

Advancing Cognitive Assessment and Training in Professional Youth Football Through Immersive Football-Specific Technology

Woohyuk Chang

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Acknowledgements

Looking back, when a student leaves home, family, and lifelong friends behind to move across the world, it says a lot about how much football means to him. But turning that overflowing passion and motivation into real knowledge and insight will be far from easy. It would be hard work in every sense.

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감사의 글

아빠, 기억할지 모르겠지만 첫 유학길에 오르기 전 2013년 겨울 아빠가 나에게 두 가지 조언을 해줬어. 최소한 10년 이상의 시간과 노력을 들여야 어느 한 분야의 전문가라는 말을 듣기 시작할 수 있다는 것. 그리고 짧다면 짧고, 길다면 길 그 10년 이상의 기간 동안 자의에 의해서든 타의에 의해서든 그 배움을 그만두어야 할 위기가 몇 번이고 올 거라는 것.

박사 논문을 제출하는 올해가 군대에 다녀온 시간을 빼면 처음 루이스에서 어학연수를 시작한 지 햇수로 딱 10년째 되는 해야. 아빠 말처럼 꾸준히 하다 보니, 2013년에는 영어로 인사조차 서툴렀던 내가 이제 박사 연구를 마치게 되었네. 이 기간 동안 나를 믿어주던 가족과 친구들, 그리고 다행히 멀리 영국에 와서도 좋은 사람들을 많이 만나서, 쉽지 않았지만 스스로 이 길을 포기하고 싶다는 생각은 하지 않았던 것 같아. 그런데 지금 생각해보니 아빠가 보이지 않는 곳에서 내 의지를 버어낸, 내 꿈을 가로막을 수 있는 다른 상황들을 모두 막아준 것 같은 느낌이 드네. 자식들 꿈 지켜주느라 매일 고생하는 우리 아빠, 누구보다 고맙고 사랑해.

엄마! 아직도 엄마가 나랑 우정이 데리고 저녁 시간 동네 태권도장이랑 검도장 다니면서 내 방과 후 학원을 찾아다니던 게 생생히 기억난다. 그때만 해도 내가 워낙 흥미를 보이는 게 없어서 엄마가 가끔 걱정도 했던 것 같은데 아들이 나중에 커서 어떤 길을 갈지 전혀 몰랐다, 그치? 내가 무언가를 이렇게 좋아하고 동경할 수 있는 원동력은 모두 어릴 적 엄마, 아빠한테서 보고 배운 것 같아. 그리고 이렇게 좋은 사람들을 많이 사귄 수 있었던 것도, 엄마가 어떻게 사람들을 존중하고 사랑하는지 나랑 우정이한테 보여줘서 가능했던 것 같고. 늘 그랬듯이 앞으로도 계속 우리에게 사랑을 알려주고 꿈을 동경하는 법을 보여주면 좋겠어. 누구보다 나와 우정이를 사랑해주는 엄마, 항상 고맙고 너무너무 사랑해.

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2026년 4월

장우혁 드림.

Declaration

I, Woohyuk Chang (WC), declare that no portion of the work referred to in this thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

In addition, the commercial provider of the technology utilised in this research provided no funding or grant support and had no involvement in the study design, data collection, data analysis, interpretation of the results, or preparation of the thesis.

Conference Communications

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Abstract

The increasing perceptual and cognitive demands of modern football have led to growing interest in technologies designed to assess and train the underlying mechanisms of decision-making processes within applied environments. Among these tools, *football-specific* assessment or training technologies typically refer to systems that attempt to integrate either generic or sport-specific perceptual stimuli with corresponding motor responses (Beavan, 2019), thereby embedding cognitive processing within perception–action coupled tasks. These approaches aim to preserve key characteristics of performance environments while maintaining experimental control. However, despite their adoption in professional settings, the methodological validity and applied utility of such systems remain insufficiently understood. This thesis therefore aimed to evaluate the SoccerBot360 (SB360), an immersive football-specific cognitive-motor assessment and training device, within an English professional youth academy context.

The first part of the thesis examined the SB360 as an assessment tool (Chapters 3 and 4). Cross-sectional findings from the U12–U21 academy players demonstrated that standardised SB360 cognitive-motor performance metrics exhibited differential sensitivity to developmental and contextual factors. Response time, particularly in tasks with consistent overt motor execution (i.e., kicking), showed systematic associations with chronological age and biological maturation, suggesting sensitivity to developmental characteristics. In contrast, executive-control and binary correctness (i.e., decisional accuracy and error-based) measures from cognitive tasks demonstrated limited differentiation across age groups but were more strongly associated with subjective workload, reflecting sensitivity to perceived cognitive demands and transient performance states. Collectively, findings indicated that SB360 performance is not solely reflective of stable cognitive ability but emerges from an interaction between cognitive task demands and motor-execution requirements.

The second part of the thesis evaluated the SB360 training protocols (Chapter 5). A longitudinal study employing a cross-over design examined a standardised 6-week training intervention in U13–U15 academy players. Results demonstrated improvements in cognitive-motor performance across both intervention and control conditions, with no significant between-group differences or consistent time-by-group interaction effects across testing points. At an individual level, considerable variability in response to the intervention was observed, with some players demonstrating performance improvements while others showed minimal or inconsistent changes. These findings highlight the importance of individualisation in cognitive training interventions, as standardised approaches may not account for differences in player needs, baseline abilities, or responsiveness to training stimuli. Collectively, findings suggest that observed group-level improvements were primarily attributable to familiarisation and repeated task exposure rather than training-specific cognitive adaptations. In addition, the relatively low training dosage and limited alignment between training and assessment tasks may have constrained the potential for transfer effects.

Overall, this thesis provides the first comprehensive applied evaluation of an integrated football-specific cognitive-motor system within a professional academy. While the SB360 demonstrates practical feasibility and value as a structured training and monitoring environment, its assessment and training outcomes require careful interpretation. Importantly, the findings highlight that the effectiveness of such technologies is contingent upon task design, sufficient familiarisation, appropriate training dosage, and the need for individualised implementation within player development programmes. This work also critically examines the definition and appropriateness of the term *football-specific* in relation to emerging cognitive testing and training technologies. Collectively, the thesis offers broader transferable insights for the development, evaluation, and applied integration of cognitive assessment and training systems in applied environments.

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List of Abbreviations

ANT	Anticipation
BA	Biological Age
BA–CA	Biological Age minus Chronological Age Offset
CA	Chronological Age
CAVE	Cave Automatic Virtual Environment
CF	Cognitive Flexibility
CRT	Choice Response Time
ES	Effect Size
EF	Executive Function
EFF	Perceived Effort
FP	Foundation Phase
EPL	English Premier League
FR	Perceived Frustration
FT	Familiarisation Test
GPS	Global Positioning System
IDP	Individual Development Plan
INH	Inhibition
LMM	Linear Mixed-effect Model
MCI	Mild Cognitive Impairment
MD	Perceived Mental Demand
MG	Mini Goals
ML	Maximum Likelihood
MT	Moving Targets
NASA	The National Aeronautics and Space Administration
OW	Overall Workload
PAH	Predicted Adult Height
PCS	Perceptual-Cognitive Skill
PD	Perceived Physical Demand
PDP	Professional Development Phase
PE	Perceived Performance
Pre-O	Pre-Orientation
REML	Restricted Maximum Likelihood
RPE	Rate of Perceived Exertion
RT	Response Time
SB360	SoccerBot360
TD	Perceived Temporal Demand
TLX	Task Load Index
VR	Virtual Reality
WM	Working Memory
YDP	Youth Development Phase

In this thesis, the term *football* is used consistently to denote *association football (soccer)*, unless otherwise specified.

Chapter 1. General Introduction

1.1 Background

Modern football is characterised by high physical intensity, rapid transitions, and continuous decision-making under time pressure (Nassis et al., 2020). Players must perceive evolving spatial-temporal information, select appropriate responses within fractions of a second, and execute technical actions with precision while performing multi-directional movements at varying intensities (Williams et al., 2023). The evolution of match demands over recent decades has intensified these requirements, with increases in high-speed running, technical actions performed under pressure, and overall match tempo (Allen et al., 2025; Barnes et al., 2014; Lago-Peñas et al., 2023; Wallace & Norton, 2014). These changes have not occurred in isolation but alongside substantial growth in sport science research and technological innovation.

From the 1960s and 1970s onwards, scientific approaches were introduced to better understand the game's physical and technical demands. Early work quantified distances covered during matches (Reilly & Thomas, 1976) and analysed technical patterns of play, such as shot frequency and effectiveness (Reep & Benjamin, 1968). By the 1980s and 1990s, systematic conditioning programmes and specialist sport science support became increasingly embedded within professional football (Bangsbo, 1994). The 2000s saw the expansion of performance analysis through video-based systems capable of examining individual and team behaviours in greater detail (Hughes & Franks, 2004). The growth of various scientific disciplines in football has resulted in the establishment of sports science departments within professional clubs and organisations to enhance match performance, reduce injuries, and optimise training methods (Reilly & Gilbourne, 2003).

In parallel, substantial investments and growth in sport measurement tools have enabled more sophisticated data collection and feedback systems in applied settings. For example, force platforms and timing gates enable objective physical benchmarking (Beato et al.,

2023; Taylor et al., 2022). Wearable devices, such as global positioning system (GPS) and inertial measurement units, allow detailed monitoring of training and match workloads (Lewis et al., 2022; Malone et al., 2017). Optical tracking systems equipped with artificial intelligence cameras now provide automated object tracking and integrated physical-technical outputs with synchronised video (FIFA, 2024). Collectively, these developments have contributed to increasingly sophisticated approaches to player development and performance optimisation.

While the quantification of physical and technical outputs has matured considerably, growing attention has shifted towards the perceptual and cognitive processes underpinning decision-making in dynamic environments. As match tempo and tactical complexity increase, competitive advantage may increasingly depend not only on physical capacity but also on the efficiency with which players perceive information, update working representations, inhibit inappropriate responses, and demonstrate flexibility in adapting behaviour (Habekost et al., 2024; Haugan et al., 2025). In cognitive psychology, such processes are often conceptualised as executive function (EF), which generally include working memory, inhibition, and cognitive flexibility (Diamond, 2013; Miyake et al., 2000). In contrast, perceptual-cognitive-skill research in sport emphasises domain-specific processes such as anticipation, pattern recognition, and perception–action coupling (Hope et al., 2024; van Maarseveen et al., 2018; Williams et al., 2023). Although conceptually distinct, both perspectives seek to explain how perceptual and cognitive mechanisms contribute to skilled performance in football.

Empirical studies over the past two decades have reported differences in cognitive performance across levels of expertise, suggesting that certain executive or perceptual-cognitive characteristics may distinguish high-performing players (Haugan et al., 2025; Scharfen & Memmert, 2019a). Parallel to this research expansion, the applied sport

industry has increasingly incorporated cognitive assessment and training technologies within working operations. Commercial platforms now integrate conventional EF paradigms, such as the number-letter task, flanker task, or *n*-back (Heilmann, Memmert, et al., 2023), with sport-specific scenarios delivered via console systems and virtual or immersive environments (Craig, 2014; Marshall et al., 2023; Panchuk et al., 2018). These systems aim to operationalise cognitive constructs in formats accessible to practitioners and athletes within applied environments (Harris et al., 2018; Renshaw et al., 2019).

Despite this growth, substantial methodological and conceptual challenges remain. A central issue concerns the trade-off between experimental control and ecological validity (Araújo et al., 2007). Laboratory-based EF tasks provide high internal control but often lack representativeness of the perceptual and motor demands of football performance (Pinder et al., 2011). Conversely, video-based or simulated decision-making tasks may enhance visual realism but are frequently constrained by limited perception–action coupling or reduced motor involvement (Dicks et al., 2010; Van der Kamp et al., 2008; van Maarseveen et al., 2018). Consequently, the extent to which such measures capture football-relevant cognitive processes remains debatable. In response to these limitations, interactive and *football-specific* assessment technologies have emerged that attempt to integrate perceptual, cognitive, and motor components within controllable environments (Beavan, 2019). By embedding decision-making within embodied, task-relevant contexts, these systems aim to bridge the gap between laboratory paradigms and real-game behaviour. Theoretical appeal and practitioner interest in such technologies are high, and professional football clubs have increasingly incorporated them into player development and talent selection processes (Beavan, Fransen, et al., 2019; Dolata et al., 2025; Heilmann et al., 2021; Knöbel et al., 2025; Rodrigues et al., 2024).

However, despite increasing adoption within professional environments, comprehensive scientific evaluation of football-specific cognitive testing and training protocols remains limited (Beavan, 2019). Although these technologies hold substantial potential to enable standardised and objective benchmarking of tactical performance, as well as the delivery of structured and scalable cognitive training programmes within football-specific contexts, much of the existing literature has focused on validating individual embedded tasks or reporting reliability metrics in isolation. In contrast, relatively little research has examined integrated assessment and training protocols as they are implemented in applied professional environments under real-world operational constraints.

As a result, the extent to which these systems provide meaningful and sensitive indicators of football-relevant cognitive performance remains insufficiently understood. This situation contrasts with the historical integration of earlier sport technologies, such as GPS and tracking systems, which underwent extensive phases of validation, reliability testing, and contextual refinement before and after becoming embedded within elite performance frameworks (e.g., Buchheit et al., 2014; Malone et al., 2020; Nosek et al., 2021). Their sustained adoption was supported by accumulating evidence demonstrating measurement accuracy, sensitivity to change, and practical utility for informing training prescription and load management. In comparison, football-specific cognitive assessment and training tools remain at a comparatively early stage of evidential maturity. For such systems to achieve equivalent legitimacy and sustained integration within professional football, systematic evaluation of their assessment and training protocols, rather than isolated task characteristics alone, is required within ecologically valid yet methodologically rigorous applied contexts.

1.2 Aims and Objectives

The present thesis aims to provide a comprehensive evaluation of an immersive football-specific cognitive assessment and training device, the SoccerBot360, when implemented within a professional academy environment. Rather than examining isolated embedded cognitive tasks in abstraction, this thesis will evaluate the measurement behaviour, sensitivity, and applied relevance of integrated SoccerBot360 testing and training protocols under real-world operational conditions.

To achieve this overarching aim, the specific objectives were:

- To characterise the cross-sectional performance characteristics of immersive football-specific cognitive assessment protocols, including age- and maturation-related differences in cognitive-motor tasks within an English professional academy population (Chapter 3).
- To determine the extent to which perceived readiness and subjective workload influence performance within the cognitive-motor assessment protocols, thereby evaluating its contextual sensitivity and applied interpretability (Chapter 4).
- To evaluate the effectiveness and responsiveness of a standardised training protocol utilising an immersive football-specific training device on the cognitive-motor performance of skilled youth football players within an elite academy setting (Chapter 5).

Chapter 2. Literature Review

2.1 Introduction

Football performance emerges from the continuous interaction of perceptual, cognitive, motor, and contextual constraints within a dynamically evolving environment (Roca et al., 2013). Contemporary professional football academies increasingly seek to advance talent development and identification processes beyond traditional evaluations of technical execution and physical capacities, incorporating structured assessments of perceptual-cognitive and executive processes that underpin adaptive on-field behaviour (Beavan, Spielmann, & Mayer, 2019; Savelsbergh, 2017). In parallel, technological advances have enabled the development of integrated cognitive-motor testing and training platforms that claim to offer ecologically valid, standardised, and scalable approaches to benchmarking and enhancing performance-related cognitive constructs (Heilmann et al., 2021; Knöbel & Lautenbach, 2023; Musculus et al., 2022).

Despite this growth, important conceptual, empirical, and methodological questions remain unresolved (Beavan, 2019). It is not always clear which mechanisms are being measured, how decision-making and related cognitive constructs are operationalised, to what extent laboratory-derived paradigms generalise to representative football contexts, and whether current tools demonstrate sufficient reliability, validity, and sensitivity for applied use within professional settings. Moreover, factors such as age, maturation, physical and mental states of players, as well as task constraints complicate both interpretation and practical implementation (Beavan, Spielmann, et al., 2020; Gilbert et al., 2025; Scharfen & Memmert, 2019a; Travassos et al., 2013).

Accordingly, this chapter critically synthesises literature across three interconnected domains: (i) the characteristics of decision-making in football and the environmental constraints in which it emerges; (ii) the perceptual-cognitive and executive mechanisms proposed to underpin skilled behaviour in football; and (iii) the assessment and training

modalities, including emerging integrated technologies, designed to measure and develop these capacities. Through this synthesis, this chapter identifies key theoretical, methodological, and applied gaps that frame the rationale for the empirical studies presented in this thesis.

