). The present behavioural findings move toward this interpretation by suggesting that competitive decisions become increasingly deliberative throughout adolescence.

These results also contribute to the broader developmental literature on cooperation and competition. Previous studies have shown that cooperation generally increases across childhood and adolescence, probably driven by improvements in perspective-taking and the ability to coordinate behaviour with others (Brocas & Carrillo, 2021; Czermak et al., 2010; Glätzle-Rützler et al., 2024; Liu et al., 2024; Westhoff et al., 2020). The present findings replicate this developmental increase in cooperation and further suggest that increasingly optimistic beliefs about others may play an important role. By contrast, comparatively little developmental work has examined competitive tacit coordination in one-shot, no-feedback settings; Brocas and Carrillo (2021) is a notable exception, though their design involved a repeated game with feedback. The current results indicate that competition does not simply represent the opposite of cooperation. Instead, it appears to engage distinct socio-cognitive processes that become increasingly prominent during adolescence.

One particularly interesting implication is that adolescence may involve not only becoming more cooperative but also becoming more strategically cautious in competitive environments. Previous work from our laboratory described this pattern as adolescent emergent competitive caution (Kurtisi et al., in prep.). The present computational results provide support for this interpretation. Rather than increasing risk-taking in competition, older participants increasingly exhibited behavioural patterns associated with deeper recursive reasoning. Much of the existing literature on the development of cooperation emphasises social preferences: motives such as fairness, reciprocity, or inequity aversion as the primary driver of cooperative behaviour (Sutter et al., 2018; Westhoff et al., 2020). The present findings suggest that social inference, in the form of beliefs about others' likely choices, may be sufficient to account for the observed patterns without invoking social preferences directly. This may be particularly true for competitive caution: to our knowledge, no existing social-preference account predicts heightened switching and response times selectively in competition but not cooperation, whereas a recursive-reasoning account does so directly. This is consistent with theoretical accounts proposing that adolescence is characterised by increasing sophistication in social cognition and reasoning about mental states rather than by simple increases in reward-seeking or risk-taking behaviour, or by changes in social preferences alone (Blakemore & Mills, 2014; Crone & Dahl, 2012; Nussenbaum & Hartley, 2019).

Taken together, the behavioural and computational findings suggest that cooperation and competition become increasingly differentiated across development. Cooperative coordination appears to be characterised by increasing willingness to rely on others and increasing confidence in successful coordination, albeit sub-optimal once beliefs become more optimistic than warranted. Competitive coordination, in contrast, appears to involve increasingly complex strategic reasoning about others' behaviour, without a corresponding change in decision consistency. These findings provide evidence that developmental changes in strategic social decision-making cannot be understood through a single dimension of risk-taking, decision consistency, cognitive maturity, or social preferences. Instead, different strategic environments recruit partially distinct socio-cognitive processes whose developmental trajectories diverge across adolescence.

5. 2. A computational approach to cooperative and competitive decision-making during adolescence

A major contribution of the present thesis is that it moves beyond behavioural descriptions and provides a computational account of developmental changes in strategic social decision-making. Whereas behavioural analyses, anchored against a non-social lottery, demonstrated that cooperation and competition follow distinct developmental trajectories, computational modelling allowed these changes to be decomposed into latent algorithms. The winning model identified four key parameters: recursive reasoning level (k), decision consistency (β), beliefs about others' choices (*k0 bias*), and risk preference (ρ). All four parameters showed significant associations with age, although the strongest and most theoretically coherent developmental effects emerged for beliefs about others, recursive reasoning, and decision consistency, respectively.

One of the central findings was that recursive reasoning increased across development. Reasoning level k showed a positive association with age and was strongly related to behavioural patterns predicted by the theoretical simulations. Participants with higher reasoning levels exhibited greater switching behaviour and longer response times in competition, and higher cooperative payoffs. These findings support the hypothesis that strategic reasoning continues to develop throughout adolescence (e.g., Westhoff et al., 2020) and are consistent with behavioural game theory accounts proposing that individuals differ in their depth of recursive thinking (Camerer et al., 2004; Nagel et al., 2018).

Importantly, the observed distribution of reasoning levels closely resembles findings from previous work. Most participants were classified at relatively low reasoning levels, with $k = 1$ being the most common estimate (Camerer et al., 2004; Nagel et al., 2018). This is broadly consistent with cognitive hierarchy models, which suggest that most individuals engage in only one or two levels of recursive reasoning rather than performing the infinitely recursive reasoning assumed by classical game theory (Camerer et al., 2004; Nagel, 1995). Although average reasoning levels in the present sample were slightly higher than typically reported in adult-only studies, this may reflect the broader developmental age range, the larger sample size, and the joint fitting of behaviour across two strategically distinct conditions.

The relationship between reasoning level and switching behaviour provides particularly strong support for the validity of the model. In competition, higher reasoning levels were associated with more switching, whereas in cooperation, the association was negative. This dissociation closely mirrors predictions generated by the simulations and reflects the fundamentally different strategic structures of the two conditions. In cooperative coordination, higher-level reasoners incline toward stable threshold strategies because reasoning supports coordination on mutually beneficial outcomes. In competitive coordination, however, higher-level reasoners continually adjust their behaviour in response to anticipated opponent strategies, producing greater switching. The fact that this theoretically predicted pattern emerged in the observed data strengthens confidence that the reasoning parameter captures genuine strategic processes rather than arbitrary statistical variations.

The strongest developmental effect was observed for beliefs about others' choices. The *k0 bias* parameter showed the strongest positive association with age among all winning-model parameters, suggesting that older participants increasingly expected their opponents to choose the risky option. This finding is particularly important because it provides a potential explanation for the age-related increase in cooperation observed behaviourally. In cooperation, optimistic beliefs about another player's willingness to cooperate directly increase the attractiveness of the risky option. Consequently, developmental increases in *k0 bias* naturally promote greater cooperative risk-taking and higher payoffs.

This interpretation is further supported by correlational analyses of the computational parameters and behavioural outcomes. Beliefs about others' choices showed a positive association with risky choices in cooperation and a negative association with risky choices in competition. This pattern closely matched the simulations' predictions and reflected the opposite strategic consequences of the same expectation across the two conditions (Chierchia & Coricelli, 2015; Chierchia et al., 2020a). If an individual expects their opponent to choose the risky option, cooperation becomes more attractive in the cooperative condition but less attractive in the competitive one. The fact that the same parameter generated opposite behavioural effects across contexts suggests that the model successfully captured meaningful social expectations/beliefs rather than a general tendency toward risk-taking.

Developmentally, increasing optimism about others' behaviour may reflect broader changes in social cognition during adolescence. Previous research suggests that adolescents become increasingly sensitive to social information, more capable of integrating others' perspectives, and more effective at using social knowledge to guide behaviour (Hofmans & van den Bos, 2022; Reiter et al., 2021). Within this framework, age-related increases in *k0 bias* may reflect developmental improvements in representing and predicting the behaviour of other people. Rather than becoming indiscriminately optimistic, older participants may become increasingly capable of forming stable expectations about others' likely choices in strategic environments.

Decision consistency also increased significantly across age. This finding replicates both the preliminary lottery analyses and a broader developmental literature demonstrating age-related reductions in decision-making inconsistency (Chierchia et al., 2023; Gopnik, 2020; Nussenbaum & Hartley, 2019; Xia et al., 2021). Participants with higher β values exhibited less switching behaviour, higher payoffs, and better performance on the matrix reasoning task. These findings suggest that developmental improvements in strategic behaviour are partly driven by increasing consistency in the implementation of decisions.

It is also worth noting that the psychometric curve-fitting procedure, which estimated β independently for each game condition, produced a better overall fit to developmental trajectories than the winning model. This is consistent with methodological recommendations to model context-specific sources of variance in decision consistency separately, where strategic environments differ substantially in their computational demands (Wilson & Collins, 2019). The finding that β was highest in cooperation, intermediate in the lottery, and lowest in competition suggests that decision consistency is not a purely domain-general trait but adapts to the strategic structure of the task. Importantly, as Schaaf et al. (2025) note, failing to account for such individual and context-specific differences in computational model parameters risks misattributing genuine parameter variation to noise, or vice versa.

However, the present findings also suggest that developmental change cannot be reduced to increasing decision consistency alone. If age-related improvements were solely driven by reductions in decision inconsistency, one would expect β to account for most of the observed behavioural variance. Instead, recursive reasoning and beliefs about others showed independent developmental associations and distinct behavioural signatures. Furthermore, simulations demonstrated that strategic reasoning and decision consistency produce qualitatively different patterns of behaviour. Higher β generates more deterministic choices, whereas higher reasoning levels generate more complex strategic behaviour, particularly in competitive environments. The simultaneous age-related increases in k, β, and *k0 bias* therefore suggest that adolescence is characterised by multiple interacting developmental processes rather than a single mechanism of cognitive maturation.

Overall, these findings indicate that developmental changes in strategic social decision-making are driven by more than increasing behavioural consistency. Adolescents appear to become more sophisticated strategic reasoners, implement their choices with increasing consistency, and develop stronger expectations about the behaviour of others. These changes provide a plausible computational explanation for the observed difference between cooperative and competitive coordination across development and suggest that strategic social behaviour becomes progressively shaped by increasingly complex representations of other people's minds.

5. 3. Risk-taking and adolescent decision-making

Although recursive reasoning, decision consistency, and beliefs about others' choices emerged as the most theoretically informative parameters, the results also revealed developmental changes in risk preferences. Risk-taking has long occupied a central position in theories of adolescent development, proposing that adolescence is characterised by heightened reward sensitivity and increased willingness to engage in risky behaviour (Steinberg et al., 2016). Consequently, one possible explanation for the age-related increase in cooperative risk-taking observed in the present study is that older participants simply became more risk tolerant. The computational results suggest that this explanation is only partially supported.