2.2 Characteristics of Decision-Making in Football

Decision-making in football does not occur in static or isolated conditions, but within a dynamic, adversarial, and continuously evolving environment defined by spatial constraint, temporal pressure, and interpersonal coordination (Heisler et al., 2023). Players must interpret complex visual information, anticipate actions, and regulate their own motor responses, while the affordance landscape changes moment-to-moment (Ashford et al., 2021; Craig & Watson, 2011). Thus, before examining the cognitive mechanisms proposed to underpin skilled football performance, it is important to first characterise the dynamic environmental context within which decisions are made.

2.2.1 Perceptual Information

Human decision-making relies fundamentally on the active gathering and processing of perceptual information from the environment. Foundational frameworks in cognitive science describe this as a dynamic cycle, where individuals continuously sample sensory cues (Neisser, 1967) and accumulate them as evidence (Gold & Shadlen, 2007) to detect possibilities for action (Gibson, 1979). Similarly, observational studies have demonstrated that skilled football players perform more exploratory behaviours (e.g., head turns; scanning) before performing technical actions, such as ball receptions or passes (Aksum, Pokolm, et al., 2021; Jordet et al., 2020), and that these behaviours are significantly associated with action success rates (Jordet et al., 2020; McGuckian et al., 2019; Pokolm et al., 2022).

To understand the mechanisms underpinning these exploratory behaviours, laboratory-based research has examined key perceptual information relevant to skilled performance, using video-based tasks and eye-tracking systems (Williams & Davids, 1998; Williams et al., 1994). These studies show that football players utilise multiple informational sources, including the ball, opponents, teammates, and space (Roca et al., 2011; Vaeyens et al., 2007). Moreover, attentional distributions shift according to task constraints. For example, when the ball was distant, players allocate more viewing time to teammates, opponents, and space, whereas when the ball is proximal, they prioritise the ball carrier while plausibly relying on peripheral vision for off-ball monitoring (Roca et al., 2013) to extract kinematic cues such as hip orientation and foot angle (Savelsbergh et al., 2002; Williams & Davids, 1998). More recently, research replicating these approaches in competitive 11 vs. 11 match play has demonstrated comparable visual stimuli that players fixate, with attention distributed across multiple areas of interest during both offensive and defensive phases (Aksum et al., 2020).

In addition to player-related cues, the physical characteristics of ball flight can also influence perceptual judgments during play. For example, ball trajectories altered by sidespin can bias judgments of the ball's future arrival location (Craig et al., 2006). Together, these findings highlight that the informational value of available stimuli is not fixed, but dynamically shaped by task constraints and situational context, requiring players to continuously recalibrate where and how they allocate visual attention to support effective decision-making during match play.

2.2.2 Spatial Constraints

Beyond individual perceptual cues, decision-making is largely regulated by the spatial constraints created by the collective movement of both teams. As teams transition between attacking and defending phases, attacking teams expand space to create passing

options, while defending teams compress space to restrict them, directly influencing the solutions available to the ball carrier and surrounding players at any given moment (Frencken et al., 2011). Therefore, football players should constantly perceive and exploit dynamic spatial affordances, such as the sudden opening of passing lanes, the availability of half-spaces, or vulnerable areas behind defensive lines (Rein et al., 2017). In football, this spatial value can be characterised by the relative location of the ball, closeness to the opposition goal, and the degree of territorial control, which is largely influenced by the density of opposing players within a given area (Fernandez & Bornn, 2018).

In line with the findings of Roca et al. (2013), the proximity of the ball, opponents, and teammates significantly influences players' perceptual-cognitive processes and subsequent behavioural responses during match play. As such, spatial constraints do not merely delimit available options but actively regulate how players search for information and select actions within the game. Related influences have been observed at broader locational levels of the pitch. For example, research examining visual exploratory behaviours has shown that players adjust their scan frequency depending on the area of the field in which they receive the ball (Aksum, Pokolm, et al., 2021; Jordet et al., 2020; McGuckian, Cole, et al., 2020). These location-dependent perceptual behaviours are closely intertwined with the informational value of the surrounding environment. Higher scanning rates have been associated with passes directed towards areas closer to the opposition goal, while action success rates tend to decrease in the opposition half, where defensive pressure and spatial congestion are typically greater (Jordet et al., 2013). Collectively, these findings highlight that players' perceptual behaviour and decision-making are strongly shaped by the spatial and locational constraints that continuously emerge during match play.

2.2.3 Temporal Constraints

In football, the successful utilisation of perceptual and spatial information is bound by temporal constraints. Research in sport expertise consistently emphasises that the ability to make accurate decisions under severe time pressure is fundamental to high-level performance, as players must integrate current situational information with stored tactical knowledge to select appropriate actions in real time (Heisler et al., 2023; Williams & Ford, 2008). Importantly, the effectiveness of decision-making is not just determined by the correctness of the selected option, but also by whether the action is accurately executed within the limited temporal window before the opportunity disappears, and whether it is precisely timed in relation to the continuously evolving situation. Empirical research further indicates that players who generate creative decisions faster than others tend to demonstrate more efficient perceptual-cognitive processing, characterised by shorter fixation durations, more targeted visual search behaviour, and reduced cognitive effort when interpreting game information (Cardoso et al., 2021; Roca et al., 2018; Williams et al., 1994).

Regarding the temporal window, laboratory-based examinations of gaze behaviours in skilled football players have shown that the average duration of eye fixations during video-based decision-making tasks is relatively short, typically ranging from 330–1,000 ms (Helsen & Starkes, 1999; Mann et al., 2009; Roca et al., 2011; Roca et al., 2013). Nevertheless, measurements obtained during competitive 11 vs. 11 football match play reveal even shorter fixation durations, averaging approximately 240 ms (Aksum, Brotangen, et al., 2021). These findings suggest that players in real-game environments perceive and act upon visual information within temporal windows that are substantially shorter than those typically observed in laboratory settings. Collectively, such rapid fixation durations reflect the extremely narrow action windows available to players during competitive match, where perceptual information must be detected, processed, and

translated into motor actions before the opportunity for effective execution disappears. Consequently, decision-making in football is inherently constrained not only by what information is available, but also by when that information emerges relative to the moment at which an action must be initiated.

2.2.4 Perception–Action Coupling

Within dynamic sports such as football, perception and action cannot be meaningfully considered as independent processes. Instead, they are functionally intertwined through what has been described as *perception–action coupling*, whereby perceptual information continuously guides motor behaviour while ongoing actions simultaneously shape the information available for further perception (Gibson, 1979; Warren, 2006). From this perspective, the decisions players make during match play emerge from continuous interactions between the athlete and the surrounding environment rather than from isolated perceptual-cognitive processes that occur prior to movement execution. As players reposition their bodies, adjust orientation relative to other players, or regulate movement speed and direction, they actively modify the perceptual information available to them, which in turn informs subsequent action possibilities (Gibson, 1979).

Empirical research in sport has demonstrated the importance of maintaining the natural coupling between perceptual information and motor responses when studying skilled performance. For example, experimental work comparing representative *in-situ* and non-representative task response designs has shown that restricting or removing the opportunity for action alters how performers use perceptual information when making decisions (Dicks et al., 2010). Similarly, fixation durations during live football matches were substantially shorter than those reported in laboratory-based tasks, where representative physical responses were restricted (Aksum et al., 2020). Although video-based perceptual-cognitive tasks have been shown to detect skill differences in football

players, their reliability for identifying more subtle within-group differences appears limited, raising concerns about their suitability for studying perceptual-motor expertise when movement responses are constrained or removed (van Maarseveen et al., 2018). Therefore, when representative motor actions are restricted or simplified, the perceptual processes observed in experimental tasks may not fully reflect how information is utilised during real match play.

Furthermore, the action possibilities that players perceive are largely constrained by their own movement capabilities. In ecological terms, these opportunities are described as *affordances*, referring to possibilities for action that emerge from the relationship between the individual and the environment (Fajen et al., 2009; Gibson, 1979). Within football, *affordances* arise from the continuously evolving spatial configuration of teammates, opponents, and the ball, but whether these opportunities are perceived as actionable depends on the player's technical skill, body orientation, movement capabilities, and the time available to execute the action (Fajen, 2007). For example, a passing lane that appears open in the environment may only be perceived as a viable option if the player possesses the technical-physical ability and temporal margin required to execute the pass successfully. Consequently, players tend to perceive and act upon *affordances* that are *functionally achievable* within their own action capabilities (Araújo et al., 2006; Davids et al., 2008). This reciprocal relationship between perception and movement highlights that decision-making in football is shaped not only by the information available in the environment but also by the performer's embodied capacity to exploit that information under the spatial and temporal constraints of the game (Fajen et al., 2009).

Collectively, these perspectives suggest that decision-making in football is best understood as an emergent process arising from the continuous coupling between perception and action, which may be difficult to isolate under controlled conditions

(Williams & Ward, 2007). The informational cues players detect, the spatial opportunities they recognise, and the temporal windows within which they must act are all embedded within an ongoing perception–action cycle. Therefore, understanding this coupling provides an important conceptual foundation for examining cognitive mechanisms that underpin expert decision-making in football.

2.2.5 Risk–Reward Trade-offs and Feedback

Decision-making in football cannot be evaluated solely in terms of whether a chosen action is objectively correct or incorrect. Instead, decisions in invasion sports often involve trade-offs between potential risks and rewards, where multiple action options may be viable depending on the tactical context and strategic priorities of the team (Gonzales et al., 2016). For instance, a player may choose between a conservative pass that maintains possession or a more penetrative pass that carries a higher probability of failure but greater potential attacking value. In this sense, decision quality reflects not only the technical correctness of an action or binary success but also the appropriateness of the risk–reward balance relative to the situational demands of the game (Levi & Jackson, 2018; Raab, 2012).

Importantly, researchers suggest that the outcomes of decisions feedback into subsequent perception and action processes. A recent theoretical model of cognition in football conceptualises each play situation as part of a continuous perception–action cycle, in which players first assess the situation, select and execute an action, and then evaluate the resulting outcome before the next cycle begins (Habekost et al., 2024). This outcome evaluation provides feedback that can influence future perception, attention, and action tendencies. In particular, discrepancies between expected and actual outcomes may modify the likelihood of selecting similar actions in future situations, consistent with

general principles of reinforcement learning and reward prediction error mechanisms (Glimcher, 2011; Schultz, 1998).

Through repeated exposure to match situations, these feedback processes contribute to the development of adaptive decision strategies in athletes. Moreover, successful outcomes based on various contextual factors, such as coach instruction, personal pressure, match scoreline or momentum (Levi & Jackson, 2018), can reinforce the perceptual cues and action tendencies that preceded them, whereas unsuccessful outcomes may lead players to adjust their future choices or risk preferences. As such, football decision-making during match play should be understood not as isolated events but as part of an ongoing learning process in which perception, action selection, and outcome feedback continuously interact across successive play situations (Habekost et al., 2024).

2.3 Underpinning Mechanisms of Expert Decision-Making

The preceding sections outlined the environmental characteristics and constraints that shape decision-making in football. To understand how skilled players successfully navigate these complex environments, researchers have sought to identify the perceptual and cognitive mechanisms that underpin expert decision-making. Broadly, two complementary research traditions have emerged within the sport expertise literature. The first focuses on sport-specific *perceptual-cognitive skills* (PCS), examining how athletes detect and interpret task-relevant information during performance situations. This perspective derives from the expert performance approach, which investigates the perceptual-cognitive processes directly linked to skilled behaviour in representative task environments (Ericsson & Smith, 1991). The second tradition adopts a broader cognitive framework, examining general *executive functions* (EFs) and cognitive component skills that may support athletic performance (Nougier et al., 1991). This line of research

investigates whether athletes demonstrate superior performance in general cognitive processes, such as attentional shift, memory capacity, or inhibitory control (Voss et al., 2010). Together, these perspectives provide complementary insights into the mechanisms that may underpin expert decision-making in football.

2.3.1 Perceptual-Cognitive Skills: The Expert Performance Approach

The expert performance approach focuses on identifying perceptual and cognitive processes that directly support skilled performance in domain-specific contexts (Ericsson & Smith, 1991; Williams & Ericsson, 2005). Within sports, this approach has typically examined how skilled athletes detect, interpret, and utilise task-relevant information when anticipating opponents' actions, selecting responses, or regulating their movements during performance situations (Williams & Ford, 2008). Experimental paradigms developed within this framework often employ sport-specific stimuli, such as video simulations, temporal occlusion techniques, or *in-situ* performance tasks to examine how athletes extract information from the environment and translate it into appropriate decisions (Dicks et al., 2010; McRobert et al., 2011; Roca et al., 2013; van Maarseveen et al., 2018; Ward & Williams, 2003; Williams & Davids, 1998). Although research examining domain-specific cognitive skills in sports often treats *decision-making* as the primary cognitive construct of interest (Kalén et al., 2021), the literature has also extensively investigated a range of other PCS.

2.3.1.1 Anticipation in Football

One of the most extensively studied PCS within this approach is anticipation, referring to the ability to predict future events based on early perceptual cues before the outcome of an action becomes fully observable (Williams & Jackson, 2019). Anticipation enables athletes to overcome the severe spatial and temporal constraints inherent in many sports, allowing them to initiate responses earlier than would be possible if they relied solely on

reactive processing (Abernethy, 1990; Williams & Jackson, 2019). In dynamic team sports, such as football, the ability to anticipate opponent behaviours or the likely evolution of play is widely considered a critical component of skilled decision-making and is often described as the capacity to read the game (Williams et al., 2023).

Early research examining anticipation frequently employed temporal occlusion paradigms, in which video sequences are stopped at specific time points before or shortly after a critical event, requiring participants to predict the likely outcome of the action. Findings from these studies consistently demonstrate that skilled athletes are able to make more accurate predictions earlier in the unfolding action sequence compared with less-skilled performers (Abernethy & Russell, 1987; Jones & Miles, 1978; Williams & Davids, 1998). These skill-based differences suggest that experts are more attuned to advance postural cues emerging from opponents' movements, such as body orientation, limb positioning, and biomechanical characteristics that signal action intentions before ball contact occurs (Savelsbergh et al., 2002; Williams & Davids, 1998). The ability to utilise such early informational cues allows skilled performers to initiate motor responses earlier, thereby increasing the likelihood of successful action execution under severe time constraints (Williams & Jackson, 2019).

Beyond the extraction of postural cues from individual players, anticipation in football is also supported by the ability to recognise patterns within evolving sequences of play. Skilled players appear capable of identifying familiar spatial configurations involving teammates, opponents, and the ball, allowing them to infer likely future outcomes based on stored representations of previously encountered game situations (North et al., 2011). Empirical evidence indicates that expert performers show superior recall and recognition of structured patterns of play compared with less-skilled players, suggesting that experience enables the development of domain-specific knowledge structures that

facilitate rapid interpretation of complex game situations (Williams & Ericsson, 2005). More recent work examining corner-kick patterns further supports this view, demonstrating that skilled players can use early relational information from attacking players' movements to anticipate the likely landing location of the ball, highlighting the importance of pattern recognition processes in anticipation (Ivosevic & Stöckel, 2025).

As such, contemporary perspectives emphasise that anticipation is not underpinned by a single perceptual process but rather emerges from the dynamic interaction of several perceptual-cognitive mechanisms (Figure 2.1). These include the extraction of postural cues, recognition of familiar patterns of play, and the use of contextual information or situational probabilities when predicting likely events (Williams & Jackson, 2019; Williams et al., 2023). Skilled performers are therefore thought to integrate multiple informational sources when generating anticipatory judgments, with the relative importance of each source varying according to task constraints and situational context (Williams, 2009). This dynamic interaction between PCS enables experts to reduce uncertainty in complex game environments and select appropriate responses before critical events fully unfold.

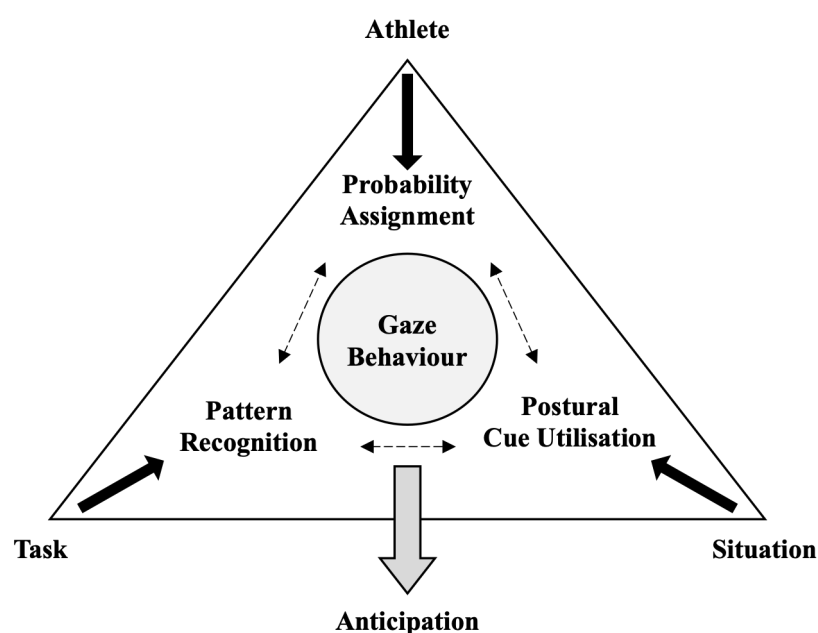


Figure 2.1 The potential interaction between perceptual-cognitive skills and constraints during anticipation processes (adapted from Williams, 2009; Williams & Ward, 2007).

2.3.1.2 Visual Search and Pattern Recognition in Football

Another key PCS examined within the expert performance framework concerns how athletes visually search for and interpret information in complex performance environments. Visual search behaviour refers to the manner in which performers allocate gaze to different areas of the visual field when attempting to extract information relevant for decision-making and action selection (Mann et al., 2007; Williams et al., 1994). Research examining gaze behaviour in sport has shown that skilled performers employ more efficient visual search strategies compared with less-skilled counterparts (Klostermann & Moeinirad, 2020), allowing experts to extract critical information more effectively.

In football-specific contexts, experimental studies using representative video-based simulations have demonstrated that skilled players distribute their visual attention across multiple informational sources, including the ball, teammates, opponents, and available space, rather than focusing narrowly on the ball carrier alone (see Section 2.2.1). For example, skilled players have been shown to employ a broader exploratory strategy, fixating on more locations within the display and extracting information from relational configurations between players and space, whereas less-skilled players tend to exhibit ball-watching behaviour characterised by prolonged fixations on the ball or ball carrier (Roca et al., 2011). These differences in visual search behaviour suggest that expertise is not merely associated with the amount of visual information sampled, but also with the efficiency with which relevant information is identified and utilised to support anticipation and decision-making.

Closely related to visual search behaviour is the ability to recognise patterns of play within evolving game situations. Pattern recognition refers to the capacity to detect structured relationships between multiple elements in the environment, such as the spatial

configuration of teammates and opponents, and to match these configurations with previously stored knowledge acquired through extensive domain-specific experience (Williams & Ford, 2008; Williams et al., 2006). Experimental paradigms examining this ability typically involve presenting athletes with structured sequences of play followed by recognition or recall tasks (Hope et al., 2024). Consistent findings demonstrate that skilled players exhibit superior recall and recognition of structured patterns compared with less-skilled groups, whereas these advantages disappear when the stimuli are randomised or lack meaningful structure (North et al., 2011; Williams et al., 2006).

Recent work has further refined understanding of how experts recognise patterns by examining the relative contribution of local and global relational information within game situations. For instance, research using point-light displays of football sequences has shown that elite players can recognise global patterns of play based on limited relational information between key players, particularly centrally positioned attackers (Hope et al., 2024). These findings suggest that experts encode relationships between players rather than relying solely on individual cues, enabling them to reconstruct broader tactical patterns from minimal information and time constraint. Similarly, studies investigating pattern recall in small-sided game (SSG) scenarios indicate that more experienced players demonstrate greater accuracy when recalling spatial configurations of players and tend to anticipate the future evolution of those configurations more effectively than less experienced players (van Maarseveen et al., 2015).

Collectively, the evidence suggests that visual search behaviour and pattern recognition operate as complementary perceptual-cognitive mechanisms underpinning expert performance. Skilled players not only extract relevant visual cues more efficiently but also integrate that information with domain-specific knowledge structures to recognise familiar patterns and anticipate the likely progression of play. These abilities allow expert

performers to rapidly interpret complex and dynamic game environments, thereby supporting more accurate and timely decision-making during match play.

2.3.2 Executive Functions: The Cognitive Component Skills Approach

In contrast to the domain-specific emphasis of the expert performance framework, the cognitive component skills approach examines whether athletes demonstrate advantages in more general cognitive processes that support goal-directed behaviour across a wide range of contexts (Nougier et al., 1991; Voss et al., 2010). Within this perspective, athletes' cognitive abilities are typically assessed using domain-general cognitive tasks that are decontextualised from sport-specific environments, thereby isolating fundamental cognitive processes rather than PCS embedded within the sporting context. The central premise of this approach is that expertise in sport may be partly supported by superior underlying cognitive abilities that extend beyond the boundaries of the sporting domain itself (Voss et al., 2010).

From this perspective, participation in complex sport environments may place sustained demands on cognitive systems responsible for monitoring multiple information sources, updating rapidly changing situational information, and suppressing inappropriate actions, which could in turn contribute to the development or refinement of underlying cognitive abilities (Miller & Cohen, 2001; Voss et al., 2010). For example, football players are required to track the movements of multiple objects simultaneously, while maintaining awareness of spatial relationships and emerging tactical opportunities, suggesting that the cognitive demands of these environments may promote enhanced attentional and information-processing capacities (Beavan, 2021). Some empirical studies support this view, reporting superior performance in tasks measuring dynamic attentional capacity among high-level athletes compared with non-athlete populations (Faubert, 2013). Such attentional skills are also positively associated with movement effectiveness (e.g.,

accuracy, balance, consistency) and efficiency (e.g., muscular activity, cardiovascular response, force production) (Wulf, 2013), as well as football skills such as dribbling (Scharfen & Memmert, 2019b). However, findings across the literature remain mixed, with other studies reporting negligible differences in attentional tasks between expert athletes and control groups, indicating that the extent to which sport participation influences domain-general cognition remains debated (Memmert et al., 2009; Verburgh et al., 2014).

Within the cognitive component skills approach, increasing attention has been directed towards executive processes as a potential cognitive foundation underpinning skilled performance in sport (Beavan, 2021). EFs are commonly defined as a family of higher-order cognitive processes that include inhibition (INH), working memory (WM), and cognitive flexibility (CF) (Diamond, 2013; Miyake et al., 2000). These processes regulate attention, update information, inhibit inappropriate responses, and flexibly adapt behaviour to meet changing task demands. As such, EFs are considered to play an important role in situations requiring rapid information processing, behavioural regulation, and adaptive decision-making under time pressure, in which characteristics that are central to performance in football (Haugan et al., 2025; Sakamoto et al., 2018; Scharfen & Memmert, 2019a; Vestberg et al., 2012).

2.3.2.1 Inhibition in Football

Inhibition (INH) refers to the ability to suppress dominant, automatic, or prepotent responses when they are inappropriate for current goals or situational demands (Diamond, 2013; Miyake et al., 2000). It includes the regulation of motor responses, interference from irrelevant stimuli, and competing thoughts or actions that may disrupt goal-directed behaviour (Aron, 2011; Friedman & Miyake, 2004). Thus, INH is central to self-regulation, enabling performers to resist impulsive reactions, delay immediate responding

when necessary, and maintain behavioural control under pressure. In applied terms, INH helps individuals avoid acting on the most obvious or habitual response when a more effective alternative is required, particularly in time-constrained and high-interference environments.

In football, inhibitory control is crucial for effective performance, as players are frequently required to suppress premature or suboptimal actions within rapidly changing situations. For example, players may need to inhibit an immediate pass, shot, or defensive challenge in order to wait for a superior option or to avoid being deceived by an opponent's action. Skilled youth football players demonstrated superior motor INH compared with amateur players, suggesting that the ability to suppress ongoing responses may differentiate higher-performing players from an early age (Verburgh et al., 2014). Huijgen et al. (2015) also reported superior inhibitory performance of EF paradigms in youth academy players competing in the highest level in Netherlands, compared with lower level players, with these differences remaining evident after controlling for training volume. Consistent with this, research conducted with highly skilled academy players in Germany demonstrated positive relationships between general inhibitory control, chronological age, and SSG performance, specifically in off-the-ball movement and recovery positioning behaviours (Heilmann et al., 2022).

Nevertheless, caution remains necessary. Although the theoretical and empirical evidence of inhibitory skills in football is consistent and compelling, most studies are cross-sectional and cannot determine whether stronger INH contributes causally to football expertise or instead develops as a consequence of prolonged engagement in demanding football environments. Even so, current evidence suggests that INH may constitute one of the core cognitive functions underpinning skilled performance and decision-making in football.

2.3.2.2 Working Memory in Football

Working memory (WM) refers to the capacity to temporarily maintain, manipulate, and update information in the service of ongoing cognition and goal-directed action (Baddeley, 2000; Cowan, 2014). Rather than functioning as a passive short-term store, it is commonly conceptualised as a limited-capacity system that supports the active retention of task-relevant information while simultaneously allowing new inputs to be integrated and prioritised (Baddeley, 2003; Diamond, 2013). In other words, WM is fundamental to behaviours, such as keeping multiple pieces of information in mind, monitoring ongoing changes in the environment, updating action plans, and coordinating responses when several alternatives must be considered at once (Engle, 2002; Miyake et al., 2000). In dynamic performance settings, this may be especially important for maintaining situational representations over brief periods, integrating present cues with prior task knowledge, and revising these representations as new information becomes available.

In football, WM has been positively linked with key performance attributes, such as technical-tactical abilities, situational awareness, and mental toughness (Glavaš, 2020; Heisler et al., 2023; Scharfen & Memmert, 2019b). Vestberg et al. (2017) reported that EF measures, including a demanding WM task, were associated with success in skilled youth football players, with stronger task performance relating to decisive match performance (i.e., the number of goals the players scored across a competitive season). Similarly, Sakamoto et al. (2018) reported that youth players selected into elite youth academy systems on talent development pathways between ages 8–11 years old outperformed non-selected players on general EF measures, including WM tasks, suggesting that such executive capacities may contribute to higher-level football performance.

However, evidence specific to WM is notably mixed. Several studies have reported no significant differences between skilled and less-skilled players in WM task performance (Huijgen et al., 2015; Verburgh et al., 2014), or no pronounced contribution of this capacity to football performance among skilled populations (Heilmann, Memmert, et al., 2023; Heilmann et al., 2022). These findings suggest that, although WM is theoretically relevant to football, its empirical relationship with football performance may be less robust or less consistently detectable in isolation than that of other EFs. Therefore, it is possible that WM contributes to football behaviour in interaction with other cognitive processes rather than emerging as a strong standalone discriminator of expertise.

2.3.2.3 Cognitive Flexibility in Football

Cognitive flexibility (CF) refers to the capacity to shift between mental sets, task rules, response strategies, or attentional priorities in response to changing environmental demands (Diamond, 2013; Miyake et al., 2000). It enables individuals to disengage from one course of action and adaptively reconfigure behaviour when previously relevant information or rules become less appropriate. Within the literature, CF is often regarded as the most complex of the three core EFs (i.e., INH, WM, CF) because it depends not only on set shifting itself but also on successful updating of relevant information in WM and suppression of previously activated but no longer appropriate responses through INH (Collins & Koechlin, 2012; Miyake et al., 2000). In practical terms, CF supports behaviours such as switching between task rules, revising decisions when new information emerges, and adapting ongoing responses to unexpected events. Accordingly, CF is particularly relevant in open, dynamic environments in which performers must continuously recalibrate behaviour in response to rapidly changing constraints (Diamond, 2013; Friedman & Miyake, 2017).

In football, CF has been proposed as especially important because its primary function aligns with the behavioural demands of the sport, where players frequently transition between attacking and defensive roles, adjust to tactical instructions, and modify decision strategies depending on contextual factors such as ball position or opponent pressure (Heilmann et al., 2022; Sakamoto et al., 2018; Vestberg et al., 2012). Empirical work provides some support for this proposition. In the study of Huijgen et al. (2015), skilled youth football players outperformed less-skilled counterparts on CF measures, while accounting for training hours and academic levels. Similarly, broader work on EFs in football suggests that the ability to flexibly revise or switch responses may contribute to more adaptive tactical behaviour and to the rapid reorganisation of action in complex match situations (Sakamoto et al., 2018; Vestberg et al., 2012).

However, the evidence remains incomplete. Similar to other EF constructs, the existing literature has not established the cause-effect relationship supported by empirical evidence, instead focusing primarily on associations with performance outcomes (Reinhard et al., 2025). Moreover, while some studies indicate that CF may differentiate higher- and lower-performing football players (Vestberg et al., 2012; Vestberg et al., 2017), most studies have relied on broader EF composites rather than isolated CF measures, making it difficult to determine the unique contribution of CF to football performance and decision-making abilities (Heisler et al., 2023; Sakamoto et al., 2018; H. E. Scharfen & D. Memmert, 2021; Vestberg et al., 2012). In addition, a methodological disparity in the measurement of CF exists, as studies employing the same EF paradigm have assessed different cognitive constructs (e.g., Ong, 2015; Radke et al., 2023; Reinhard et al., 2025). Accordingly, although existing evidence suggests that CF is relevant to skilled football behaviour, more precise and longitudinal research is required to clarify the extent to which this function independently underpins expert decision-making.

2.4 Assessment of Cognitive Skills in Football

The assessment of cognitive skills in sports has largely been informed by two distinct research traditions: *domain-specific* and *domain-general* cognitive functions and skills (Kalén et al., 2021). As outlined in Section 2.3, the PCS perspective focuses on the processes through which athletes perceive, interpret, and utilise task-relevant information within representative performance environments (Williams & Ericsson, 2005; Williams & Ford, 2008). In contrast, the cognitive component skills approach examines whether athletes demonstrate superior performance in general cognitive processes, including EFs, using tasks that are typically decontextualised from sport-specific settings (Voss et al., 2010).

From a methodological perspective, these approaches can be further differentiated based on the nature of *task stimuli* and *response modalities*. For example, Kalén et al. (2021) proposed a set of moderator definitions to distinguish between levels of task specificity. General stimuli do not depict sport movements, movement sequences, or contextualised sport situations (but schematic representations of sport situations fall in this category). In contrast, sport-specific stimuli present sport movements, movement sequences, and/or situational contexts, typically through images or video-based displays instead of schematic representations. With respect to response modalities, general responses do not require the execution of sport-specific movements, whereas sport-specific response formats require participants to produce motor actions that simulate performance within a real sport context.

Across the 142 sport cognitive studies included in the recent meta-analysis by Kalén et al. (2021), task designs more frequently employed sport-specific stimuli than general stimuli, whereas response formats were predominantly general rather than sport-specific. This pattern was particularly evident in studies of cognitive decision-making (e.g., skills

to choose among action options, comprising judgment, or anticipation tasks), where most tasks incorporated sport-representative stimuli (88%), while sport-specific response formats remained relatively uncommon (26%). In contrast, studies examining basic cognitive (e.g., processing speed, attention, and short-/long-term memory) and higher-cognitive functions (e.g., EFs) largely relied on generalised task designs in both stimulus (63–79%) and response (82–95%) components. Methodologically, this distribution indicates that the literature has prioritised perceptual and contextual representativeness at the level of stimulus presentation, but to a lesser extent at the level of motor-execution. This discrepancy between stimulus and response formats especially apparent in decision-making research, where tasks often preserve sport-specific informational constraints but simplify the associated action requirements.

The moderator analyses reported by Kalén et al. (2021) further indicate that *stimulus specificity* is more influential than *response specificity* in differentiating higher- and lower-skilled athletes. After controlling for cognitive constructs, tasks using sport-specific stimuli produced significantly larger effects than those using general stimuli, with this difference driven primarily by cognitive decision-making tasks. In this domain, effect sizes were substantially greater under sport-specific compared with general stimulus conditions, whereas no significant differences were observed for basic or higher-order cognitive functions. In contrast, *response specificity* did not significantly moderate effect sizes, despite a tendency for larger estimates in tasks requiring sport-specific responses. However, complementary meta-analytic evidence focusing specifically on decision-making tasks in sport suggests that expertise effects are more consistently observed when participants are required to execute sport-specific actions rather than provide verbal or simplified responses (Travassos et al., 2013). This apparent discrepancy may, in part, reflect the limited number of studies employing sport-specific response designs in the Kalén et al. (2021) analysis, particularly within higher-order cognitive domains, thereby

constraining the strength of conclusions regarding response specificity. Taken together, these findings suggest that enhancing sport-specificity at the level of perceptual information is critical for discriminating expertise, while also indicating that the role of response formats remains underexplored and warrants further empirical investigation.