In the preliminary lottery analyses, participants displayed a general tendency toward risk aversion. Risk tolerance increased modestly with age, as reflected by the positive association between the power utility parameter α and age. This finding aligns with studies reporting developmental reductions in risk aversion and increasing willingness to engage with uncertain outcomes across adolescence (e.g., Tymula et al., 2012). Similarly, in the winning model, the CRRA parameter ρ showed a significant negative association with age, indicating a gradual decrease in risk aversion across development.

At first glance, these findings may appear to provide a straightforward explanation for the age-related increase in cooperative risk-taking. However, several observations suggest that changes in risk preferences alone cannot account for the developmental patterns observed in the present study. First, the association between age and risk preference was relatively small compared to the developmental effects observed for beliefs about others' choices, recursive reasoning, and decision consistency, respectively. Second, age-related increases in risky choice were considerably stronger in cooperation than in competition. If developmental changes were primarily driven by a domain-general increase in risk tolerance, one would expect comparable increases in risky choices across both contexts. Instead, risk-taking increased selectively in cooperation, suggesting that social expectations and strategic reasoning play a substantial role (e.g., Reiter et al., 2019).

The behavioural correlates of the risk preference parameter further support this interpretation. As expected, higher values of ρ, corresponding to greater risk aversion, were associated with lower probabilities of choosing the risky option in both cooperation and competition. More risk-averse participants also earned lower payoffs across both games, indicating that willingness to tolerate uncertainty was beneficial in the strategic environments employed here. These findings provide evidence that the parameter captured meaningful individual differences in risk attitudes rather than statistical noise.

At the same time, interpretation of the developmental association between ρ and age warrants caution. The direction of the effect is not entirely consistent with the broader developmental literature. Some studies have reported an inverted-U trajectory in risk-taking, with risk-seeking peaking during mid-to-late adolescence before declining into adulthood (Ciranka & van den Bos, 2021; Steinberg et al., 2016), whereas others have reported more gradual age-related decreases in risk-taking (Defoe et al., 2015). The relatively linear pattern observed in the present study, therefore, does not map perfectly onto either account.

One possible explanation is that the risk preference parameter in the winning model captures more than pure risk attitude. The parameter showed a moderate positive association with decision consistency, suggesting some degree of shared variance between the two constructs (for similar concerns, see Camerer et al., 2004, and Wilson & Collins, 2019). This relationship may arise because highly deterministic participants produce behavioural patterns that are easier to fit using a stronger utility curve, particularly when multiple latent parameters are estimated simultaneously. Indeed, parameter recovery analyses indicated that risk preference was recovered reliably, but it remains possible that part of the age-related variance attributed to ρ reflects interactions with other processes represented in the model.

A second possibility is that developmental changes in strategic social behaviour are fundamentally different from developmental changes observed in non-social risk-taking tasks. Traditional developmental studies often examine risk-taking in individual decision-making contexts in which outcomes depend primarily on chance. In contrast, the present task required participants to make decisions under social uncertainty, where outcomes depended on another person's behaviour. Under such conditions, willingness to choose the risky option may be driven less by reward sensitivity and more by expectations about others, confidence in one's predictions, and the ability to represent another person's intentions (e.g., Chierchia et al., 2020a; Yoshida et al., 2010). Consistent with this interpretation, the strongest developmental effects observed in the present study were for parameters directly linked to social reasoning rather than to risk preference itself.

This distinction may help explain why *k0 bias* showed stronger developmental associations than ρ. In cooperation, choosing the risky option is beneficial only if one expects the other player to do the same. Consequently, developmental increases in cooperative risk-taking can emerge even without substantial changes in underlying risk tolerance. Older participants may choose the risky option more frequently, not because they become more tolerant of uncertainty, but because they increasingly expect successful coordination. The strong association between *k0 bias* and cooperative risk-taking supports this interpretation. This condition-specificity is also supported at the behavioural level: the probability of choosing the risky payoff increased significantly with age in cooperation, while competition and the lottery followed comparably flat trajectories and did not differ from one another. The association between age and risky choice is therefore sensitive to strategic context, and age-related change was not a general feature of decision-making under uncertainty, but specific to the cooperative condition, matching the pattern observed for *k0 bias* itself.

In sum, the findings suggest that risk preferences contribute meaningfully to strategic decision-making but do not provide the primary explanation for developmental changes in cooperation and competition. While participants became slightly more risk tolerant with age, the most substantial developmental effects were observed in parameters reflecting recursive reasoning, decision consistency, and beliefs about others' choices. These results challenge accounts that explain adolescent social behaviour primarily in terms of changing reward sensitivity and instead support a more nuanced view in which developmental improvements in social cognition and strategic thinking play a central role.

5. 4. Conceptual considerations

Certain conceptual considerations warrant discussion. A central challenge in developmental research concerns the interpretation of age-related change. Although the present findings suggest developmental increases in recursive reasoning, decision consistency, and beliefs about others' choices, these processes are unlikely to develop independently. Rather, adolescence is characterised by simultaneous changes in cognitive abilities, social cognition, and reward processing (Crone & Dahl, 2012; Fuhrmann et al., 2015). Consequently, the observed developmental trajectories may reflect interactions among multiple processes rather than isolated mechanisms.

The findings also raise broader questions regarding the nature of cooperation and competition. Traditional accounts often conceptualise these forms of social behaviour as opposite ends of a single dimension. The present results challenge this view. Cooperation and competition exhibited distinct developmental trajectories, different behavioural patternss, and different computational mechanisms. In particular, switching behaviour in competition appeared to reflect strategic sophistication rather than increased decision inconsistency. These findings suggest that cooperation and competition should be conceptualised as partially distinct forms of social interaction that recruit overlapping but non-identical underlying processes.

A related conceptual issue concerns the interpretation of recursive reasoning itself. While reasoning level k is frequently interpreted as a measure of strategic sophistication, it may capture multiple underlying processes. Higher reasoning levels may reflect improvements in working memory, executive functioning, perspective-taking, or general intelligence. The observed associations with matrix reasoning support the idea that recursive reasoning is partly grounded in broader cognitive abilities. At the same time, the modest effect sizes suggest that strategic reasoning cannot be reduced to intelligence alone. Future work should therefore aim to disentangle the cognitive and social components contributing to recursive thinking.

The role of beliefs about others' choices also deserves further consideration. The strong developmental increase in *k0 bias* and its association with cooperative risk-taking suggest that social expectations play a central role in strategic behaviour. However, the psychological interpretation of this parameter remains open. Increasing *k0 bias* may reflect optimism about others, improved social prediction, greater trust, or increased sensitivity to social norms (e.g., Glätzle-Rützler et al., 2024; Reiter et al., 2021). Distinguishing among these possibilities represents an important area for future research.

Finally, the present findings contribute to ongoing debates regarding adolescent risk-taking. Influential theories have emphasised heightened reward sensitivity as a defining feature of adolescence (Shulman et al., 2016; Steinberg et al., 2016). The current results suggest a more nuanced picture. While risk preferences contributed to behaviour, the strongest developmental effects emerged for parameters associated with strategic reasoning and beliefs about others. This finding highlights the importance of examining adolescent decision-making within social contexts rather than focusing exclusively on individual risk-taking.

More broadly, the present thesis supports the view that adolescent development involves increasingly sophisticated social cognition and strategic reasoning. Understanding these processes requires integrating perspectives from developmental psychology, behavioural economics, computational modelling, and sociometrics. Such interdisciplinary approaches are likely to provide a more complete account of how individuals learn to navigate increasingly complex social environments across development.

5. 5. Practical implications

Understanding how cooperation and competition develop has important practical implications for educational, social, and clinical contexts. Adolescence is a period characterised by increasing social complexity, and successful navigation of social environments often depends on the ability to anticipate and respond to others' behaviour. The present findings suggest that strategic reasoning and social expectations/beliefs continue to mature throughout adolescence, highlighting the importance of supporting opportunities for social learning and cooperative interaction during this developmental period. The findings may also inform educational interventions aimed at promoting cooperation and social problem-solving (e.g., Paluck et al., 2016). Since beliefs about others' behaviour play an important role in cooperative outcomes, fostering trust and positive social expectations may enhance collaborative behaviour in schools and peer groups. Similarly, recognising that competition recruits distinct socio-cognitive processes may help educators design environments that encourage healthy forms of competition while minimising maladaptive social dynamics. More broadly, computational approaches to social development may have applications in clinical and applied settings. Difficulties in social reasoning and strategic interaction are characteristic of several developmental and psychiatric conditions (e.g., Liu et al., 2024). Computational modelling offers a promising framework for identifying specific mechanisms underlying these difficulties and may ultimately contribute to more targeted assessment and intervention strategies.

Chapter 6 – Limitations

Several methodological limitations should be considered when interpreting the findings of the present thesis. First, the cross-sectional design limits conclusions regarding developmental change. Although age-related associations were observed across a large developmental sample spanning childhood to adulthood, cross-sectional data cannot distinguish developmental processes from cohort effects or individual differences unrelated to maturation. Consequently, the observed age-related increases in recursive reasoning, decision consistency, and beliefs about others' choices should not be interpreted as direct evidence of within-individual developmental trajectories. Longitudinal studies that follow the same individuals across adolescence would provide stronger evidence of the developmental mechanisms underlying strategic social decision-making.