2.4.1 Domain-Specific Cognitive Paradigms

Domain-specific experimental paradigms in football have predominantly employed stimuli that preserve key spatiotemporal and kinematic characteristics of competitive performance environments. Most commonly, these paradigms have relied on video-based simulations of match scenarios, enabling the systematic examination of PCS under controlled yet representative conditions (Williams & Ford, 2008). Such approaches allow researchers to manipulate informational constraints while maintaining a degree of ecological validity that is not achievable in purely abstract laboratory tasks. Within this framework, two broad strands of research can be identified based on their primary measurement focus: (i) paradigms targeting higher-order PCS, such as anticipation, decision-making, and pattern recognition, and (ii) paradigms examining visual search and gaze behaviours.

2.4.1.1 Higher-Order Perceptual-Cognitive Skills

A substantial body of research has utilised video-based simulations to examine higher-order PCS, including anticipation, pattern recall, decision-making, and creativity (Hadlow et al., 2018). These studies typically present participants with competitive match footage or structured sequences derived from SSG, often filmed from a broadcast or elevated tactical perspective to preserve relational information between players and space (Roca & Ford, 2020; van Maarseveen et al., 2018; van Maarseveen et al., 2015). In addition, a number of paradigms have adopted footage recorded from a first-person perspective of the receiving or defending player, with clips presented on large displays or

virtual reality (VR) environments (Hadlow et al., 2018; Murr et al., 2020; Roca et al., 2011; Roca et al., 2013; Roca et al., 2018; Williams & Davids, 1998). In some cases, schematic or animated (e.g., symbols or point-lights) representations have also been employed to isolate specific tactical patterns (Hope et al., 2024), offering enhanced experimental control through precise manipulation and reliable reproduction of play sequences relative to live-action filming. Under such conditions, domain-specific cognitive constructs may be assessed using comparatively decontextualised stimuli (Kalén et al., 2021).

Across these paradigms, a range of experimental protocols have been developed to systematically assess different components of PCS. One of the most widely used approaches is the temporal occlusion paradigm, in which video sequences are truncated at critical moments prior to action execution (e.g., ball contact), requiring participants to anticipate future outcomes based on advance kinematic and contextual cues (Williams & Ford, 2008). These tasks are typically administered in a trial-by-trial (scenario-by-scenario) format, enabling repeated measurement of response time and accuracy, as well as standardised comparisons across individuals or skill groups. In addition, structured decision-making tasks often require participants to select the most appropriate action from a set of predefined options presented either during or immediately following each clip (e.g., Murr et al., 2020), thereby operationalising decision-making as the selection of an optimal response under constrained conditions.

More open-ended paradigms have also been employed to capture broader aspects of decision-making behaviour. For example, some studies have assessed creative decision-making by evaluating the originality, fluency, and flexibility of responses generated across scenarios (Mummert, 2015; Roca et al., 2018), while others have examined pattern recognition through tasks requiring the reconstruction of player configurations (van

Maarseveen et al., 2018; van Maarseveen et al., 2015) or the recognition of previously presented tactical schematics (Hope et al., 2024). In tasks involving objectively defined response criteria, expert-derived benchmarks (often established by UEFA-qualified football coaches) are typically used to determine the optimality or originality of decisions, thereby providing domain-relevant standards for performance evaluation.

However, despite the use of sport-specific stimuli, many of these paradigms rely on general response modalities (e.g., verbal reports or button-press), thereby decoupling perception from action (Hadlow et al., 2018). Some research suggests that such designs may not reliably reflect on-field performance, particularly when representative motor responses are absent, highlighting the limitations of relying on visual representativeness alone without preserving perception–action coupling (van Maarseveen et al., 2018). This limitation aligns with the findings of Travassos et al. (2013), which highlight the importance of incorporating functional movement responses (e.g., kicking a ball) within experimental designs to more accurately capture applied perceptual-cognitive expertise.

2.4.1.2 Visual Search, Gaze Behaviours

A related line of research has focused on visual search strategies and gaze behaviours underpinning anticipation and decision-making processes. Similar to higher-order PCS paradigms, these studies have predominantly employed video-based simulations of match scenarios, often presented from a player’s perspective to approximate the visual information available during performance (Roca et al., 2011; Roca et al., 2013; Roca et al., 2018; Vaeyens et al., 2007; Williams & Davids, 1998). These stimuli are typically displayed on large screens or immersive environments, allowing participants to engage with life-size representations of play while maintaining experimental control over stimulus presentation (Williams & Ford, 2008).

Across these paradigms, experimental protocols are designed to quantify how performers allocate visual attention to key informational sources within the environment. Most commonly, mobile eye-tracking technology (e.g., Tobii Pro Glasses, Sweden or Applied Science Laboratories, USA) is integrated with video-based tasks to capture gaze behaviour metrics, such as fixation duration, fixation location, number of fixations, and scan patterns (Roca et al., 2013; Vaeyens et al., 2007). In some designs, temporal occlusion is applied to examine how gaze behaviours adapt under varying informational constraints, providing insight into how performers utilise advance cues during anticipation (Roca et al., 2011; Roca et al., 2013; Vater et al., 2016).

More representative approaches have also been employed to examine gaze behaviour under conditions that preserve perception–action coupling. For example, *in-situ* paradigms have embedded participants within controlled set-play scenarios or full 11 vs. 11 competitive match environments, allowing simultaneous measurement of gaze behaviour and motor responses under realistic task constraints (Aksum, Brotangen, et al., 2021; Aksum et al., 2020; Dicks et al., 2010). These designs aim to capture how visual information is used to regulate action in real time, rather than how it is processed in isolation. Consequently, dependent variables in these paradigms extend beyond gaze metrics to include behavioural outcomes, such as movement responses, player-to-ball distance, and following action types (e.g., control, pass, dribble).

Nevertheless, increased representativeness in *in-situ* paradigms introduces a trade-off with experimental control. The integration of perception and action makes it more difficult to isolate specific perceptual-cognitive processes, as observed behaviours reflect the emergent interaction between informational constraints, task demands, and individual action capabilities rather than discrete cognitive components (Araújo et al., 2006; Davids et al., 2008). In contrast, laboratory-based gaze paradigms offer greater control and

precision in measurement but often decouple perception from action by requiring simplified or no motor responses, which may introduce discrepancies between observed behaviours in experimental settings and those expressed during real-world performance (Aksum et al., 2020; Dicks et al., 2010). As such, while gaze-based measures obtained under controlled conditions provide valuable insight into attentional strategies and information pickup, they may not fully capture how visual search processes are functionally integrated with action during performance (Pinder et al., 2011). Therefore, these findings highlight the importance of considering both methodological approaches when interpreting visual search behaviour in football.

2.4.2 Domain-Generic Cognitive Paradigms

Domain-generic cognitive paradigms assess athletes' cognitive abilities using standardised laboratory-based tasks that are largely decontextualised from sport-specific environments. These paradigms are typically grounded in cognitive psychology and neuropsychology, with a particular focus on EFs (Diamond, 2013; Miyake et al., 2000). Methodologically, these tasks are characterised by abstract or symbolic stimuli, constrained response formats, and high levels of experimental control, allowing for the isolation of specific cognitive processes.

These paradigms often employ simplified response modalities, such as paper-and-pencil formats or computer-based button-press (Chan et al., 2008; Diamond, 2013), which serve to minimise motor and contextual demands and reduce extraneous variability unrelated to the targeted cognitive construct (Erb et al., 2025; Foster et al., 2022). This high level of control also enables the precise quantification of temporal performance indices commonly used to infer cognitive processing. In the literature, *reaction time* is often defined as the interval between stimulus onset and the initiation of a response, reflecting the combined duration of stimulus evaluation and response preparation processes

(Houlihan et al., 1994). In more fine-grained paradigms, reaction time can be decomposed into subcomponents, including *initiation time* (time from stimulus onset to movement onset), *movement time* (time from movement onset to response completion), and overall *response time* (RT), which captures the total duration from stimulus presentation to task completion (Erb et al., 2025). This decomposition allows researchers to distinguish between cognitive and motor contributions to performance, with earlier components more closely associated with stimulus evaluation and decision processes, and later components reflecting motor-execution demands.

While temporal performance indices are commonly used in these paradigms, minimising motor involvement is particularly important, as performance measures based on response speed are susceptible to confounding influences from motor execution. For instance, cognitive processing speed is notoriously difficult to assess accurately when tasks rely on timed motor responses, as observed performance may reflect motor constraints rather than underlying cognitive capacity (Pettit et al., 2013). Accordingly, the use of simplified or constrained response modalities in such cognitive paradigms is intended to reduce *noise* introduced by motor variability and enhance the construct validity of cognitive measures (Foster et al., 2022).

Alongside temporal metrics, these paradigms also quantify performance accuracy (i.e., response selection or inhibitory regulation), typically operationalised as binary outcomes (i.e., correct or incorrect) across trials, enabling the calculation of aggregate accuracy rates and error proportions (von Bastian et al., 2020). In tasks involving more continuous or spatially defined responses, accuracy may also be expressed as graded error metrics, such as the deviation between the participant's response and a target stimulus or event. For example, well-established computer-based paradigms such as the Vienna Test System (SCHUHFRIED GmbH, Mödling, Austria) have been used to assess time- and

movement-based anticipation abilities using standardised domain-general tasks, providing an additional perspective on cognitive performance that complements EF measures (Schumacher et al., 2018). Such task performance can be evaluated based on the magnitude of error relative to the actual outcome (i.e., accuracy in hitting a target) (Heilmann et al., 2021; Wulf, 2013).

Together, RT and accuracy measures provide complementary indices of performance, allowing researchers to better characterise underlying cognitive processes. In addition, similar to film-based PCS paradigms, most domain-generic tasks are administered on a trial-by-trial basis, enabling repeated measurement under controlled conditions and facilitating reliable estimation of performance indices. However, as discussed in earlier sections, this reductionist approach also limits the representativeness of perceptual and action demands inherent to football performance. As such, while domain-generic paradigms may provide valuable insight into individual cognitive capacities, their relevance to applied football contexts remains a topic of ongoing debate.

2.4.2.1 Assessment of Inhibition

INH is most commonly assessed using well-established conflict and response inhibition paradigms derived from experimental psychology. Among these, the Stroop task (Stroop, 1935) remains one of the most widely used measures of interference control, requiring participants to suppress an automatic response in favour of a task-relevant response. Within such paradigms, *congruent* conditions involve alignment between task-relevant and task-irrelevant stimulus dimensions (e.g., the word ‘red’ displayed in red ink), facilitating performance, whereas *incongruent* conditions introduce conflict (e.g., ‘red’ displayed in blue ink), requiring suppression of a prepotent response. Performance is typically indexed by slower RT and increased error rates in incongruent relative to congruent trials, reflecting the cognitive cost of resolving stimulus-response conflict.

Variants, such as numerical or size congruity tasks, further demonstrate interference from irrelevant stimulus dimensions (Henik & Tzelgov, 1982). Similarly, the Eriksen flanker task (Eriksen & Eriksen, 1974) assesses inhibitory control by requiring participants to respond to a central target stimulus while ignoring surrounding distractors, with incongruent flankers reliably producing slower and less accurate responses due to response competition. Across these paradigms, INH is operationalised as the suppression of task-irrelevant information or prepotent responses under conflict, typically quantified via RT and accuracy differences.

In addition to interference control tasks, response inhibition is frequently assessed using paradigms such as the Go/No-Go and stop-signal tasks, which withholding or cancelling motor responses. In the stop-signal paradigm, participants attempt to inhibit an ongoing response following a stop cue, enabling estimation of stop-signal reaction time (SSRT) as an index of inhibitory latency (Logan & Cowan, 1984; Verbruggen et al., 2004). These tasks complement conflict-based paradigms by isolating action cancellation rather than stimulus conflict resolution. Evidence suggests that interference control and response inhibition rely on partially distinct yet interacting mechanisms (Verbruggen et al., 2004). Collectively, these paradigms provide controlled measures of inhibitory function.

2.4.2.2 Assessment of Working Memory

WM is commonly assessed using continuous updating paradigms, most notably the *n*-back task, which has been widely employed in both behavioural and neuroimaging research. In this paradigm, participants are presented with a sequential stream of stimuli and are required to indicate whether the current stimulus matches one presented '*n*' trials previously, thereby placing demands on the online maintenance, monitoring, and updating of information (Jaeggi et al., 2010). Task difficulty is systematically manipulated by varying the value of '*n*' (e.g., 1-back, 2-back, 3-back), with increasing load associated

with greater WM demands and typically reflected in reduced accuracy and increased RT. Performance is typically quantified using response accuracy (i.e., hit rates, false alarms) and RT, allowing for the examination of both efficiency and accuracy of updating processes. Despite its widespread use, the n -back task is recognised as a multifaceted paradigm that engages not only WM processes but also additional cognitive functions, including attention, INH, and interference resolution (Jaeggi et al., 2010), and its validity as a pure measure of WM capacity remains subject to ongoing debate (Miller et al., 2009).

In contrast, span-based paradigms such as the Corsi Block-Tapping task (Corsi, 1972), provide a more direct assessment of visuospatial WM capacity. In this task, participants observe a sequence of spatial locations (typically blocks) and are required to reproduce the sequence in either the same or reversed order, with sequence length progressively increasing until failure (Arce & McMullen, 2021). Performance is commonly indexed by the longest correctly reproduced sequence (i.e., Corsi span), providing an estimate of visuospatial storage capacity. Unlike continuous updating paradigms, span tasks emphasise short-term storage and serial recall processes, with backward conditions additionally placing demands on manipulation and executive control (Kessels et al., 2000). These paradigms are widely used in both experimental and clinical contexts due to their relative simplicity and ease of administration, although variations in task implementation and digital adaptations may influence the specific cognitive processes being measured (Claessen et al., 2015). Collectively, n -back and span-based paradigms capture complementary aspects of WM, reflecting differences between dynamic updating processes and capacity-limited storage systems.

2.4.2.2 Assessment of Cognitive Flexibility

CF is most commonly assessed using task-switching paradigms, which examine the ability to shift between different task sets, rules, or stimulus-response mappings. In these

paradigms, participants are required to alternate between two or more tasks, with performance compared between *switch-trials* (where the task changes) and *non-switch-trials* (repeat-trials; where the same task is performed consecutively) (Kiesel et al., 2010). A well-replicated finding is the presence of switch costs, characterised by slower RT and increased error rates in switch relative to repeat-trials, reflecting the cognitive demands associated with reconfiguring task sets and resolving interference from previously relevant rules (Kiesel et al., 2010). These paradigms typically employ simple, abstract classification tasks (e.g., judging digits as odd/even or letters as vowel/consonant), allowing precise measurement of performance under controlled conditions (Rogers & Monsell, 1995). Accordingly, CF is operationalised as the efficiency with which individuals can disengage from a prior task set and engage a new one, often quantified in both RT and response accuracy. As with other domain-generic paradigms, these tasks predominantly rely on simplified, button-press response modalities, which enhance experimental control but may limit the extent to which they capture the dynamic and context-dependent nature of CF required in applied football environments.

2.5 Influential Factors on Cognitive Performance

Cognitive performance is influenced by a range of interacting factors spanning developmental, physiological, and psychological domains (Furley et al., 2023). Within both general cognitive science and applied sport contexts, variables such as age, maturity, fatigue, and psychological states have been shown to shape cognitive performance. Understanding these influences is critical when interpreting cognitive assessment outcomes, particularly in youth academy football environments where performance is evaluated across heterogeneous developmental stages and operational constraints.

2.5.1 Chronological Age

Chronological age is one of the most consistently reported determinants of cognitive performance. Developmental research demonstrates that core EFs emerge in early-childhood and continue to improve throughout adolescence (Best & Miller, 2010). Large-scale lifespan studies indicate that EF development follows a non-linear trajectory, characterised by rapid improvements during adolescence and stabilisation into early-adulthood (Tervo-Clemmens et al., 2023), alongside broader lifespan patterns suggesting peak performance in early-adulthood followed by gradual decline (Ferguson et al., 2021). Importantly, different EF components exhibit distinct developmental timelines, highlighting the need to consider age-related heterogeneity when interpreting cognitive performance (Huizinga et al., 2006).