Second, although parameter recovery analyses supported the validity of the computational model, recovery differed across parameters. Recovery was strong for decision consistency, beliefs about others' choices, and risk preference, whereas recovery of reasoning level k was more moderate. In particular, the recovered values of k clustered around intermediate levels of reasoning. This limitation is not unique to the present study and reflects a broader challenge in computational modelling of recursive reasoning (Camerer et al., 2004; Nagel et al., 2018). Future work could improve parameter identifiability by increasing the number of trials, employing adaptive task designs, or integrating multiple strategic tasks that place different demands on recursive reasoning.

A third methodological consideration concerns the joint estimation of parameters across games. The winning model estimated a common decision consistency parameter across cooperation, competition, and lottery conditions. Posterior predictive checks indicated that this approach reproduced risky choice trajectories relatively well but showed reduced fit for switching and entropy, particularly in older participants. The improved fit obtained with game-specific psychometric estimation suggests that decision consistency may vary across contexts. Strategic environments differ substantially in their computational demands, and individuals may adapt their decision strategies accordingly. Future models could therefore allow additional context-specific parameters while balancing improvements in fit against increases in model complexity.

Relatedly, the moderate positive association observed between risk preference and decision consistency suggests a possible trade-off between parameters. Although recovery analyses indicated satisfactory parameter estimation overall, computational models frequently encounter challenges due to partially overlapping parameter spaces. In the present study, the CRRA risk parameter may have absorbed variance associated with other processes, particularly decision consistency. This possibility is especially relevant given that the developmental trajectory of risk preference differed somewhat from previous findings in the literature. Future work could compare alternative utility functions or employ hierarchical Bayesian approaches that better account for parameter uncertainty.

Another limitation concerns the operationalisation of social cognition. The present study inferred latent socio-cognitive processes from behavioural data and computational parameters rather than measuring them directly. Although associations with matrix reasoning and peer network centrality provided external validation, no direct measures of ToM, perspective-taking, or social cognition were included (as in Coricelli & Nagel, 2009, or Hill et al., 2017). Consequently, interpretations linking recursive reasoning to mentalising remain indirect. Future research could combine computational modelling with behavioural measures of ToM, social cognition tasks, or neuroimaging methods to more directly examine the mechanisms underlying strategic development.

A major limitation of the present study is that the computational model did not explicitly account for social preferences. Strategic behaviour in social interactions is influenced not only by beliefs and recursive reasoning but also by motives such as fairness, reciprocity, altruism, and inequity aversion (Fehr & Schmidt, 1999; Sutter et al., 2018). For example, cooperation may arise from a preference for equitable outcomes rather than from expectations about others' behaviour, while competition may reflect concerns about relative payoffs. By omitting these social preference mechanisms, the model may have attributed some socially motivated behaviour to strategic reasoning or risk-related processes (as in Westhoff et al., 2020). It is worth noting, however, that most established social preference models predict effects that are symmetric across cooperative and competitive contexts, as a shared concern for fairness or relative payoff. To our knowledge, no existing social-preference account predicts the specific asymmetry observed in the present findings, namely, elevated switching and slower response times in competition, with no corresponding behavioural signature in cooperation. This asymmetry is more plausibly explained by recursive reasoning, which produces different behavioural patterns in these two conditions. However, incorporating established models of social preferences alongside recursive reasoning represents an important direction for future research and may provide a more complete understanding of developmental changes in social decision-making.

Finally, while the large sample size represents a major strength of the study, some additional analyses relied on smaller subsamples. In particular, peer network analyses were restricted to participants with available social network data. Replication in larger and more diverse samples would strengthen confidence in the generalisability of these findings.

Altogether, these limitations do not undermine the central conclusions of the present thesis but instead highlight promising directions for future work. Computational developmental research remains a rapidly evolving field, and continued methodological refinement will further improve our understanding of how strategic social decision-making emerges across development.

Chapter 7 – Conclusion

The present thesis investigated age-related changes in strategic social decision-making across cooperation and competition using computational modelling. Building on previous findings, the study examined how recursive reasoning, decision consistency, beliefs about others' choices, and risk preferences contribute to behaviour in two tacit coordination games: cooperation and competition.

Behavioural analyses demonstrated that cooperation and competition follow distinct developmental trajectories relative to the non-social lottery baseline. Cooperation was characterised by increasing risky choice and increasing payoffs across age, a pattern absent in both competition and the lottery – propensity for cooperation signature, whereas competition exhibited elevated switching behaviour and longer response times relative to both cooperation and the lottery – competitive caution signature. Computational modelling further revealed that these behavioural differences reflect distinct underlying cognitive mechanisms. Recursive reasoning, decision consistency, and beliefs about others' choices all increased across development, whereas changes in risk preference were comparatively modest.

The winning model successfully captured key features of behaviour and demonstrated meaningful associations with external measures of non-verbal reasoning and social integration. Together, these findings suggest that developmental changes in strategic social behaviour are driven not only by changes in risk-taking but also by increasingly sophisticated social reasoning and more stable implementation of strategic decisions.

The present findings also have several theoretical implications. Firstly, they provide evidence that cooperation and competition are not simply opposite ends of a single continuum but instead recruit partially distinct processes. Cooperative coordination appears to rely heavily on optimistic, and sometimes excessively optimistic, expectations about others and successful coordination, whereas competitive coordination places greater demands on recursive reasoning and strategic differentiation. Secondly, the findings contribute to developmental decision sciences by demonstrating that recursive reasoning continues to develop across adolescence. While developmental research on recursive reasoning has previously been conducted using other paradigms (e.g., Czermak et al., 2010; Westhoff et al., 2020), the present results indicate that strategic depth within tacit coordination conditions here continues to develop well into young adulthood. This extends cognitive hierarchy and level *k* frameworks into a developmental context and highlights the value of integrating behavioural game theory with developmental psychology, particularly given that adolescence is characterised by a broader social re-orientation toward peers and increasingly complex social environments (Nelson et al., 2016; Cheng et al., 2024), within which strategic reasoning about others necessarily operates. Thirdly, the study demonstrates the utility of computational modelling for developmental research. Traditional behavioural measures alone cannot distinguish among competing underlying explanations. By decomposing behaviour into latent parameters, computational approaches lean toward a more mechanistic account of developmental changes and allow theoretical predictions to be tested more directly (Bolenz et al., 2017; van den Bos et al., 2018). Lastly, the findings support contemporary perspectives emphasising the importance of social cognition in adolescent development. Developmental changes in strategic behaviour appear to be shaped not only by changes in reward processing but also by increasingly sophisticated representations of other people's minds (Blakemore & Mills, 2014; Frith & Frith, 2021).

These findings also carry practical implications for educational, social, and clinical contexts, such as supporting cooperative behaviour in schools and informing computational approaches for identifying mechanisms underlying difficulties in strategic social reasoning in clinical populations (see section 5. 5).

In conclusion, the present thesis demonstrates that cooperation and competition follow distinct developmental trajectories and are shaped by multiple interacting socio-cognitive processes. By integrating developmental psychology, behavioural economics, computational modelling, and sociometrics, this thesis provides new insight into how individuals learn to navigate complex social environments across development and highlights the value of computational approaches for understanding social decision-making.

Appendices

Lottery model simulations

Simulations of the lottery were performed. Simulation results confirmed that the model generates plausible behaviour across the parameter space. At the trial level, risk-taking decreased monotonically as safe payoffs increased for all risk preferences (i.e., α), with the indifference point falling at approximately expected value of 7.5 for risk-neutral agents (α = 1.00), shifted to the left for risk-averse agents (α = .70), and shifted to the right for risk-tolerant agents (α = 1.49), confirming that the CE-symmetric selection of α values produced more balanced deviations around risk neutrality. Higher decision consistency (i.e., higher β) values yielded more deterministic threshold behaviour and greater differentiation of risk attitude at the aggregate level (Figure 10).

A noteworthy pattern emerged regarding choice entropy: entropy was U-shaped as a function of safe payoff, peaking near each agent's CE, and decreased with β as expected. However, entropy also scaled with α such that risk-averse agents exhibited systematically higher entropy than risk-tolerant agents, even at equivalent β values. This could be because the power utility function with $\alpha < 1$ grows sublinearly, the expected utility difference between the risky and safe options varies more gradually across safe payoffs, which widens the uncertainty region around the indifference point and produces higher choice entropy across all β levels.