Within football-specific populations, similar age-related trends have been observed. Longitudinal evidence in highly skilled youth academy players indicates that both domain-generic and domain-specific cognitive abilities improve markedly between 10–15 years of age, with some abilities plateauing during later adolescence despite continued exposure to elite training environments (Beavan, Chin, et al., 2020). Cross-sectional work further shows that chronological age explains substantial variance in EF performance during adolescence (Heilmann et al., 2022). Complementary findings using PCS tasks, such as 360° multiple object tracking, also demonstrate significant age-related improvements in highly skilled youth players, with older age groups outperforming younger cohorts before performance stabilises in later developmental stages (Ehmann et al., 2022).

2.5.2 Biological Maturation

Biological maturation refers to the timing and tempo of progression towards an adult biological state, encompassing structural, hormonal, and neurological development

(Laureys et al., 2021; Malina et al., 2004). During adolescence, maturation is accompanied by substantial changes in brain structure and function, particularly within the prefrontal cortex, which underpins EFs (Johnson et al., 2009; Kolk & Rakic, 2021). These neurodevelopmental processes include synaptic pruning, myelination, and changes in gray and white matter, contributing to more efficient cognitive processing across adolescence (Gilbert et al., 2025). Consequently, age-related improvements in EF observed in developmental research are often interpreted as reflecting underlying neuromaturational processes. Recently, research examining maturation alongside EFs in the general youth population indicates that biological maturity status can contribute to cognitive performance independently of chronological age (Gilbert et al., 2025; Laureys et al., 2021). However, it is important to note that much of this evidence is derived from laboratory-based cognitive paradigms employing constrained response modalities, where motor demands are minimised. Therefore, it may not fully account for the interaction between maturation and motor skills, which may have substantial impact on perceptual and cognitive processes in real-life settings (Leonard, 2016; Shi & Feng, 2022).

Some evidence suggests that maturation is associated with PCS relevant to football performance. For example, maturation has been positively related to peripheral perception and faster responses to visual stimuli in youth football players (Gonçalves et al., 2020), and to improved signal detection and tactical behaviour efficiency in SSG (Gonçalves et al., 2021). However, findings are not consistent across domains. A recent study reported that while biological maturity was a significant predictor of motor performance, it did not significantly influence perceptual-cognitive measures such as visuospatial WM or spatial visualisation (Lola et al., 2026). Similarly, evidence from youth football cohorts suggests that while maturation may contribute to variance in EF, its influence is often smaller or less consistent compared to chronological age and sport-related experience (Heilmann, Memmert, et al., 2023). Collectively, these findings

highlight the potential relevance of biological maturation to cognitive performance. However, despite this link, empirical investigations explicitly examining this relationship remain limited across domains (Gilbert et al., 2025).

2.5.3 Fatigue

Fatigue is a multifaceted construct typically distinguished into physical fatigue, arising from prolonged or intense neuromuscular activity, and mental fatigue, resulting from sustained cognitive effort (Marcora et al., 2009; Rampinini et al., 2008). Both forms have been shown to influence cognitive performance by altering attentional resources, executive control, and information processing efficiency (Almonroeder et al., 2018; Eddy et al., 2015; van der Linden et al., 2003). From a neurocognitive perspective, mental fatigue is associated with reduced activity within prefrontal networks, which underpin EFs (Boksem et al., 2005). In experimental settings, mental fatigue induced through prolonged cognitive tasks has been linked to impairments in decision-making, increased response variability, and slower RT, although effects on accuracy are less consistent (Gantois et al., 2020; Lorist et al., 2005). Similarly, physical fatigue has been shown to influence cognitive performance through both central and peripheral mechanisms, including altered arousal, reduced attentional capacity, and changes in perceptual sensitivity (Almonroeder et al., 2018; Goepp et al., 2024). Importantly, these effects are often task- and metric-dependent (Van Cutsem et al., 2017), with some studies reporting decrements in response speed (Radel et al., 2018), others in accuracy (Goepp et al., 2024), suggesting that fatigue may differentially impact specific components of cognitive processing.

Collectively, existing evidence indicates that fatigue may influence both cognitive performance and motor execution. However, the majority of studies have been conducted under controlled laboratory or experimental conditions, typically inducing fatigue

through standardised cognitive or physically demanding tasks rather than reflecting fatigue accumulated through real-world training, competition, or daily activities. Importantly, qualitative evidence from elite sport contexts indicates that fatigue is perceived by athletes and staff to not only develop acutely but also accumulate over time through repeated exposure to cognitive, emotional, and environmental demands (Russell et al., 2019). These demands may arise from a wide range of sources, including training, competition, media, and lifestyle factors, highlighting that fatigue in applied settings is multidimensional and less controllable than in experimental paradigms. As such, the extent to which naturally occurring physical and mental fatigue experienced by athletes influences cognitive performance and subsequent behavioural responses remains unexplored in the literature.

2.5.4 Motivation and Emotions

The foundational review in psychology conceptualises cognitive control as inherently embedded within motivational decision-making processes (Botvinick & Braver, 2015). Rather than being deployed automatically, cognitive control is proposed to reflect a cost–benefit computation in which the expected value of exerting control is weighed against its associated effort demands. This framework suggests that the engagement of executive processes is contingent upon the perceived utility of task performance, aligning with reward-based models of control allocation. At the neural level, motivational incentives have been shown to modulate cognitive processing through interactions between prefrontal control systems and dopaminergic reward pathways, influencing functions such as active maintenance in WM, preparatory attention, and goal-directed decision-making (Braver et al., 2014).

Empirical evidence further demonstrates that both extrinsic and intrinsic motivational factors can shape cognitive control dynamics. For example, reward incentives have been

shown to enhance proactive control by facilitating anticipatory task preparation and reducing interference effects in paradigms such as task-switching and flanker tasks (Yee & Braver, 2018). Beyond externally manipulated incentives, individual differences in intrinsic motivation, such as achievement motivation, have also been shown to modulate cognitive control adaptations. Specifically, individuals with higher achievement motivation demonstrate more efficient conflict-driven adjustments in attention and response selection compared to those with lower motivation (Zhao et al., 2018). Collectively, these findings suggest that motivation may operate as a central mechanism regulating when, how, and to what extent cognitive control processes are engaged, rather than merely acting as an external modulator of performance outcomes.

The neuroscience literature further emphasises that cognition and emotion are not separable systems but arise from integrated and dynamically interacting neural networks, whereby affective and cognitive processes jointly shape behaviour, rather than operating independently (Pessoa, 2008). From a functional perspective, emotional states can influence core executive processes such as attention, WM, and INH by altering the allocation of cognitive resources and the salience of task-relevant information (Schmeichel & Tang, 2015). However, recent evidence indicates that key emotional dimensions, valence (positive vs. negative) and arousal, can both facilitate and impair EF performance depending on task demands, emotional intensity, and individual differences (Hou & Cai, 2022; Lautenbach, 2025). For instance, heightened arousal may enhance attentional focus under certain conditions, while excessive or task-irrelevant emotional activation may disrupt goal-directed processing. Accordingly, the effects of emotion on EFs appear highly context-dependent, reflecting dynamic interactions between affective states, cognitive demands, and environmental constraints.

2.6 Training of Cognitive Skills in Football

The training of PCS and EF (also referred to as brain training; Renshaw et al., 2019) in sports has received increasing attention with the emergence of both sport-specific and domain-general training approaches. Within the sport science literature, domain-specific PCS training methods are designed to enhance abilities such as anticipation, decision-making, and visual search through structured exposure to sport-specific stimuli, including video-based simulations, temporal occlusion paradigms, and scenario-based decision-making tasks typically using match footage (Broadbent et al., 2015). These approaches are often implemented in controlled off-field environments (e.g., large-screen or VR-based systems), with athletes required to make perceptual judgements or verbal/motor responses to evolving game situations. In doing so, they aim to replicate key informational and temporal constraints of performance while reducing physical load (Broadbent et al., 2015; Thatcher et al., 2021).

However, despite the development of structured PCS training paradigms, training activities targeting decision-making and broader tactical understanding in professional football are more commonly delivered through performance analysis formats (outside of on-pitch coaching), particularly via video-based feedback sessions (Farrow, 2014; Mackenzie & Cushion, 2013). These typically involve the presentation of match and training footage to either individual or a group of players in meeting-room settings, where coaches and analysts highlight key tactical moments, facilitate discussion, and provide corrective or reinforcing feedback (Groom et al., 2011; Wright et al., 2016). While these practices are central to applied football, they are rarely conceptualised or implemented as formalised *cognitive training* interventions, and typically involve less experimental control and standardisation than research-based paradigms. In applied settings, *cognitive training* is commonly delivered through computerised, domain-generic paradigms via repetitive and adaptive tasks (e.g., multiple object tracking or response inhibition tasks),

often presented in gamified formats (Lumsden et al., 2016). These interventions are typically administered through commercial cognitive training tools, often in screen-based environments (Harris et al., 2018; Renshaw et al., 2019).

Nevertheless, the effectiveness of such cognitive training remains a subject of ongoing debate, particularly regarding whether improvements transfer to real-world performance (Broadbent et al., 2015; Fransen, 2024). A growing body of evidence suggests that training effects are often highly task-specific, with limited generalisation beyond the trained context, especially in domain-general cognitive training (Gobet & Sala, 2023). In response, contemporary frameworks have emphasised the importance of task design characteristics, including the nature of stimuli and responses, as well as the training dosage, in determining the likelihood of meaningful skill transfer to sport performance (Hadlow et al., 2018; Walton et al., 2018). As such, understanding how cognitive skills can be effectively trained in football requires consideration of several key factors underpinning training design and implementation.

2.6.1 Cognitive Training Modalities

Cognitive training in football can be delivered through a range of modalities that differ in the nature of the stimuli presented, the response requirements imposed on the athlete, and the extent to which perception–action coupling is preserved (Harris et al., 2018). Importantly, many of these modalities are also commonly used for assessment purposes, reflecting a substantial overlap between training and testing approaches within the cognitive performance literature (Guo et al., 2025). The distinction between training and assessment is often determined more by task structure, feedback provision, and intended outcomes than by the underlying technology or paradigm itself. Accordingly, the following section reviews key cognitive training modalities based on their defining task

characteristics, with particular attention to how each modality constrains perception, information processing, and action execution.

2.6.1.1 Video-Based Cognitive Training

Video-based training represents one of the most established modalities for developing PCS in sports and is predominantly aligned with domain-specific PCS paradigms (Broadbent et al., 2015). Consistent with the testing methods described in Section 2.4, these approaches typically involve the presentation of match footage or structured game scenarios from broadcast, tactical, or first-person perspectives, with sequences often manipulated through temporal occlusion or editing to control the availability of advance information (Farrow, 2014; Hadlow et al., 2018). Tasks are commonly delivered in controlled, off-field environments (e.g., meeting room or laboratory settings), where players observe evolving situations and provide responses through verbal reports, written selections, or simulated sport actions, such as kicking a stationary ball (Hadlow et al., 2018).

The defining characteristic of video-based modalities is the reliance on representative visual stimuli combined with relatively constrained response formats. These tasks typically preserve key informational variables, such as player positioning, movement patterns, and spatiotemporal relationships (Farrow, 2014). Accordingly, perceptual processing is primarily centred on visual information, with action components simplified or separated from the broader movement context of performance. In applied settings, video-based approaches are frequently embedded within conventional performance analysis processes (Farrow, 2014), where coaches guide attention towards specific cues and facilitate reflective discussion rather than requiring real-time decision execution (Groom et al., 2011).

2.6.1.2 Computerised Cognitive Training

Computerised cognitive training represents a widely adopted modality characterised by the use of digital platforms to deliver structured tasks targeting specific cognitive processes, such as EFs (Owen et al., 2010). These interventions are often positioned as cost-effective and scalable alternatives to traditional face-to-face formats, offering flexible, individualised, and easily accessible training environments (Kueider et al., 2012). In contrast to coach-led approaches, computerised systems enable self-paced engagement, real-time feedback, and automated adjustment of task difficulty, allowing standardised yet adaptive training protocols. Tasks are typically delivered in controlled, screen-based environments using abstract or simplified stimuli, with responses executed through constrained input devices such as keyboards, mice, or touchscreens (Harris et al., 2018).

From a task design perspective, computerised cognitive training is characterised by repetitive, trial-based structures requiring rapid responses to visual or symbolic cues under tightly controlled temporal conditions. For example, systems such as IntelliGym (ACE Applied Cognitive Engineering Ltd, USA) utilise (football) game-like environments with schematic representations of spatial and tactical information, requiring interaction via keyboard or mouse inputs (Savelsbergh, 2017), while tools such as NeuroTracker (CogniSens Athletics Inc, Canada) involve tracking multiple moving targets using 3D visual displays and responding through selection-based inputs (Moen et al., 2018; Romeas et al., 2016). Similarly, commercial training programmes targeting general attentional abilities and EFs are accessible via mobile devices, where users engage in gamified cognitive tasks (Harris et al., 2018; Heilmann, Formenti, et al., 2023). Across these approaches, interaction is typically discrete rather than continuous, feedback is immediate, and task demands are centred on isolated perceptual-cognitive processing within highly controlled environments.

2.6.1.3 Virtual Reality

VR refers to the use of computer-generated, 3D environments (or 360° video presented in a VR headset; Le Noury et al., 2022) that allow users to interact with simulated spaces in real time, typically through immersive displays and sensory interfaces (Slater & Sanchez-Vives, 2016). Within sport contexts, VR-based cognitive training applies this technology to the design of structured tasks intended to develop perceptual-cognitive processes under controlled yet visually enriched conditions (Gray, 2019). These systems are commonly delivered through head-mounted displays, with visual scenes updated in real time in response to user inputs (Hadlow et al., 2018; Thatcher et al., 2021). Compared to 2D screen-based task presentations, VR can provide greater fidelity of visual perception. Specifically, these systems offer heightened immersion alongside more accurate depth perception and judgment of spatial proximity between simulated objects (Kittel et al., 2019; McIntire et al., 2014; Slater, 2009). However, its visual correspondence, defined as the extent to which presented stimuli resemble those encountered in real-world competition, is substantially influenced by the quality of graphical rendering and simulation within the system (Connolly et al., 2025).

From a task design perspective, VR-based training is characterised by the integration of dynamic visual stimuli, which may be sport-specific or general, with interactive yet constrained response modalities. Conceptually, VR football systems integrate immersive scene construction, avatar modelling, motion capture or positional tracking, and interactive interfaces to simulate game scenarios and movement patterns (Zhao & Guo, 2022). Players are typically required to scan the environment and select responses through handheld controllers or simulated sport-specific actions (Fortes et al., 2021; Thatcher et al., 2021; Zhao & Guo, 2022). For example, VR-based heading tasks immerse players in simulated ball-flight environments in which they time and coordinate movement

responses without physical ball contact, thereby preserving selected perceptual and temporal features while simplifying the physical execution demands (Marshall et al., 2023). As such, VR modalities can be positioned between traditional video-based and more fully embodied training approaches, combining increased perceptual immersion with constrained action execution within controlled environments.

2.6.1.4 Cave Automatic Virtual Environment (CAVE)

The sport science literature has seen a growing number of studies investigating immersive technologies, including augmented reality (AR), mixed reality (MR), and VR (see Milgram & Kishino, 1994 for definitions), for training and assessment purposes (Wirth et al., 2022). Within this broader spectrum, Cave Automatic Virtual Environment (CAVE) systems represent one such approach (Le Noury et al., 2022). CAVE is characterised by projection-based immersive environments in which visual scenes are displayed on multiple surrounding surfaces, allowing users to perceive and interact with virtual content while maintaining natural body movements (Cruz-Neira et al., 1993). These systems typically consist of room-scale, partially or fully immersive wall-projection setups that provide stereoscopic visualisation and wide fields of view, enabling users to move freely within the environment and explore dynamic visual scenes from a first-person perspective (Figure 2.2). Compared to conventional screen-based displays (e.g., Farrow, 2014), these systems allow athletes to become more immersed in the performance environment, which may enhance the representativeness of task presentation by more closely approximating real-world perceptual conditions (Williams & Ericsson, 2005).

Within football contexts, CAVE systems have been utilised to examine and train PCS under more representative spatial conditions compared to traditional monitor- and screen-based tasks. For example, simulated football environments presented within this format allow players to track teammates and opponents while moving within the space,

introducing additional perceptual and motor constraints associated with real-game situations (Vu et al., 2026). Similarly, immersive large-scale projection systems, such as the Helix (Anton Paar SportsTec GmbH, Austria; Figure 2.2), have been employed in professional environments to deliver both domain-specific and general cognitive training tasks, including multiple object tracking and attention-based exercises, within fully or semi-immersive environments that extend beyond traditional screen-based paradigms (Ehmann et al., 2022; Krupitzer et al., 2022).

A recent review on technology-based football training by Jia et al. (2024) has classified cognitive training that incorporates football-specific motor execution, such as passing and dribbling (e.g., Heilmann et al., 2021), within the category of CAVE environments. Despite their shared use of immersive projection-based formats and positioning within the same CAVE spectrum, football-specific training systems that integrate full football-action response modalities, rather than controller- or button-based inputs, are reviewed separately in the following section.



Figure 2.2 Image of the Helix-Arena, a CAVE system utilised in a professional football context (TSG 1899 Hoffenheim, 2020).

2.6.1.5 Football-Specific Cognitive-Motor Training Technology

Alongside immersive and projection-based systems, a growing number of football-specific technologies have been developed to integrate perceptual-cognitive processing with sport-specific motor execution within a single training environment (Figure 2.3). Early conceptualisation of such systems can be traced to Beavan (2019), where these training and testing modalities were collectively described as *football-specific assessment tools*. However, this terminology has not been widely standardised, and subsequent research has largely examined individual technologies in isolation rather than as a coherent category or under broader classifications (e.g., Jia et al., 2024). This modality is characterised by real-time coupling of perceptual stimuli and executable football actions (Beavan, 2019), although task structure, stimulus design, and player interaction differ across systems.

For example, the Footbonaut (CGoal, Germany; Figure 2.3a), one of the most extensively studied football-specific systems, operates within an immersive 360° environment. Players receive balls projected from multiple directions at programmable speeds and trajectories. Responses are directed towards illuminated target gates without simulated game visuals. The system primarily constrains perception through light-based cues while maintaining high variability in ball delivery (Beavan, Fransen, et al., 2019; McGuckian, Beavan, et al., 2020; Saal et al., 2018). Similarly, the Okkulo system (Okkulo Ltd, UK; Figure 2.3b) operates within a frontal (goal-facing) configuration rather than a full 360° setup. Balls are projected from forward directions, and responses are directed towards illuminated targets without simulated contextual visuals. The system uniquely manipulates visual processing by altering spectral lighting conditions and intensities, targeting cone and rod photoreceptor activity to influence visuomotor response speed (Rodrigues et al., 2024).

In contrast, other systems incorporate simulated perceptual stimuli within immersive environments. The SoccerBot360 (SB360; Umbrella Software Development GmbH, Germany; Figure 2.3c) uses a circular 360° projection wall onto which task stimuli are displayed, with players responding by passing the ball against the wall (Heilmann et al., 2021). Both visual and auditory stimuli can be systematically manipulated via software, enabling integration of varying cognitive tasks with football-specific actions. The Skills.Lab Arena (Anton Paar SportsTec GmbH, Austria; Figure 2.3d) extends this approach within a large-scale, multi-directional environment. Unlike the SB360, it integrates ball-projection systems, alongside large visual simulation screens and motion tracking technologies. Players perform tasks involving passing, shooting, dribbling, and ball control under dynamic scenarios, allowing simultaneous assessment of technical execution and motor-cognitive performance (Dolata et al., 2025).

Collectively, these technologies are characterised by the integration of perceptual stimuli with football-related motor actions within the same task environment, distinguishing them from previously reviewed modalities that typically isolate cognitive processes or rely on simplified response formats. However, as outlined above, the degree of representativeness varies across systems depending on how perceptual information, task constraints, and response demands are designed and coupled.



Figure 2.3 Football-specific training and assessment technologies. (a) Footbonaut (Borussia Dortmund, n.d.), (b) Okkulo (Okkulo Ltd., n.d.), (c) SoccerBot360 (Norwich City Football Club, 2021), and (d) Skills.Lab Arena (FC Bayern München, 2021).

2.6.2 Dose–Response Relationship

Evidence regarding the dose–response relationship of cognitive training in sport remains largely limited, particularly in skilled populations (Walton et al., 2018). Although cognitive training is increasingly used in applied settings, there is little direct evidence establishing how much training is required, how often it should be delivered, or how dosage should differ across training modalities. This limitation is especially clear for video-based and football-specific technology-based training interventions, where published work has largely focused on task design, validity, or acute effects rather than systematic manipulation of session duration, weekly frequency, or intervention length. Previously, Walton et al. (2018) have suggested cognitive training designs targeting athletic performance (supervised training 2–3 times a week, 40–60 min per session). However, they also acknowledged that these suggestions were primarily based on their personal reflections rather than empirical evidence base. As such, no robust dosage recommendations can currently be derived for most football-relevant cognitive training systems (Harris et al., 2018).

The clearest dose-related evidence comes from the broader computerised cognitive training literature, although it is derived primarily from non-athletic, clinical, or older populations, and existing evidence still provides some tentative reference points. In healthy older adults, computerised cognitive training appears most effective when delivered in sessions of at least 30 min, no more than three times per week, with group-based rather than unsupervised home-based administration (Lampit et al., 2014). Clinical dose–response work suggests that, in adults aged 40 to under 60 years with mild cognitive impairment (MCI), optimal cognitive gains are at around 25 to <30 min per day, 6 days per week (Liu et al., 2024). Similarly, Vander Zwalm et al. (2025) indicated that at least 10 sessions (15-min per day) may be required before depression-related cognitive control training effects emerge. Broader non-pharmacological intervention research in MCI further suggests that cognitive interventions are often effective when delivered 1–2 times per week, for 60–120 min per session, over a minimum duration of 12 weeks under supervision (Shao et al., 2022).

A similar pattern is evident in the broader VR-based literature. Some recent studies suggest that VR can be used to deliver structured cognitive or cognitive-motor training, including in athletes, but the evidence base remains small and heterogeneous. For example, Casella et al. (2024) reported improvements following a 5-week VR reaction training protocol using 30-min sessions once per week, while Anguera et al. (2025) described a 10-week intervention involving 24 sessions that combined VR- and tablet-based cognitive training in junior tennis players. More broadly, Gonzalez-Fernandes et al. (2025) showed benefits of a 6-week VR mental skills intervention in highly skilled athletes. However, these studies do not establish a clear dose–response curve. In addition, most available VR dose-related evidence still comes from non-sport populations, such as older adults or clinical groups (e.g., Liao et al., 2019; Navarro-Ramos et al., 2025; Wu & Zhang, 2025; Yu et al., 2024).

In contrast to the broader cognitive training literature, the optimal dose for football-specific cognitive-motor training technologies remains largely undefined. To date, only two intervention studies have been published within this domain. Heilmann et al. (2021) examined cognitive-motor performance following 12-month SB360 training interventions. However, they did not employ a control group and standardise training frequency and session duration. In contrast, Rodrigues et al. (2024) reported a 6-week intervention using the Okkulo system that consisted of two weekly 30-min sessions, demonstrating improvements in several visual and visuomotor measures. However, despite this clearer dosage prescription, the underlying task characteristics, response modalities, and targeted cognitive skills for training differ substantially from other systems, particularly in terms of visual manipulation strategies and motor interaction constraints.

Overall, the strongest evidence regarding dose–response relationships in cognitive training derives from computerised and VR-based interventions in non-athletic, clinical, and older populations, whereas evidence from sport science research remains limited across all training modalities. Importantly, the broader literature indicates that optimal training dose is both population-dependent and sensitive to the specific cognitive processes targeted, suggesting that findings from one context may not be readily generalised to others. Consequently, there is a clear need for intervention research in football that systematically manipulates session duration, frequency, and programme length across different technologies before dosage prescriptions can be considered empirically grounded. In the absence of such evidence, it may be more appropriate to draw transferable insights from existing research in terms of study design, analytical approaches, and interpretation frameworks, rather than attempting to directly generalise dose-related findings across populations, modalities, and cognitive domains.

2.6.3 Challenge Point

The Challenge Point Framework (CPF), proposed by Guadagnoli and Lee (2004), provides a theoretical basis for understanding how task difficulty influences learning. The CPF posits that optimal learning occurs when practice conditions are matched to the learner's skill level such that the task provides an appropriate amount of functional difficulty, defined as the information available to the performer that can be meaningfully processed and used to improve performance (Guadagnoli & Lee, 2004). Within this framework, nominal task difficulty reflects the inherent demands of the task, whereas functional difficulty emerges from the interaction between task demands and individual characteristics, such as skill level, experience, and current state. Accordingly, learning is expected to be constrained when tasks are too simple, due to insufficient informational challenge, but also when tasks are overly complex, as performers may be unable to extract and utilise relevant information. This perspective highlights the importance of calibrating task difficulty to optimise learning rather than immediate performance, particularly in complex and dynamic domains (Farrow & Robertson, 2017; Soderstrom & Bjork, 2015).

In the context of cognitive training, challenge points have clear relevance, as many training tasks are designed by manipulating stimulus complexity, temporal constraints, and response demands. In the general cognitive training literature, increasing task difficulty through adaptive algorithms (e.g., computerised *n*-back tasks) has been associated with improvements in cognitive performance, suggesting that maintaining an appropriate level of challenge may facilitate cognitive adaptation (Jaeggi et al., 2008; Klingberg, 2010). However, when examining cognitive-motor tasks in sport-specific contexts, the relationship between task difficulty and learning outcomes appears more complex. For example, increasing task difficulty has been shown to influence perceptual and cognitive effort, but without clear differentiation between difficulty levels in learning outcomes (Taghi et al., 2025). Similarly, recent motor learning research suggests that

higher task difficulty does not necessarily produce superior learning effects compared with easier task settings and may even suppress the benefits of other learning mechanisms, such as autonomy and cognitive engagement (Bright et al., 2025). These findings contrast with the more linear assumptions often implied in general cognitive training paradigms (e.g., Jaeggi et al., 2008; Klingberg, 2010) and highlight the complexity of applying challenge-based principles within dynamic cognitive-motor environments.

Consistent with this, recent reviews emphasise that, despite its theoretical relevance, the application of the CPF to cognitive training remains underexplored, particularly in ecologically valid sport settings (Thomas et al., 2025). Importantly, the application of such frameworks to sport-specific cognitive-motor training is further complicated by the multidimensional nature of task difficulty. In sports like football, challenge is not determined solely by cognitive load, but by the interaction of perceptual-cognitive and motor demands. Accordingly, the same nominal task may impose different functional difficulty depending on how these constraints are configured and on the capabilities of the performer. Contemporary skill acquisition frameworks emphasise that effective practice design should balance challenge with representativeness and transfer, ensuring that increased difficulty remains functionally relevant to performance contexts (Hodges & Lohse, 2022; Williams & Hodges, 2023). Collectively, despite strong theoretical support, there remains a lack of empirical evidence examining how task difficulty should be systematically manipulated within cognitive training interventions in football.

2.6.4 Skill Transfer

A central issue in cognitive training is not simply whether performance improves on the trained task, but whether such gains transfer beyond the training context to other tasks. In sport, this question is particularly important, as cognitive training is often justified by its presumed impact on in-game behaviour (Fransen, 2024). Moreover, although there is a

growing body of research demonstrating that PCS can be trained, relatively few studies have successfully translated these findings into training tools that are consistently accessible and practically useful for coaches and athletes in applied environments (Belling & Ward, 2015).

Skill transfer is typically distinguished as near or far. *Near transfer* refers to improvements in tasks that are structurally similar to the trained activity, whereas *far transfer* refers to improvements in more distally related tasks or real-world outcomes (Sala et al., 2019). In the cognitive literature, near or far transfer remains limited (Gobet & Sala, 2023). A large-scale review has shown that domain-general cognitive training reliably improves performance on trained tasks, with weaker and inconsistent effects on closely related tasks, and little evidence for generalisation to broader cognitive or everyday functions (Simons et al., 2016). Similarly, controlled intervention research has demonstrated that, despite substantial improvements during training, no meaningful transfer to untrained cognitive domains is observed (Owen et al., 2010). Even in cases where transfer has been reported (e.g., WM training improving fluid intelligence; Jaeggi et al., 2008), these effects appear highly dependent on the amount of training and task similarity, which reinforces the importance of shared underlying processes. More recent large-scale trials further suggest that improvements in targeted cognitive functions do not necessarily translate to broader behavioural or neural outcomes, providing strong evidence for limited far transfer from general cognitive paradigms (Ganesan et al., 2024).

A similar pattern is evident in sport. Empirical research examining cognitive training in football and other dynamic sports has reported improvements in trained tasks, but limited evidence for transfer to sport-specific performance. For example, PCS training in a 360° CAVE environment improved task-specific performance but did not transfer to either related perceptual-cognitive measures or football performance outcomes (Ehmann et al.,

2022). Likewise, commercial cognitive training tools, such as NeuroTracker, has demonstrated improvements in the trained task without corresponding gains in general EF measures, suggesting limited generalisation beyond task-specific demands (Moen et al., 2018). These findings are consistent with broader sport cognition literature indicating that training effects are typically narrow, with adaptations closely aligned to the specific informational and task constraints of the training environment rather than general cognitive enhancement (H.-E. Scharfen & D. Memmert, 2021).

Collectively, these findings suggest that skill transfer in cognitive training is highly constrained by the similarity between training and performance demands. In the context of football, this implies that improvements in isolated cognitive tasks should not be assumed to generalise to on-field behaviour without sufficient correspondence in perceptual-cognitive and motor-execution constraints (van Maarseveen et al., 2018). As such, transfer should be considered in relation to the representativeness of the task, the preservation of perception–action coupling, and the extent to which the training environment affords functional behaviours relevant to performance. However, it remains difficult to measure these components collectively under standardised and controlled conditions in football, while preserving their natural properties (Williams & Ford, 2008). From this perspective, the critical question may not be simply whether cognitive training transfers in a broad sense, but also what forms of transfer are theoretically plausible and empirically scalable within specific training contexts.

2.7 Methodological Considerations for Cognitive Research

The evaluation and application of cognitive training and assessment in sports are inherently dependent on the methodological quality of the tasks, measurements, and analytical approaches employed. As highlighted in the preceding sections, issues surrounding task design, measurement properties, and the interpretation of findings play

a critical role in determining the extent to which cognitive outcomes are meaningful, reliable, and transferable to performance contexts.

2.7.1 Validity

Validity refers to the extent to which a test or task measures what it is intended to measure and whether the inferences drawn from its outcomes are meaningful within the target context (Messick, 1995). In cognitive research, this extends beyond abstract measurement accuracy to include the degree to which tasks capture the underlying processes relevant to performance. Within sport contexts, it is particularly important because cognitive tasks are often used as proxies for complex, context-dependent behaviours, such as decision-making and anticipation (Williams & Ericsson, 2005). As such, a valid cognitive assessment or training task should not only demonstrate internal consistency, but also reflect the functional demands of the sport environment in which performance is ultimately expressed.

A key distinction within sport cognition is between *construct validity* and *ecological validity*, both of which have been conceptualised and operationalised differently across the literature. *Construct validity* refers to whether a task or simulation accurately captures the underlying processes and competencies it is intended to measure (Strauss & Smith, 2009). Within simulation research, this is often operationalised through the ability of a task to differentiate between individuals of varying expertise levels and to reflect meaningful variations in performance (Harris et al., 2020). In this context, *construct validity* is demonstrated when performance within a simulated training or testing environment corresponds with real-world skill level, such that more skilled performers consistently outperform less skilled individuals on relevant task metrics (Wood et al., 2020). More broadly, this perspective emphasises that *construct validity* is not necessarily determined by the realism of a task's appearance, but by the extent to which it preserves

the functional relationships between perception, cognition, and action that underpin performance.

In contrast, *ecological validity* has been conceptualised within ecological psychology as the extent to which perceptual information available in a task reliably specifies environmental states relevant for action (Araújo et al., 2007). Importantly, this definition differs from interpretations that equate *ecological validity* with the degree to which a task resembles real-world situations (e.g., Rogers et al., 2005). As originally defined by Brunswik (1956), *ecological validity* refers to the statistical relationship between environmental cues and the distal states they specify, rather than the representativeness of the task itself. However, in the literature, the term has frequently been used to describe the *generalisability* of findings to real-world performance contexts, often conflating it with broader notions of external validity or task realism (Araújo et al., 2007). From an ecological dynamics perspective, emphasis is instead placed on the alignment between task constraints and the behavioural setting, such that performers are exposed to information sources and action possibilities that are functionally relevant to the target performance environment (Pinder et al., 2011). This has led to the adoption of concepts, such as representative learning design, which emphasises the need to preserve perception–action coupling and the informational constraints that underpin behaviour in sport-specific contexts.