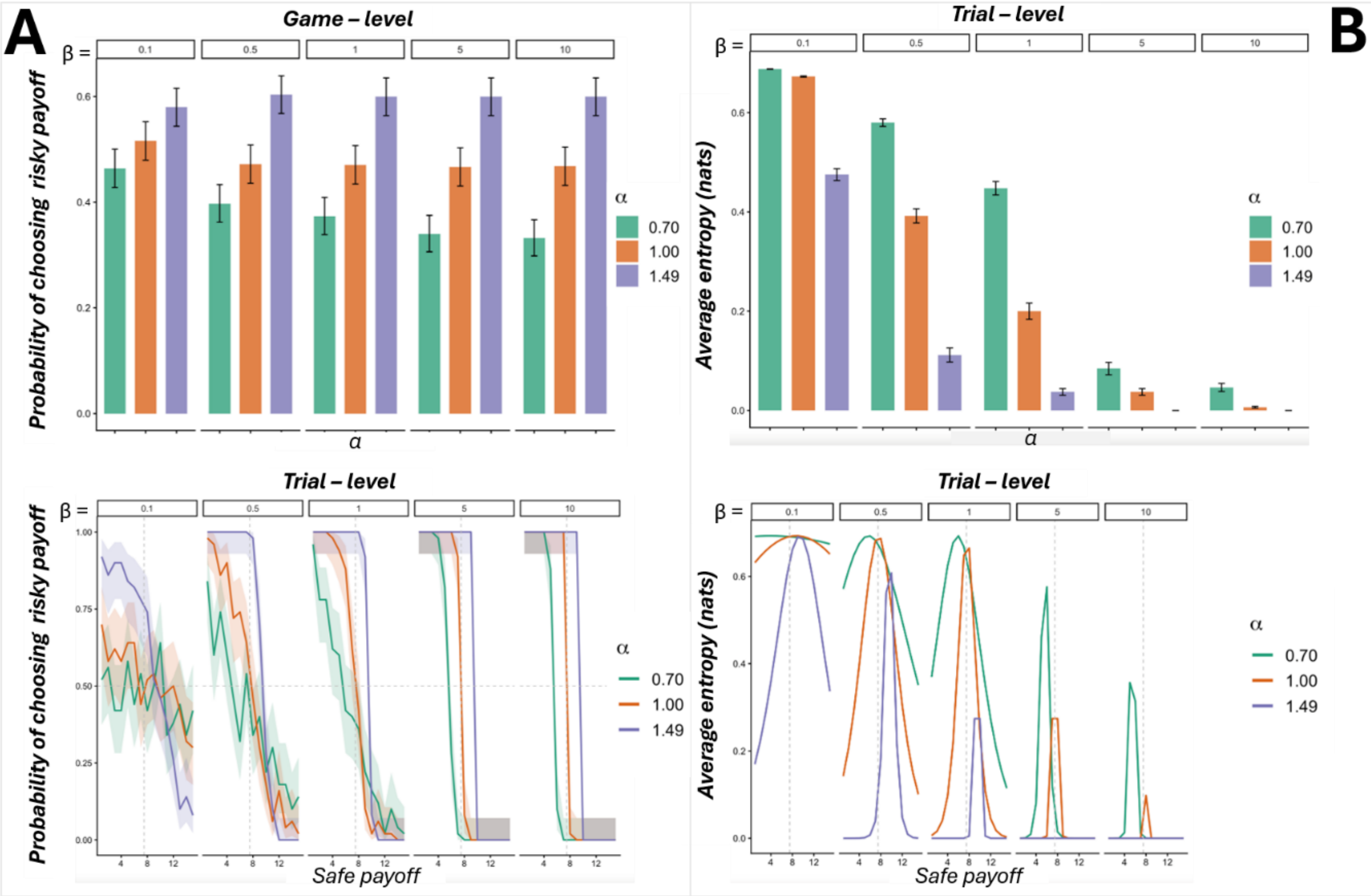

Figure 10. Lottery model simulations: effects of risk preference α and decision consistency β on choice probability and entropy. **(A) Probability of choosing the risky payoff. Top:** game-level average probability, faceted by β (.1–10) and coloured by α (.70, 1.00, 1.49; risk-averse, neutral, risk-tolerant), with error bars. **Bottom:** trial-level probability of choosing the risky payoff as a function of safe payoff, faceted by β and coloured by α, with shaded bands. **(B) Choice entropy (nats). Top:** trial-level average entropy, faceted by β and coloured by α, with error bars. **Bottom:** entropy as a function of safe payoff, faceted by β and coloured by α.

Cooperation and competition model simulations at the trial level

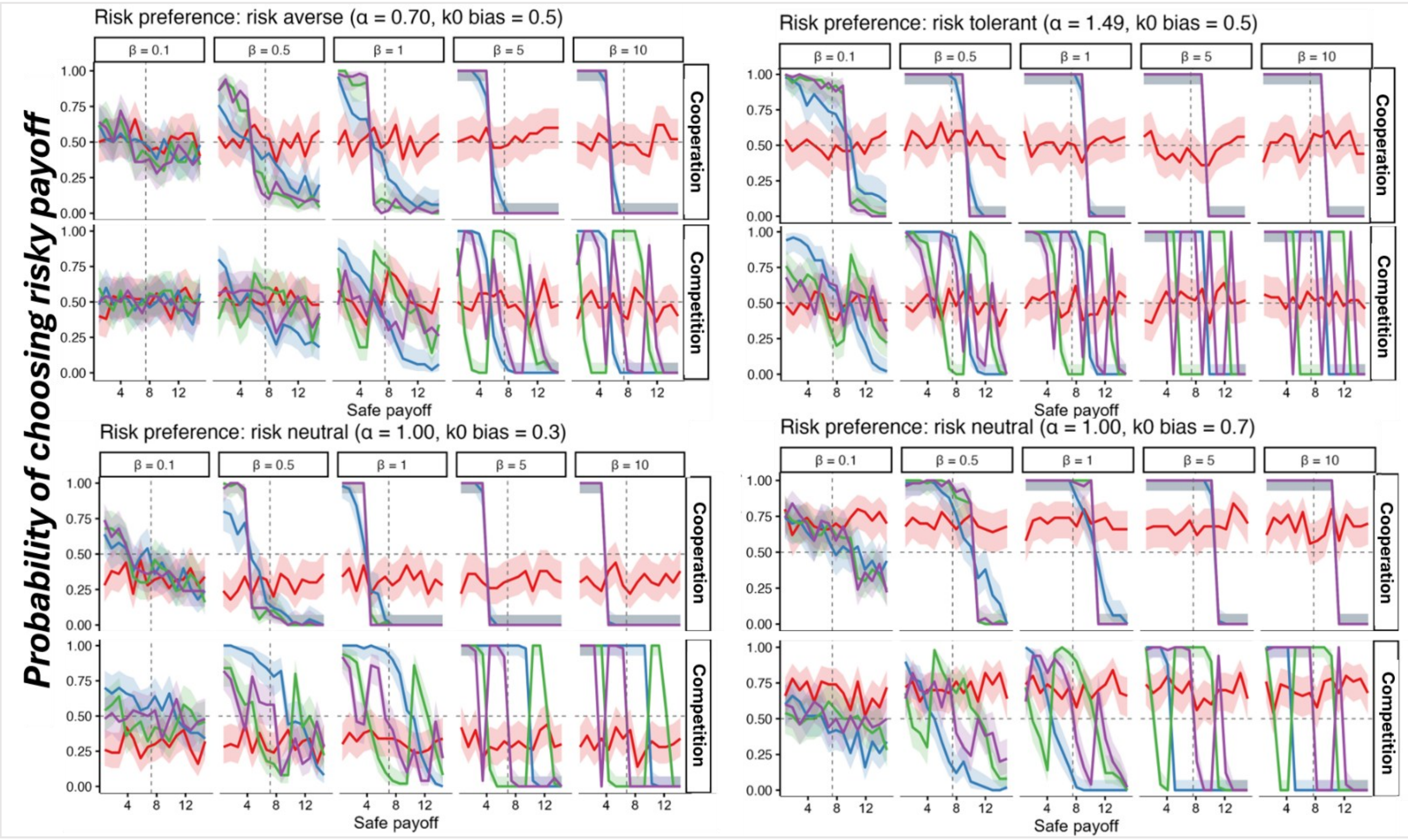

Figure 11. Full trial-level simulation results across all combinations of risk preference α and beliefs about others' choices k0 bias. Each of the four quadrants shows probability of choosing the risky payoff as a function of safe payoff, for cooperation (top row) and competition (bottom row), faceted by decision consistency (β = .1, .5, 1, 5, 10) and coloured by reasoning level (k = 0–3; red = 0, blue = 1, green = 2, purple = 3). Quadrants correspond to: risk-averse preference with unbiased beliefs (α = .70, *k0 bias* = .5; top left); risk-tolerant preference with unbiased beliefs (α = 1.49, *k0 bias* = .5; top right); risk-neutral preference with pessimistic beliefs (α = 1.00, *k0 bias* = .3; bottom left); and risk-neutral preference with optimistic beliefs (α = 1.00, *k0 bias* = .7; bottom right). The dashed vertical line marks the indifference point (safe payoff = 7.5); the dashed horizontal line marks chance-level responding (i.e., p = .5).

<u>Cooperation and competition model simulations at the game level</u>

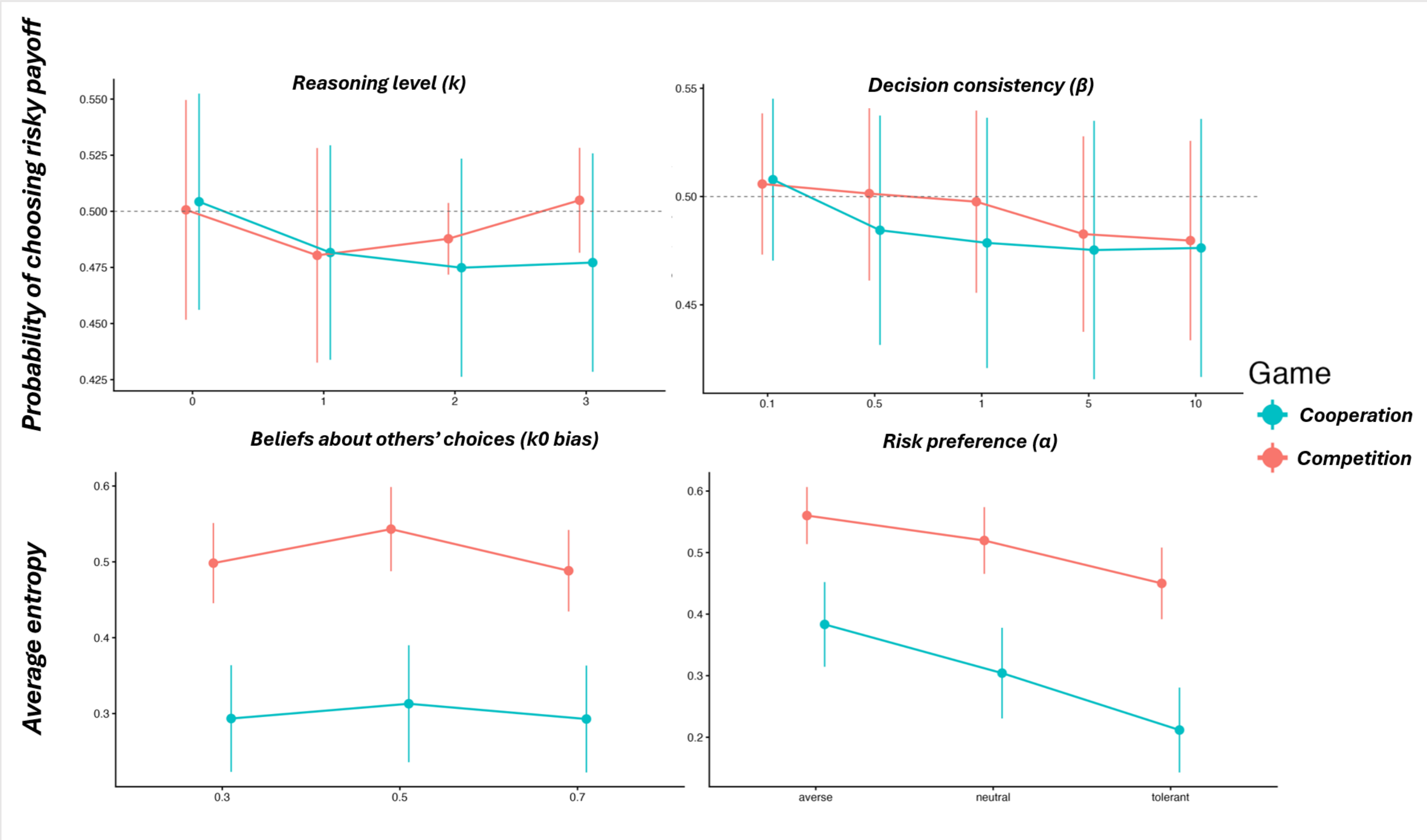

Figure 12. Aggregate-game-level probability of choosing the risky payoff and average entropy as functions of reasoning level, decision consistency, beliefs about others' choices, and risk preference. Points show means with 95% confidence intervals, collapsed across all other simulated parameters. **Top left:** probability of choosing the risky payoff as a function of reasoning level (k = 0–3). **Top right:** probability of choosing the risky payoff as a function of decision consistency (β = .1, .5, 1, 5, 10). Neither k nor β showed a consistent effect on mean risk-taking in either game. **Bottom left:** average entropy (nats) as a function of *k0 bias* (.3, .5, .7); *k0 bias* had no meaningful effect on entropy in either game. **Bottom right:** average entropy as a function of risk preference (α; averse, neutral, tolerant); entropy declined with increasing risk tolerance in both games and was higher in competition than in cooperation.

Winning model parameter distributions

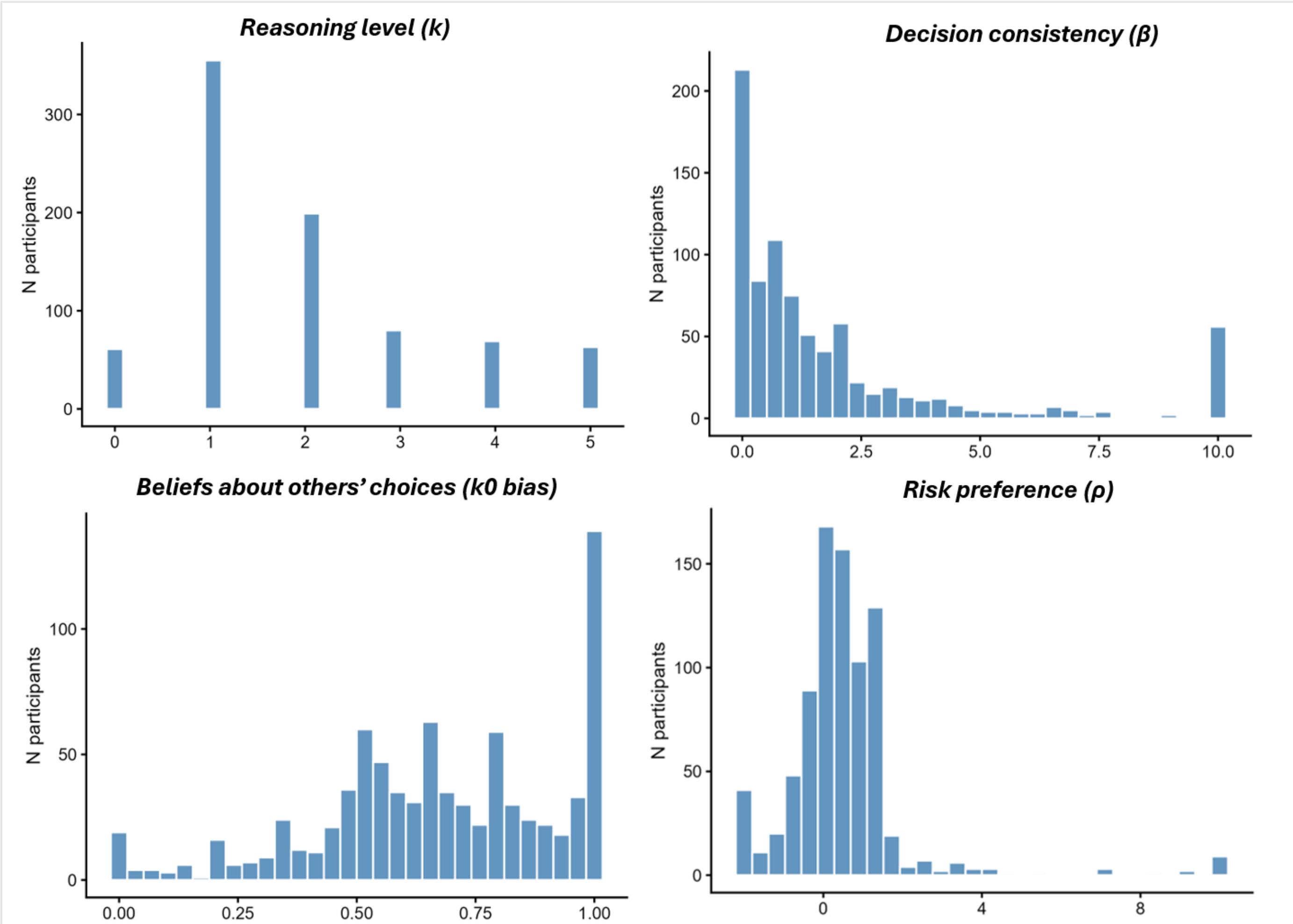

Figure 13. Distribution of individual-level parameter estimates across participants (N = 827) for the four winning model parameters.

<u>Posterior predictive checks for disaggregated decision consistency parameter</u>

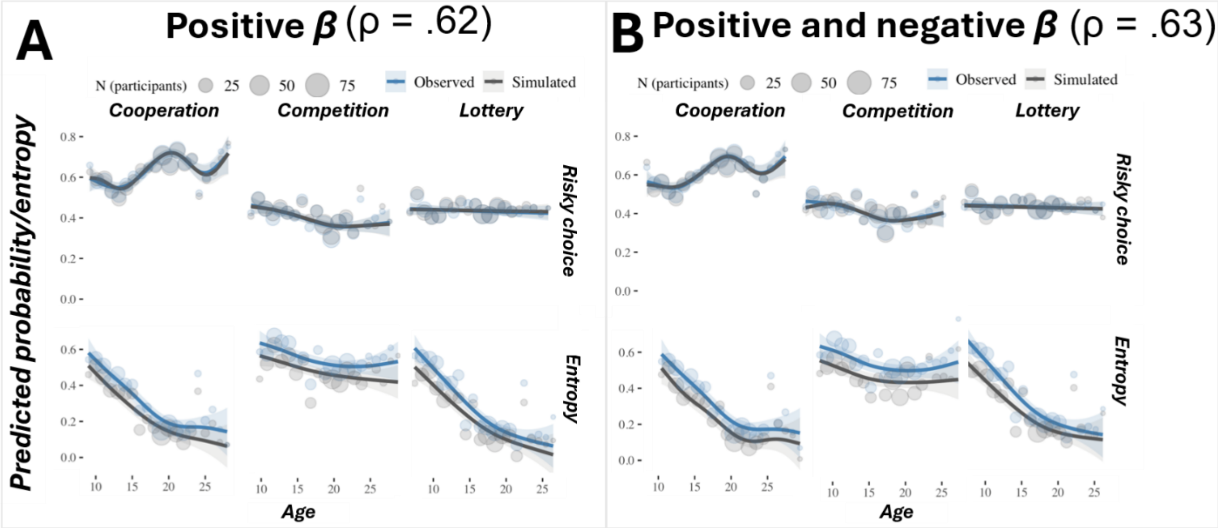

Figure 14. Posterior predictive checks under condition-specific decision consistency (β) specifications. Predicted probability/entropy as a function of age, shown separately for cooperation, competition, and lottery (columns), and for probability of choosing the risky payoff, and entropy (rows). Blue lines and shading represent observed data (LOESS smooth with 95% CI); grey lines represent model-simulated data. Point size reflects the number of participants at each age. **(A) Psychometric model with β constrained to positive values** ($\rho = .62$). **(B) Psychometric model with β with both positive and negative values** ($\rho = .63$). Both disaggregated specifications reproduced the age-related decline in entropy more closely than the winning model (section 4. 3, Figure 7, panel C), particularly in cooperation and lottery, though an underestimation of entropy by the simulated data persisted across all three conditions.