Building on these conceptual ambiguities, Suchy et al. (2024) critically reviewed the neuropsychological literature and identified substantial inconsistency in how *ecological validity* has been defined, operationalised, and evidenced. In particular, they highlighted that many studies claiming *ecological validity* rely on tasks designed to resemble real-world activities without demonstrating that performance on these tasks meaningfully predicts behaviour in everyday settings. Thus, they argue that the field has often

overestimated the ecological relevance of such assessments, due in part to a conflation between *ecological validity* and related but distinct constructs such as *face validity* (i.e., users' subjective perceptions of the realism of a task or simulation; Harris et al., 2020) and *verisimilitude*. Therefore, they call for greater conceptual clarity and more rigorous methodological approaches, emphasising the need to distinguish between: (i) how realistic a task appears; (ii) how well it captures underlying cognitive processes; and (iii) whether it can directly predict real-world functioning. This distinction is particularly important in applied sport, where perceptual-cognitive assessment tools are frequently justified based on their apparent similarity to performance environments, despite limited evidence of their predictive or functional validity.

2.7.2 Fidelity

Fidelity refers to the degree to which a training or assessment environment reproduces aspects of the real-world task or system, and is often discussed in relation to how closely a simulation matches reality (Harris et al., 2020). However, fidelity is a multidimensional construct, encompassing not only the physical appearance of a task but also the perceptual, cognitive, and behavioural processes it elicits (Gray, 2019; Perfect et al., 2014). Early work in simulation research distinguished between *engineering fidelity*, which focuses on the accurate replication of system components, and *perceptual* or *functional fidelity*, which reflects how the simulation is experienced and utilised by the performer (Perfect et al., 2014). Importantly, high fidelity in one dimension does not necessarily translate to effective learning or transfer, and excessive emphasis on surface realism may overlook the functional requirements of performance (Harris et al., 2020).

Within sport and cognitive training contexts, fidelity is commonly conceptualised in terms of *physical* and *psychological fidelity*. *Physical fidelity* refers to the extent to which the sensory and structural features of the environment resemble those of the real-world task,

including visual detail, spatial layout, and movement dynamics (Harris et al., 2020). In contrast, *psychological fidelity* refers to the degree to which the simulation elicits the same perceptual, cognitive, and decision-making processes as the real task (Gray, 2019). From a learning perspective, *psychological fidelity* has been emphasised as an important consideration for transfer, as it reflects the extent to which performers engage with task-relevant information and action possibilities in a functionally similar manner (Gray, 2019; Pinder et al., 2011). Accordingly, environments with high visual realism may still be limited if they fail to preserve key informational constraints or support appropriate perception–action coupling. Conversely, environments that emphasise *psychological fidelity* but lack sufficient physical correspondence may also constrain performance, as mismatches in spatial, temporal, or movement characteristics can alter action execution and perceptual calibration.

2.7.3 Reliability

Reliability refers to the extent to which a measurement produces consistent and stable results across repeated assessments under comparable conditions (Atkinson & Nevill, 1998). In cognitive research, reliability is critical because performance outcomes are often derived from reaction time, accuracy, or error-based metrics, which can be influenced by both true changes in ability and random measurement error. Therefore, establishing reliability is essential for determining whether observed differences reflect meaningful performance variation or noise within the measurement system (Batterham & Hopkins, 2006).

Within sport and cognitive testing contexts, reliability is commonly assessed using test-retest designs, where performance is measured across multiple sessions to quantify consistency over time (Atkinson & Nevill, 1998). However, cognitive tasks often present unique challenges for reliability, as performance can be affected by factors such as

familiarity with the task, learning effects, fatigue, and fluctuations in attention or motivation (Schmidt & Lee, 2011). In particular, repeated exposure to cognitive tasks may lead to systematic improvements unrelated to true cognitive development, complicating the interpretation of test-retest reliability (Simons et al., 2016; Soveri et al., 2018). As a result, reliability should be considered alongside protocol design factors, including adequate familiarisation and control of testing conditions (see Section 2.7.5 for further detail on familiarisation).

2.7.4 Sensitivity

Sensitivity refers to the ability of a measurement to detect meaningful changes or differences in performance, particularly when such changes are small but practically relevant (Currell & Jeukendrup, 2008). In cognitive research, sensitivity is critical because performance outcomes, such as reaction time and accuracy, often exhibit relatively small variations, especially in skilled populations (Beavan, Spielmann, et al., 2020). As such, a sensitive measure should be capable of distinguishing true changes in performance from background variability and measurement noise.

The sensitivity of a task is closely related to its reliability, as unreliable measures inherently limit the ability to detect meaningful change (Hedge et al., 2018). However, sensitivity is not solely determined by measurement error, but also by the scaling, variability, and responsiveness of the outcome variables used. For example, tasks that produce ceiling effects in accuracy or restricted variability in RT may reduce the capacity to detect improvement, even when underlying performance has changed (Wang et al., 2008). Similarly, the selection of outcome metrics (e.g., overall accuracy, error types, RT distributions) can influence the sensitivity of the assessment, particularly in cognitively demanding tasks where different performance components may respond differently to training (Ratcliff & McKoon, 2008).

In sport science, the examination of sensitivity and related measurement properties (e.g., standard error of measurement, minimal detectable change) has been more extensively investigated within physiological and biomechanical assessment domains, particularly in relation to neuromuscular and performance monitoring in athletes (Franceschi et al., 2023; Salter et al., 2024; Serafim et al., 2025). In contrast, comparable evaluation of sensitivity within cognitive assessment protocols remains relatively limited.

2.7.5 Familiarisation

Familiarisation refers to the process by which individuals become accustomed to the structure, demands, and response requirements of a task prior to formal assessment (Moon et al., 2024). In contrast, habituation typically refers to a decrease in behavioural or neural response to repeated, non-salient stimuli, reflecting reduced responsiveness rather than stabilisation of task performance (Merchie & Gomot, 2023). Given that cognitive training and testing have only recently been introduced into applied sports, familiarisation can be particularly important when assessing longitudinal performance changes, as initial performance is often influenced by novelty, uncertainty, and task-specific learning rather than underlying cognitive ability (Simons et al., 2016). Accordingly, early trials or sessions may not provide an accurate representation of true performance capacity without appropriate familiarisation procedures prior to data collection (Friebe et al., 2023; Soveri et al., 2018).

In football, cognitive training intervention studies often rely on pre–post testing designs to evaluate training effects (e.g., Heilmann, Formenti, et al., 2023; Schumacher et al., 2020; Theofilou et al., 2022), frequently without incorporating sufficient familiarisation or additional baseline assessments (Ashouri et al., 2023). As the broader cognitive literature has demonstrated, such inadequate familiarisation procedures may lead to incorrect interpretation of cognitive interventions, particularly when improvements

reflect task exposure rather than true cognitive adaptation. Therefore, the design of cognitive testing protocols should incorporate sufficient familiarisation sessions and account for the potential influence of learning effects when interpreting repeated measures data.

2.7.6 Analytical Approach

Cognitive research has traditionally been grounded in group-level analytical approaches, where the primary objective is to identify systematic effects of experimental manipulations on average performance across participants. This approach, rooted in experimental psychology, prioritises within-subject effects and seeks to minimise between-subject variability in order to isolate underlying cognitive mechanisms (Cronbach, 1957). As a result, many well-established cognitive tasks are optimised to produce robust and replicable group-level effects, rather than to capture meaningful variation between individuals (Hedge et al., 2018).

However, this emphasis on group-level analysis presents limitations when the objective is to understand individual differences in cognitive performance. A key issue highlighted in the literature is that tasks producing strong experimental effects often exhibit low between-subject variability, thereby reducing their reliability for distinguishing individuals, a phenomenon referred to as the *reliability paradox* (Hedge et al., 2018). In this context, robust within-subject effects do not necessarily translate into reliable individual difference measures, as condition-based contrasts may fail to capture stable between-participant variation (Infantolino et al., 2018). Recent work has also questioned whether commonly used cognitive tasks are capable of reliably capturing inter-individual variation. For example, variability in test-retest reliability across cognitive tasks suggests that many experimental paradigms may not provide stable individual-level measures, despite their widespread use in research contexts (Pennington et al., 2025).

This limitation is further compounded by the fact that many neuroimaging studies report group averages while overlooking meaningful heterogeneity within samples, despite evidence that individual differences in cognition, affect, and performance can substantially influence behaviour and outcomes (Parasuraman & Jiang, 2012). This raises important concerns not only about task design but also about the interpretation of cognitive data, particularly when group-level findings are assumed to generalise to individuals. As such, measures that are highly effective for experimental inference may be poorly suited for applied contexts.

In applied domains, analytical approaches should prioritise both statistical validity and practical relevance. The primary objective of professional football academies is the long-term development of individual players (Dowling et al., 2018; Layton et al., 2023). As highlighted in talent identification research, reliance on aggregated group data may obscure meaningful individual trajectories and limit the practical utility of findings for decision-making (Bergkamp et al., 2019). In this context, analytical approaches that incorporate individual-level analysis may provide more informative insights for applied practice. Accordingly, researchers and practitioners should adopt integrative analytical frameworks that combine group-level evidence with individual-level interpretation to better align research outputs with applied performance contexts (Owen et al., 2022).

2.7.7 Interpretation (Generalisability vs Transferability)

Interpretation of findings in quantitative research has traditionally centred on the concept of *generalisability*, defined as the extent to which results obtained from a sample or the statistics derived from it can be extended to a broader population or range of situations (de Leeuw et al., 2022; Polit & Beck, 2010). Within experimental psychology, this is typically achieved through statistical inference, where group-level effects are assumed to reflect broader principles of cognition. However, growing concerns across psychology

and sport science have highlighted substantial limitations in this assumption. In particular, the *generalisability crisis* has demonstrated that many findings are based on narrowly specified models that fail to account for variability across stimuli, contexts, and populations, thereby limiting the scope of valid inference (Yarkoni, 2020). These concerns are further reinforced by large-scale replication efforts, which have shown that a substantial proportion of findings cannot be consistently reproduced (Mesquida et al., 2022; Open Science Collaboration, 2015), raising questions about whether results can be meaningfully generalised across contexts.

In applied domains, these limitations are further amplified by differences between research and practice environments. Translating findings from controlled laboratory settings to real-world contexts requires substantial modification of study design, including consideration of contextual and implementation-related variables that are often omitted in experimental research. These variables can play a critical role in determining where and for whom an intervention is effective, suggesting that effects are contingent on context rather than universally applicable (de Leeuw et al., 2022). Consequently, even when empirical effects are observed, it may not be appropriate to assume that they apply broadly across populations, tasks, or environments. This issue is particularly relevant in cognitive training research, where substantial variation exists in task characteristics, measurement approaches, and participant populations, limiting the extent to which findings can be generalised across studies or applied settings.

In contrast, the concept of *transferability* provides an alternative perspective, focusing on the extent to which findings, insights, or methods can be meaningfully applied to other contexts. Originating in qualitative research, *transferability* emphasises context-dependent interpretation rather than universal generalisation, recognising that findings are inherently shaped by the conditions under which they are produced (Drisko, 2024;

Lincoln & Guba, 1985). Unlike generalisation, which assumes that effects should replicate across settings, *transferability* considers whether knowledge can be adapted to new contexts based on similarities in conditions, constraints, and underlying mechanisms. However, despite its relevance, the distinction between *generalisability* and *transferability* has been poorly articulated within the literature, with the latter receiving comparatively limited attention (Drisko, 2024).

From this perspective, *transferability* in cognitive and sport science research may be considered at multiple levels. First, findings themselves may be transferable in terms of conceptual insights, such as understanding task constraints, perceptual demands, or learning mechanisms that can inform practice across contexts. Second, methodological approaches may also be transferable, including study designs, analytical frameworks, and measurement strategies that can be adapted to different populations or environments (Bekhor & Prato, 2009). This distinction is particularly important in cognitive research, where direct generalisation of findings is often limited, but broader insights and methodological principles may still provide meaningful guidance for both research and applied practice. Accordingly, advancing the field may require a shift from asking whether findings generalise to considering how and under what conditions knowledge can be meaningfully transferred to inform both research and practice.

2.8 The SoccerBot360

The purpose of this thesis is to examine the applied utility of a football-specific technology, the SoccerBot360 (SB360). The SB360 is an immersive cognitive-motor assessment and training system designed to simulate football-related perceptual and action demands within a controlled environment (Heilmann et al., 2021). The system consists of 32 vertical panels (1 m wide × 2.5 m high) arranged in a circular formation with a diameter of approximately 10 m, creating a 360° interactive space (Figure 2.3c and

2.4). Task stimuli are presented via six ceiling-mounted projectors, while performance data are captured using a high-speed camera (Sony CMOS sensor; 120 frames per second) positioned centrally within the system. This configuration enables the integration of perceptual, cognitive, and motor responses within a standardised yet dynamic testing environment.

Although the SB360 has been among the most extensively studied football-specific technologies, alongside the Footbonaut, the literature remains relatively limited. The currently available SB360 research can broadly be divided into two strands: *assessment-oriented* studies (Knöbel & Lautenbach, 2023; Knöbel et al., 2025; Knöbel et al., 2024; Musculus et al., 2022) and a single *training-oriented* intervention study (Heilmann et al., 2021). In line with the focus of this thesis, the literature has attempted to develop and examine the SB360 as a *football-specific* cognitive-motor assessment and training system within talent identification and talent development contexts. Collectively, the literature has made an important initial contribution by moving cognitive diagnostics beyond conventional button-press paradigms towards a more football-specific setting. Nevertheless, the evidence base remains narrow to support strong conclusions regarding ecological validity, diagnostic value, or training effectiveness within applied contexts.

Cognitive-motor assessments have formed the dominant focus of the SB360 literature. Studies have developed (what they termed) *football-specific* versions of core EF tasks by adapting computerised paradigms, including the flanker (INH), number-letter (CF), *n*-back (WM) tasks, into settings requiring football-specific motor responses such as passing (Knöbel & Lautenbach, 2023; Musculus et al., 2022). This approach attempts to address concerns outlined in earlier sections, namely that conventional cognitive paradigms often demonstrate strong experimental control but limited *perception–action coupling* in football contexts. Convergent validity between computerised and SB360 task

versions was reported, particularly for CF and WM. In contrast, the flanker (INH) task did not demonstrate acceptable convergent validity and subsequently required revision with modified visual stimuli in a follow-up study (Musculus et al., 2022). This pattern is important methodologically as it suggests that adding football-specific response modalities does not automatically secure validity. Moreover, while these studies establish initial measurement validity, their applied utility in football contexts remains largely untested.

More recent work has begun to examine contextual influences and applied relevance. Knöbel et al. (2024) investigated the interaction between emotional states and EF performance using both computerised and SB360 tasks in highly skilled youth academy players, reporting that affective states were associated with performance variability, with patterns differing across task formats. This suggests that SB360 performance is sensitive to situational factors rather than reflecting stable cognitive ability alone, reinforcing concerns around measurement sensitivity and interpretation in applied environments. Extending this, Knöbel et al. (2025) examined associations between EF performance, age effects, coaches' subjective evaluations of players' future potential, and career progression to senior levels in German professional youth academy players. They reported no meaningful predictive value of general EF measures (both computerised and SB360 tasks) for football-related coach ratings or career progression, while SB360 CF performance followed general developmental trends, with increasing age associated with faster RT. Collectively, these findings suggest that SB360-derived metrics may have limited direct prognostic value in elite football talent identification. However, the literature has yet to clearly establish what individual SB360 performance metrics represent within football contexts, which may explain their limited prognostic value despite the integration of football-specific action components.

In addition, evidence for SB360 as a cognitive training intervention remains minimal. Heilmann et al. (2021) conducted a 12-month intervention in German professional youth academy players, using a pre–post design without familiarisations and a control group. The training intervention incorporated multiple SB360 training-mode games, but programme details were not reported. They compared pre- and post-intervention testing performance using a battery of SB360 testing-mode games (anticipation, choice response time, WM, and INH), with reported improvements in all performance metrics following the intervention. However, the absence of familiarisations, a control condition, and standardisation of training dosage constrain interpretation. Accordingly, observed improvements may reflect maturation, task familiarity or learning effects rather than intervention-specific adaptations. Moreover, despite including a broad age range (11–17 years), the analytical approach did not account for age-related effects or inter-individual variability, thereby further limiting the interpretation of the findings.

Overall, the SB360 literature provides an important initial step towards integrating cognitive and motor demands within football-specific assessment and training environments. However, current evidence is largely confined to early-stage validation and exploratory studies, with limited support for the applied utility of the SB360 for diagnostic or training purposes. Therefore, the current state of the literature suggests that the SB360 should be viewed as a potential but still developing methodological platform, rather than an established evidence-based tool for cognitive diagnosis or training in football. The technology requires more rigorous, contextually grounded research to establish its applied value in elite football to justify claims regarding its validity and efficacy.