Difference-score (deltas) posterior predictive checks across models

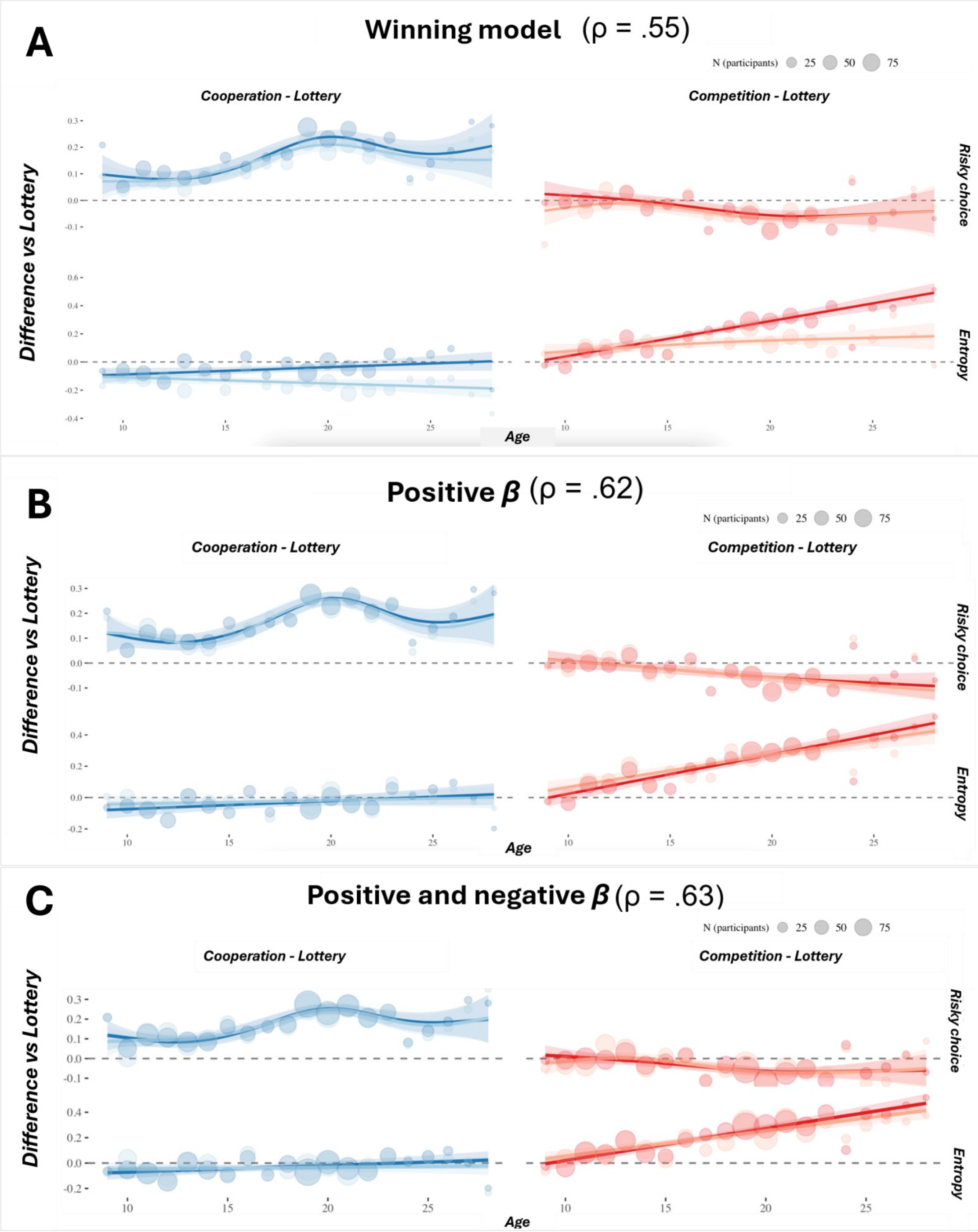

Figure 15. Difference-score (delta) posterior predictive checks relative to the lottery baseline, across model specifications. Each panel shows age-related trajectories of cooperation–lottery (blue, left) and competition–lottery (red, right) difference scores, separately for the proportion of risky choices (top row) and choice entropy (bottom row).

Solid lines show observed data; lighter shaded lines show model-simulated data; point size reflects the number of participants at each age. The dashed horizontal line marks no difference from the lottery baseline. Overall correspondence between observed and simulated trajectories (Spearman ρ) is reported above each panel**. (A) Winning model, with decision consistency β parameter estimated jointly across conditions** (ρ = .55). **(B) Disaggregated psychometric model with condition-specific β constrained to positive values** (ρ = .62). **(C) Disaggregated psychometric model with condition-specific β with both positive and negative values** (ρ = .63). Across all three specifications, the cooperation–lottery contrast for risky choice showed a positive age trend, well recovered by simulation, while the competition–lottery contrast was smaller and more variable. For entropy, the competition–lottery contrast increased with age in the observed data; this increase was underestimated in the simulated data across all three models, with the degree of underestimation increasing across the developmental range.

Lottery preliminary model fitting

For the lottery model fitting (here $N = 748$), MLE was applied to participants' trial-level choices under both the power utility (α) and the CRRA utility function (ρ). Model comparison indicated that the power utility model (i.e., α) provided a better fit for the majority of participants, AIC (94.8%) and BIC (94.8%), confirming it is more suitable for operationalising utility for the subsequent analyses.

The median estimated α across participants was .83 (range: .05–5.00). A one-sample Wilcoxon signed-rank test indicated that the median α differed significantly from 1 (V = 89,697, $p < .001$), suggesting a systematic tendency toward risk aversion in the sample. Spearman rank correlations revealed a small but significant positive association between α and age across the full age range (ρ = .14, $p < .001$), which was also present within the developmental subsample (ρ = .15, $p < .001$; age $\leq$ 28), indicating a modest increase in risk tolerance with age. The decision consistency parameter β showed a significant positive association with age across the full sample (ρ = .37, $p < .001$) and in the developmental subsample (ρ = .36, $p < .001$; age $\leq$ 28). These results are consistent with known age-related reductions in decision inconsistency and provide an initial sanity check on the model. This preliminary analysis compared power utility (α) and CRRA (ρ) specifications at the individual-subject level using lottery trials only; a separate, later model comparison across all three conditions jointly (section 4. 3.) favoured the CRRA parameterisation, which is used throughout the main results.

Cooperation and competition preliminary model fitting

MLE was applied to participants' trial-level choices in the competition and coordination games jointly (full sample, N = 827), fitting three continuous parameters: risk preference α (i.e., power utility), decision consistency β, and *k0 bias*, while selecting reasoning level (k = 0–3) by model comparison per participant using a multi-start L-BFGS-B optimizer with 10 random starting points per level k.

Spearman rank correlations between estimated parameters and age were computed in the developmental subsample (age ≤ 28). Reasoning level k also showed a small positive association with age ($\rho = .12$, $p < .001$), supporting the hypothesis that strategic reasoning depth increases across childhood and adolescence. β showed a small positive association with age ($\rho = .07$, $p < .05$), consistent with age-related reductions in decision inconsistency and replicating the pattern observed in the preliminary lottery fitting. *k0 bias* showed the strongest positive association among the four parameters ($\rho = .19$, $p < .001$), indicating that older participants held increasingly optimistic prior beliefs about the opponent's propensity for risk-taking. α showed no significant association with age ($\rho = .02$, $p = .56$).

Winning model parameter intercorrelations

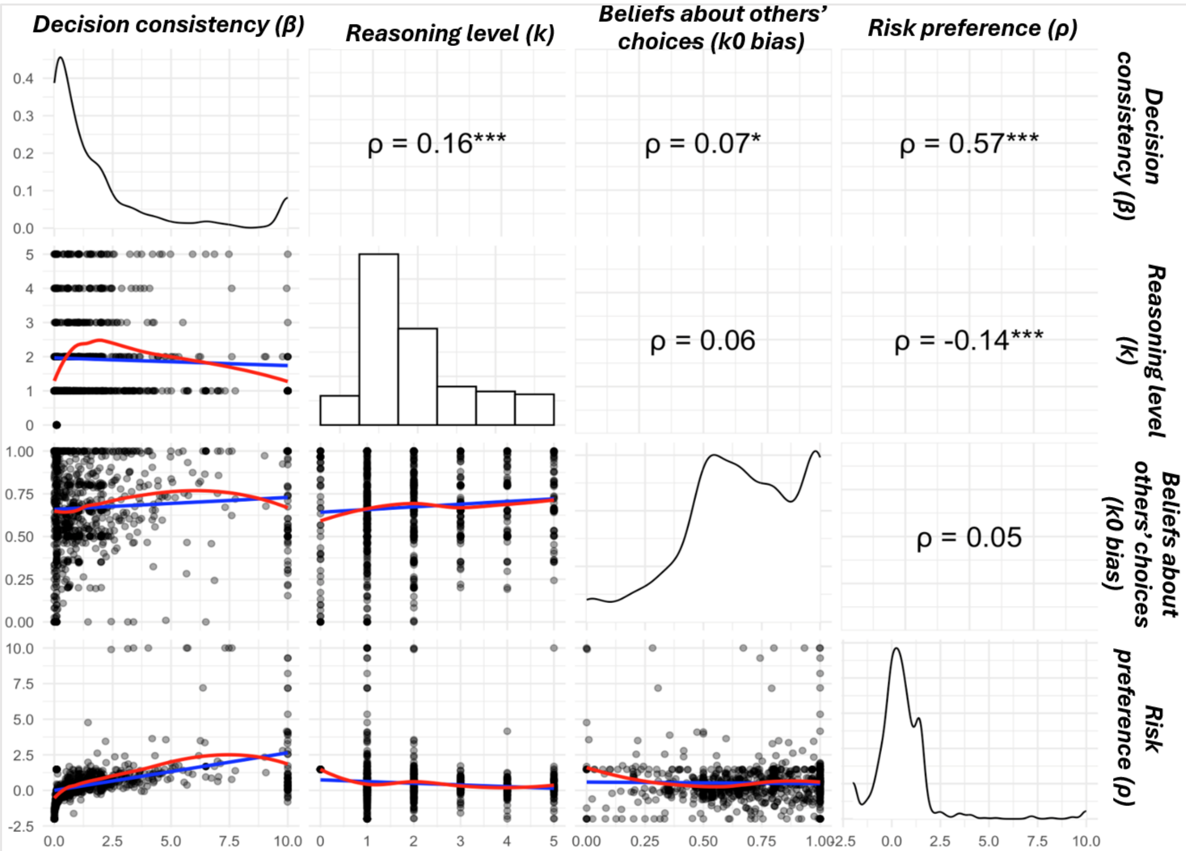

Figure 16. Winning model parameter intercorrelations. Pairwise scatterplots (below diagonal), Spearman correlations (above diagonal), and univariate density/histogram distributions (diagonal) for the four winning-model parameters: reasoning level (k), decision consistency (β), beliefs about others' choices (*k0 bias*), and risk preference (ρ). Blue lines show linear fits; red lines show LOESS smooths. Note: ***$p < .001$, **$p < .01$, *$p < .05$, ns: $p > .05$.

Parameter estimates associations with behavioural measures

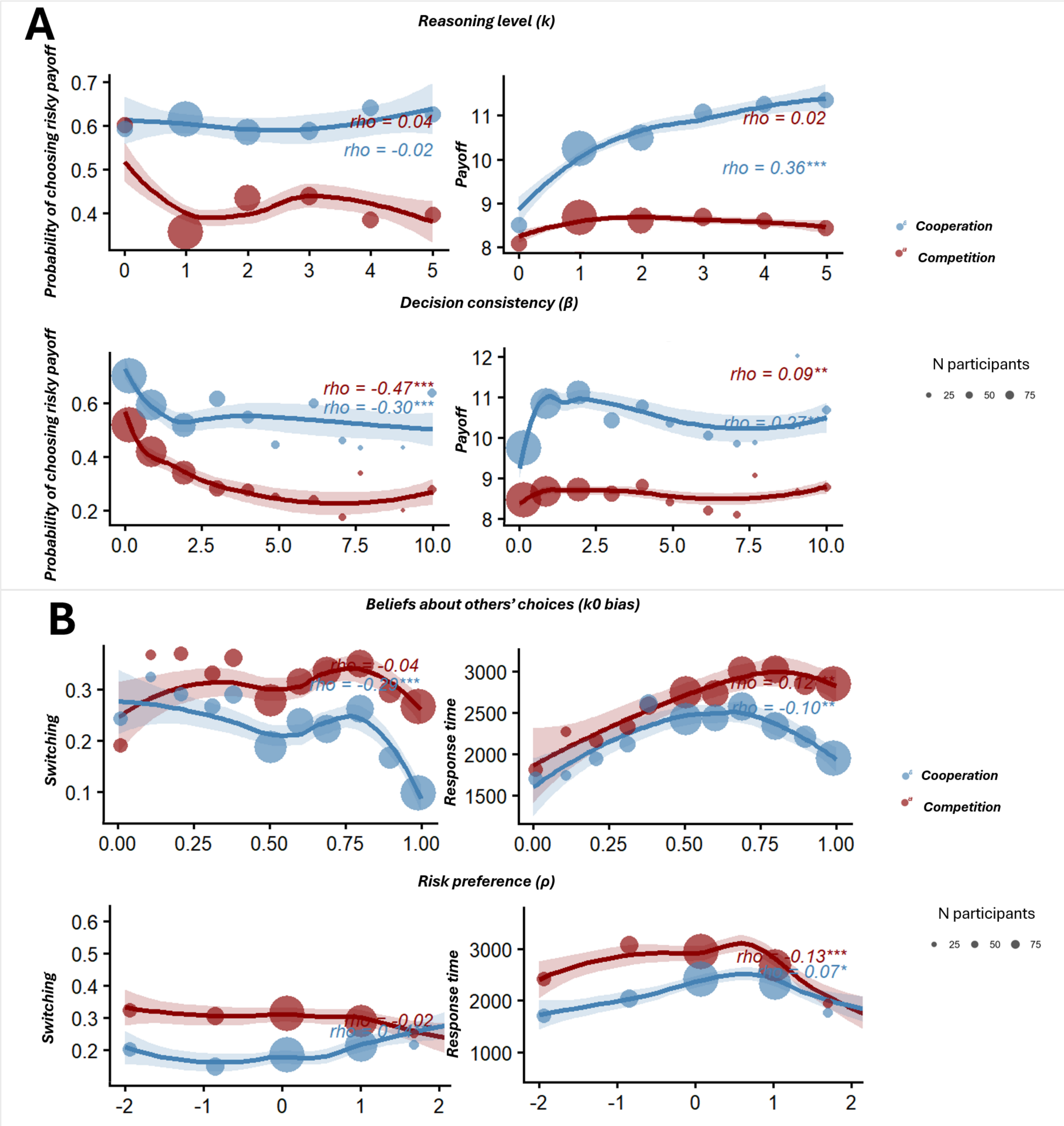

Figure 17. Associations between winning model parameter estimates and behavioural outcomes. Each panel shows LOESS with 95% confidence intervals fitted to participant-level data as a function of each model parameter. Point size reflects the number of participants at each parameter value. Spearman rank correlations (rho) with significance levels are displayed for each condition. **(A) Reasoning level (*k*) and decision consistency (*β*). Top left:** probability of choosing the risky payoff showed no significant association with *k* in either game. **Top right:** payoff showed no significant association with *k* in competition but a positive association in cooperation. **Bottom left:** probability of choosing the risky payoff decreased with *β* in both competition and cooperation. **Bottom right:** payoff increased with *β* in both competition and cooperation. **(B) Beliefs about others' choices (*k0 bias*) and risk preference (*ρ*). Top left:** switching showed no

significant association with *k0 bias* in competition but a negative association in cooperation. **Top right:** response time showed a small positive association with *k0 bias* in competition and a small negative association in cooperation. **Bottom left:** switching showed no significant association with risk preference in competition but a small positive association in cooperation. **Bottom right:** response time showed a small positive association with risk preference in cooperation and a small negative association in competition. Note: ***$p < .001$, **$p < .01$, *$p < .05$, ns: $p > .05$.

Psychometric curve fitting

Two psychometric curve-fitting procedures were applied separately for each game condition (cooperation, competition, lottery) to estimate game-specific β and *k0 bias*, with β constrained to positive values β = [0, 10] in the primary model, or allowing negative β = [-10, 10] values in the secondary model, and *k0 bias* = [0, 1] applied in both cases. Median β estimates differed across conditions in the primary model: cooperation (*Mdn* = 1.31, *M* = 5.01, *SD* = 4.77), lottery (*Mdn* = .91, *M* = 4.38, *SD* = 4.69), and competition (*Mdn* = .31, *M* = 2.45, *SD* = 4.03). Highest β in cooperation, intermediate in the lottery, and lowest in competition match theoretical expectations, since this condition involves alternations that produce inherently variable choice patterns even for "rational agents", attenuating the psychometric signal. Mean *k0 bias* estimates were comparable across the cooperation (*Mdn* = .63, *M* = .63, *SD* = .30) and competition (*Mdn* = .63, *M* = .62, *SD* = .32) conditions, but lower in the lottery condition (*Mdn* = .43, *M* = .46, *SD* = .26). The comparable *k0 bias* across the two social games, combined with the finding that k0 bias has opposite directional effects on risk-taking in cooperation versus competition, suggests that participants maintain similar optimistic priors about opponent risk-taking regardless of game context, but these priors translate into opposite strategic responses due to the payoff structure. In the secondary model, median β estimates showed the same ordering as in the primary model: cooperation (*Mdn* = 1.31, *M* = 5.01, *SD* = 4.77), lottery (*Mdn* = .91, *M* = 4.37, *SD* = 4.69), and competition (*Mdn* = .31, *M* = 2.42, *SD* = 4.11). Mean k0 bias estimates were likewise comparable across models: cooperation (*Mdn* = .63, *M* = .63, *SD* = .29), competition (*Mdn* = .60, *M* = .60, *SD* = .30), and lottery (*Mdn* = .45, *M* = .47, *SD* = .25).

Cross-game Spearman rank correlations for β in the primary model were strongest between cooperation and lottery (ρ = .56, p < .001), with weaker but significant correlations between cooperation and competition (ρ = .26, p < .001) and between competition and lottery (ρ = .27, p < .001). This pattern suggests that individual differences in choice consistency exhibit meaningful, context-specific variation, with the cooperation–lottery similarity reflecting the shared structure of these two conditions (consistent-threshold choices) relative to the more volatile competition condition. Cross-game correlations for *k0 bias* showed a qualitatively different pattern: cooperation and lottery were positively correlated (ρ = .34, p < .001), while both cooperation–competition (ρ = −.13, p < .001) and competition–lottery (ρ = −.40, p < .001) showed negative correlations, suggesting that prior beliefs about opponent risk-taking are systematically reversed between cooperative and competitive contexts. This anti-correlation between the social games is theoretically meaningful: participants who expect opponents to risk frequently (high *k0 bias*) are incentivised to cooperate in cooperation but to deviate in competition, generating opposite choice tendencies from the same prior belief. The positive correlation between lottery and cooperation *k0 bias* further suggests that a general disposition toward optimism or ambiguity tolerance underlies both the lottery and cooperative contexts, while competitive contexts recruit a qualitatively different set of social expectations. The secondary model reproduced this pattern closely: β correlations were again strongest between cooperation and lottery (ρ = .54, p < .001), followed by cooperation–competition (ρ = .25, p < .001) and competition–lottery (ρ = .25, p < .001); *k0 bias* again showed a positive cooperation–lottery correlation (ρ = .33, p < .001) alongside negative correlations between competition and both other games (competition–cooperation, ρ = −.16, p < .001; competition–lottery, ρ = −.37, p < .001).

Inter-correlations between β and *k0 bias*, computed both within and across games, were generally small. In the primary model, within-game correlations ranged from ρ = .09 (lottery) to ρ = .24 (cooperation), while cross-game correlations (e.g., β in one condition against *k0 bias* in another) ranged from ρ = .05 to ρ = .12, all positive. In the secondary model, the within-game β–*k0 bias* correlation was significant in cooperation (ρ = .19, p < .001) and lottery (ρ = .07, p < .05), but not in competition (ρ = −.04, p > .05). Cross-game correlations in the secondary model were similarly small, ranging from ρ = .02 (p > .05) to ρ = .11 (p < .01), with most reaching significance.

In the primary model, β showed significant positive associations with age in cooperation (ρ = .41, p < .001) and lottery (ρ = .45, p < .001), but not in competition (ρ = .06, p > .05). *k0 bias* showed significant positive associations with age in cooperation (ρ = .19, p < .001) and competition (ρ = .15, p < .001), but not in lottery (ρ = .05, p > .05). The secondary model produced closely comparable results: β increased with age in cooperation (ρ = .36, p < .001) and lottery (ρ = .45, p < .001) but not competition (ρ = .05, p > .05), while *k0 bias* increased with age in cooperation (ρ = .18, p < .001) and competition (ρ = .10, p < .01) but not lottery (ρ = .05, p > .05).

Associations of computational parameters and non-verbal reasoning abilities

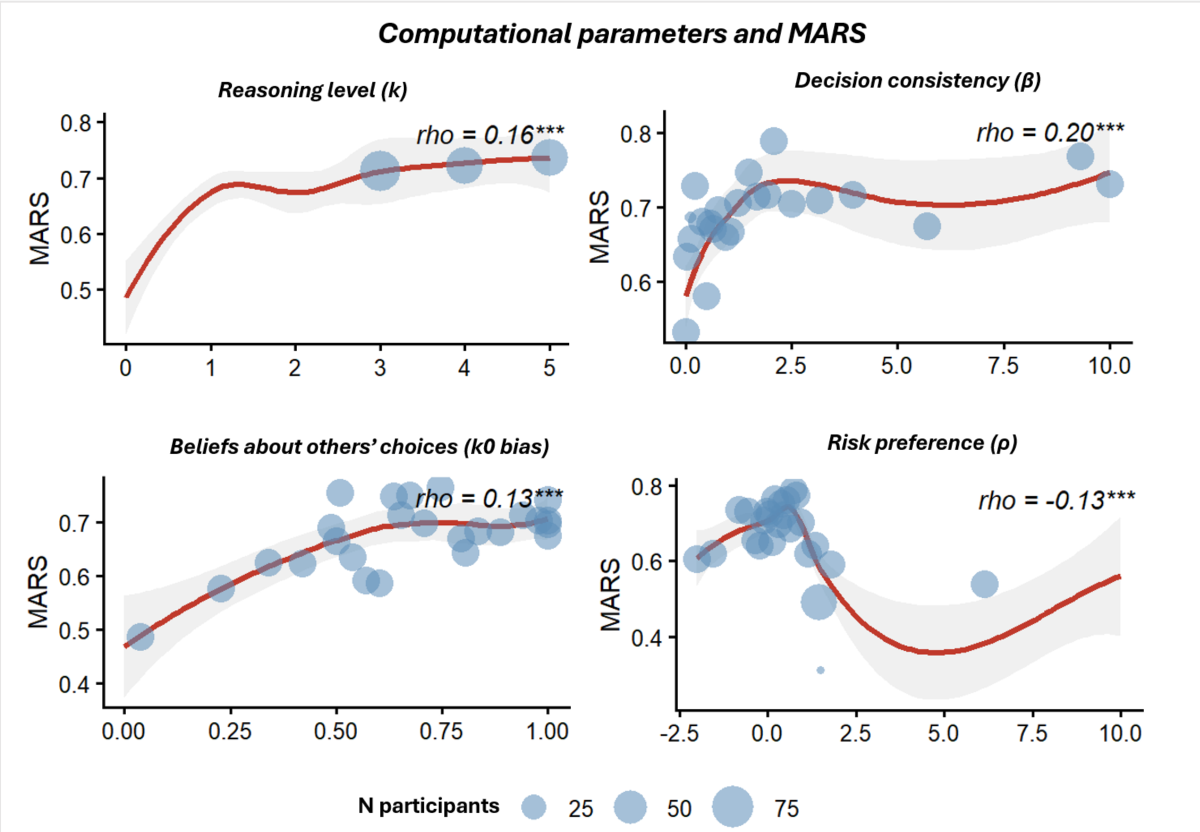

Figure 18. Winning model parameters and non-verbal reasoning abilities (MaRs-IB; Zorowitz et al., 2023). Each panel shows LOESS smooths with 95% confidence intervals fitted to participant-level data as a function of each winning-model parameter, with matrix reasoning scores (MARS) on the y-axis. Point size reflects the number of participants at each parameter value. Spearman rank correlations (rho) with significance levels are displayed in each panel. **Top left:** reasoning level (*k*). **Top right:** decision consistency (*β*). **Bottom left:** beliefs about others' choices (*k0 bias*). **Bottom right:** risk preference (*ρ*). All four parameters showed significant positive associations with MARS, except risk preference, which showed a negative association. Note: ****p* < .001, ***p* < .01, **p* < .05, ns: *p* > .05.

Associations of decision consistency parameter and social integration measures

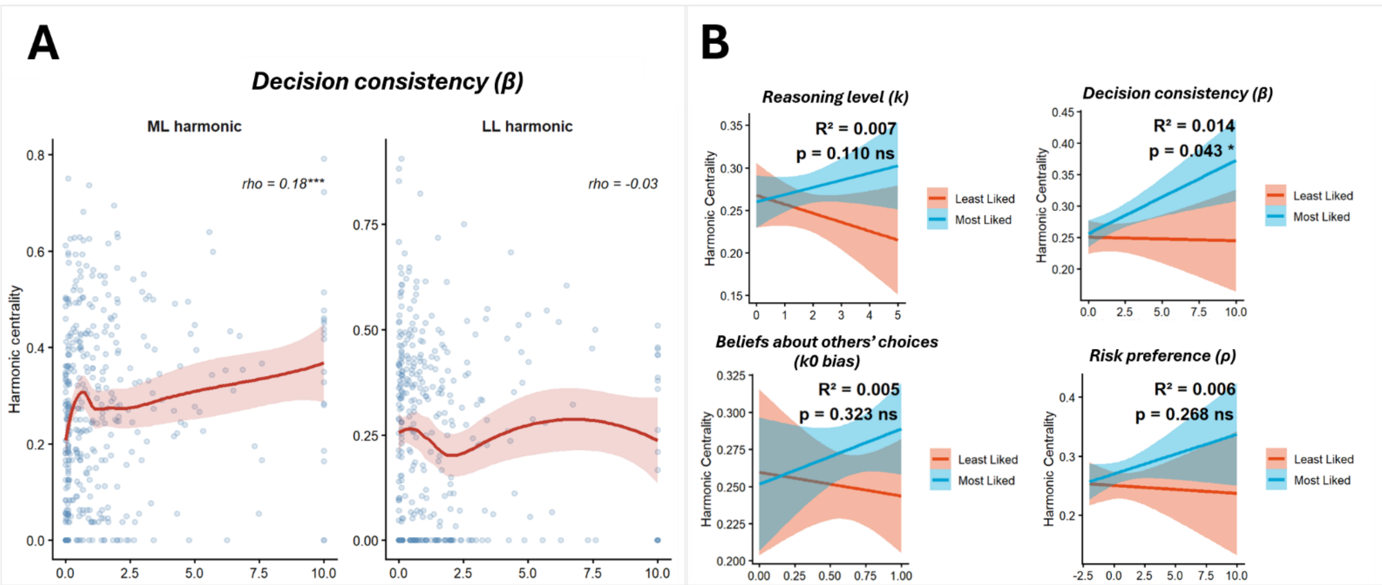

Figure 19. Associations of decision consistency and social integration measures. **(A) Correlation between decision consistency (*β*) and harmonic centrality.** Shown separately for the most-liked (ML, left) and least-liked (LL, right) peer nomination networks. Each point represents one participant; the red line shows a LOESS smooth with 95% confidence interval. Spearman rank correlations (rho) are displayed for each network. **(B) Network × Parameter interaction models.** Each panel shows harmonic centrality as a function of a winning model parameter, with separate linear fits for the least-liked and most-liked networks, shaded by 95% confidence interval. R^2 and *p*-values refer to the Network × Parameter interaction term from each model. Only the Network × decision consistency (*β*) interaction was significant, indicating that the positive association between *β* and centrality was stronger in the most-liked than in the least-liked network. Note: ****p* < .001, ***p* < .01, **p* < .05, ns: *p* > .05.

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