Figure 2.4 Image of the SoccerBot360 (Umbrella Software Development GmbH).

2.9 Summary

This chapter synthesised literature on the perceptual, cognitive, and motor demands underpinning football performance, highlighting the dynamic and constraint-driven nature of decision-making in the sport. Two complementary perspectives were reviewed: domain-specific PCS, which emphasise representative task environments, and domain-general EFs, which focus on underlying cognitive control processes. While both approaches offer valuable insights, the literature highlights ongoing challenges in how these constructs are operationalised, measured, and interpreted within football contexts. In particular, traditional laboratory-based paradigms provide strong experimental control but limited ecological validity, whereas more representative approaches often lack sufficient validation and empirical evidence supporting their effectiveness.

The review further identified important methodological and applied limitations in current cognitive assessment and training research, including issues related to validity, fidelity, sensitivity, and generalisability. Emerging football-specific technologies, such as the SB360, attempt to bridge the gap between laboratory control and real-world representativeness by integrating perceptual-cognitive and motor components within standardised environments. However, the existing evidence base remains limited, with most studies focusing on isolated task validation rather than integrated protocols

implemented in applied settings. Consequently, the extent to which such technologies provide meaningful, sensitive, and practically useful indicators of football-relevant cognitive performance remains unclear. These gaps provide the rationale for the present thesis, which aims to evaluate the applied utility of the SB360 within an English professional youth academy.

**Chapter 3. What Makes a Cognitive Test ‘Football-Specific’? A Cross-
Sectional Examination of Cognitive-Motor Performance Using a
Football-Specific Assessment Tool in an English Professional Academy**

3.1 Abstract

Purpose: Despite the increasing use of *football-specific* cognitive assessment technologies in professional academies, it remains unclear whether such systems can differentiate players across developmental stages or reflect underlying cognitive constructs in applied environments. This study examined age-related effects on standardised SoccerBot360 (SB360) cognitive-motor performance in skilled male youth players. **Methods:** Using a cross-sectional design, U12–U21 players completed a battery of SB360 assessments that consisted of cognitive flexibility (CF: $n = 80$) and working memory (WM: $n = 125$) tasks. A three-stage analytical approach was applied: (i) exploratory comparisons across academy age bands, (ii) primary analyses of associations between chronological age (CA) and test performance, and (iii) secondary analyses comparing CA and biological maturation within adolescent subsamples (U13–U15). **Results:** Performance differences were most evident between the youngest and oldest cohorts, with limited differentiation within adjacent age bands. Primary analyses demonstrated significant age-related improvements in CF response time (RT), whereas switch cost and accuracy remained stable across CA. WM outcomes showed minimal age sensitivity. Secondary analyses indicated that during early adolescence (U13–U14), biological maturation explained additional variance in CF RT beyond CA, whereas switch cost was not associated with CA, biological age (BA), or maturity timing (BA–CA). RT measures requiring overt motor responses were more sensitive to developmental differences than switch cost or accuracy measures. **Conclusion:** The SB360 assessment appears more suitable for monitoring individual developmental changes and broader age-related trends than differentiating players within narrow age groups. Overall, findings highlight the need for caution when interpreting such systems as *football-specific* cognitive assessments, as performance is substantially influenced by motor-execution demands alongside, rather than purely reflecting, underlying cognitive constructs.

3.2 Introduction

Executive functions (EFs) refer to a set of higher-order cognitive control processes that support goal-directed behaviour, particularly in dynamic and unpredictable environments (Miller & Cohen, 2001). Among these, cognitive flexibility (CF), working memory (WM), and inhibition (INH) are considered core components, enabling individuals to maintain and manipulate task-relevant information, shift between competing rules or demands, and suppress prepotent responses or interference (Diamond, 2013). In football, these capacities are theoretically relevant to adapting to changing tactical contexts, selecting actions under temporal pressure, and coordinating perception with action execution (Williams & Ericsson, 2005).

Empirical studies have reported that high-skilled players or those who are selected for elite academy systems on talent development pathway tend to outperform lower-level or non-selected peers on tasks indexing executive control demands (Sakamoto et al., 2018; Verburgh et al., 2014). Meta-analytic evidence indicates small-to-moderate advantages for expert athletes across EF measures, with larger effects typically observed in tasks requiring greater cognitive control rather than simple reaction speed alone (Scharfen & Memmert, 2019a). Recent reviews further highlight that executive and related cognitive processes are frequently discussed in relation to successful football performance and talent selection, while emphasising that findings depend on task characteristics and measurement approach (Haugan et al., 2025; Triggs et al., 2025). Collectively, the literature positions EFs as theoretically relevant constructs for understanding skilled football performance while also underscoring that their empirical expression likely depends on task structure and response modality.

EFs have most commonly been assessed using laboratory-based paradigms designed to isolate cognitive processes by minimising motor and contextual demands (Erb et al., 2025;

Foster et al., 2022), often employing simplified response modalities such as paper-and-pencil tasks or computer-based button-press (Chan et al., 2008; Diamond, 2013). These approaches have been instrumental in establishing current understanding of EFs across multiple scientific domains, including sport science. In football, such paradigms have demonstrated age-related improvements in EF performance across broad developmental windows, particularly from early- to late-adolescence (Beavan, Spielmann, et al., 2020; Heilmann, Memmert, et al., 2023), reflecting well-established EF developmental trajectories during this period (Huizinga et al., 2006; Tervo-Clemmens et al., 2023). Together, these findings demonstrate that laboratory-based assessments are effective for identifying broad developmental trends in EFs, underscoring age as a key determinant of EF development throughout adolescence.

Nevertheless, the extent to which performance on traditional EF tasks generalises to complex, real-world behaviour has been a long-standing consideration, particularly within neuropsychology and clinical science, where these paradigms have been extensively employed in applied settings such as clinical assessment, diagnosis, and rehabilitation (Burgess et al., 2006; Chan et al., 2008). Parallel concerns have emerged in football research, where the suitability of traditional EF or perceptual-cognitive skills (PCS) assessments for capturing the demands of in-game decision-making has been critically examined. Empirical work grounded in representative designs indicates that tasks lacking sport-specific perception–action coupling may underestimate or mischaracterise cognitive processes underpinning skilled football performance (Dicks et al., 2010; van Maarseveen et al., 2018). In particular, the absence of representative task stimuli and sport-specific motor execution has been identified as a key limitation when inferring real-world performance from laboratory-based measures (Kalén et al., 2021; Mann et al., 2007; Triggs et al., 2025).

Building on these concerns, a growing body of research, alongside technological advancements in the sports industry, has sought to develop *football-specific* assessment tools that preserve key features of cognitive control while embedding them within representative perceptual and motor contexts (Beavan, 2019). Within this framework, immersive and semi-immersive systems have been introduced to assess and train EFs or sport-specific PCS by integrating physical and technical components of the game within dynamic and unpredictable task environments (Beavan, Fransen, et al., 2019; Dolata et al., 2025; Heilmann et al., 2021; Rodrigues et al., 2024). The SoccerBot360 (SB360) represents one such approach, providing a controlled yet more sport-specific testing environment in which standard EF paradigms are embedded within football-specific motor demands (Knöbel & Lautenbach, 2023; Musculus et al., 2022).

As reviewed in Chapter 2, researchers have developed standardised SB360 cognitive-motor tasks to assess core EFs within football-specific environments. Musculus et al. (2022) examined the convergent validity of the number-letter task (CF; Kiesel et al., 2010) and the flanker task (INH; Eriksen & Eriksen, 1974). Similarly, Knöbel and Lautenbach (2023) validated the *n*-back task to assess WM. Both studies stated that their motivation was to design tasks grounded in the expert performance framework (Ericsson & Smith, 1991; see Section 2.3.1) and the cognitive component skills approach (Nougier et al., 1991; see Section 2.3.2), with the aim of isolating executive processes while embedding them within representative football actions. This rationale is supported by previous literature indicating that expertise effects are more pronounced when response modalities include sport-specific motor actions (e.g., passing, dribbling) in PCS or decision-making assessments (Murr et al., 2018; Travassos et al., 2013).

Despite these advances in testing modality and validation, no research has assessed EFs in football players using the SB360 for talent identification or talent development

purposes at the time of commencing the present study. In other words, although previous validation studies characterised the SB360 as a *football-specific* testing environment, the functional utility of these tasks for real-world applications remains unclear. Moreover, despite the emphasis on perception–action coupling underpinning the development of this integrated testing modality, prior validation work has primarily focused on cross-task associations rather than task affordances and corresponding performance outcomes. Consequently, understanding of its diagnostic value and potential applications in football is yet to be demonstrated, which may constrain both optimisation of the system and the direction of future research (Murr et al., 2018; Robertson & Schmitter-Edgecombe, 2017).

Moreover, evaluation of the SB360 requires consideration of its motor-execution components. Within the system, task response modalities involve *football-specific* actions, whereas the task stimuli primarily target domain-generic executive processes. Previous research suggests that biological maturation may contribute to EF performance independently of age (Gilbert et al., 2025; Laureys et al., 2021). However, these findings have largely been derived from computerised paradigms employing simplified response modalities that minimise motor demands. Therefore, such findings primarily reflect developmental changes in brain structure and function underpinning executive processes (Johnson et al., 2009; Kolk & Rakic, 2021), rather than the musculoskeletal development required to execute more complex motor actions. In contrast, the SB360 performance may be influenced not only by maturational changes in EFs but also by concurrent development of motor-execution capacities due to its sport-specific response modality. Consequently, it remains unclear whether chronological age (CA) and biological maturation exert distinct influences on SB360 performance.

This limitation is especially relevant as the motor-execution capacities directly engaged by SB360 task responses (e.g., kicking) are known to be influenced by both CA and

biological maturity in youth football players (Cerrah et al., 2024). Professional football academy structures, which are organised primarily by CA teams and grouped into developmental phases based on consecutive age bands, may obscure within-group variation in biological maturity (Mann & van Ginneken, 2017). Accordingly, distinguishing the relative contributions of CA and biological maturity is essential for interpreting SB360 cognitive-motor performance in youth academy contexts, where substantial maturation-related differences are frequently observed within adjacent age groups (Deprez et al., 2013; Rommers et al., 2018; Wenger & Csapo, 2025).

As highlighted in Chapter 2, it remains difficult to isolate cognitive processing from motor execution, particularly in tasks involving timed responses (Pettit et al., 2013). In this context, the emergence of football-specific technologies has not necessarily resolved the noise introduced by motor variability. Although previous SB360 research has also reported positive associations between age and cognitive testing performance (Heilmann et al., 2021), whether such integrated cognitive-motor measures primarily reflect developmental changes in cognitive functions, motor-execution capacity, or their interaction remains insufficiently understood. Moreover, despite the increasing adoption of such systems, their applied use within professional football environments remains largely unexamined. Therefore, this study aimed to examine developmental variation in SB360 testing performance in highly skilled youth football players, with specific focus on previously validated CF and WM task outcomes.

To address these gaps, three complementary analytical stages were implemented. First, *exploratory analysis* examined whether SB360 performance differed across the academy pathway, operationalised by developmental phases and age-group teams, to determine whether the assessment is sensitive to developmental differences within highly skilled youth players. Second, *primary analysis* evaluated continuous associations between CA

and task outcomes, given that CA is a key determinant of cognitive performance in skilled youth football players (Beavan, Chin, et al., 2020; Heilmann et al., 2022). Third, *secondary analysis* compared CA and biological maturity indicators as competing predictors within early- and mid-adolescent subsamples, as motor-executed task responses may be influenced by biological maturation within similar age groups (Cerrah et al., 2024; Wenger & Csapo, 2025). Collectively, this multi-stage approach was designed to clarify the developmental determinants of SB360 cognitive-motor performance and to inform its applied interpretation for benchmarking and player evaluation within professional academy contexts.

3.3 Methods

3.3.1 Participants

3.3.1.1 Exploratory and Primary Analysis Sample

Exploratory and primary analyses were conducted using the same cross-sectional dataset comprising male youth football players registered at a Category One (highest tier) English Premier League (EPL) academy. Data were collected during the 2022-23 and 2023-24 seasons. Participants in the CF test comprised 80 players (age: 15.9 ± 2.6 years; training age: 9.5 ± 2.9 years; height: 177.4 ± 11.0 cm; body mass: 67.6 ± 14.1 kg), and participants in the WM test comprised 125 players (age: 15.6 ± 2.4 years; training age: 9.3 ± 2.7 years; height: 175.8 ± 11.5 cm; body mass: 65.8 ± 14.0 kg). All participants were enrolled in U12–U21 teams and were injury free for a minimum of 3 months prior to testing. The current study categorised participants based on developmental phases adapted from the Elite Player Performance Plan (EPPP) by the Premier League (2012): Foundation Phase (FP; U12), Youth Development Phase (YDP¹; U13–U14 and YDP²; U15–U16), and Professional Development Phase (PDP; U17–U21) for the exploratory analyses. All participants had no prior experience of the selected SB360 cognitive tasks (CF and WM). Developmental phase and team-wise demographic characteristics of participants included

in the exploratory and primary analyses are presented in Table 3.1. Ethical approval was obtained from Liverpool John Moores University's Research Ethics Committee (Ref: 23/SPS/003; Appendix 1).

3.3.1.2 Secondary Analysis Sample

The secondary analysis examining biological maturity utilised a distinct but related dataset that partially overlapped with the primary analysis sample. These analyses focused on players for whom maturation data were available and for whom biological maturity was considered a distinguishing factor influencing motor performance among peers of a similar CA. Accordingly, only players from the U13–U15 teams were included in the secondary analysis. To increase the available sample size, the dataset was supplemented with CF and WM testing data from additional U13–U15 players within the same academy, collected during the 2024-25 season. To maintain developmental specificity, analyses were stratified by age group, with players categorised into U13-U14 (CF: $n = 32$, WM: $n = 33$) and U14-U15 (CF: $n = 29$, WM: $n = 27$) subsamples based on their CA at the time of testing. These age bands were selected to reflect key phases of adolescent growth and maturation in youth players (Deprez et al., 2013; Rommers et al., 2018; Wenger & Csapo, 2025), while minimising excessive age range heterogeneity within each subsample. The maturation and demographic characteristics of participants across subsamples and cognitive tasks are presented in Table 3.2.

Biological maturity estimation procedures followed the guidelines proposed by Towlson et al. (2021). First, percentage of predicted adult height (%PAH) for each participant was estimated using the Khamis-Roche method (Khamis & Roche, 1994), which incorporates participants' CA, height, body mass, and their mid-parent height (i.e., mean height of biological parents). Anthropometric measurements were collected by academy sport science and medical staff using standardised mechanical height (seca 213, seca GmbH &

Co. KG., Hamburg) and weight (seca 875 Electronic Class III, seca GmbH & Co. KG., Hamburg) measurement devices. Parental heights were self-reported to academy sport science staff, and a correction filter described by Epstein et al. (1995) was applied to reduce the risk of systematic overestimation. Participants' biological age (BA) was subsequently estimated from their %PAH in relation to CA using the UK 1990 growth reference data (Freeman et al., 1995). In addition, BA minus CA offset (BA–CA) was calculated to index maturity timing relative to age matched peers (Arede et al., 2024; Curnyn et al., 2025) and to facilitate direct comparison with CA and BA as predictor variables in the statistical models.

Table 3.1 Sample characteristics for the exploratory and primary (chronological age) analyses.

Phase	Team	Cognitive Flexibility (CF)					Working Memory (WM)				
		<i>n</i>	Age (years)	Training age (years)	Height (cm)	Body mass (kg)	<i>n</i>	Age (years)	Training age (years)	Height (cm)	Body mass (kg)
FP	U12	4	11.9 ± 0.5	5.7 ± 0.6	157.8 ± 5.7	43.4 ± 5.2	6	12.0 ± 0.3	5.6 ± 0.8	159.9 ± 5.2	44.4 ± 4.8
YDP ¹	U13	13	12.7 ± 0.5	6.4 ± 1.6	162.8 ± 10.3	47.3 ± 8.5	24	12.8 ± 0.3	6.9 ± 1.1	161.7 ± 7.6	48.4 ± 6.9
YDP ¹	U14	8	14.0 ± 0.3	8.2 ± 1.2	177.8 ± 4.7	65.3 ± 5.6	15	13.8 ± 0.4	7.3 ± 1.2	169.4 ± 12.3	58.4 ± 10.6
YDP ²	U15	13	14.9 ± 0.4	8.7 ± 1.7	180.6 ± 8.0	65.9 ± 7.7	20	14.9 ± 0.5	8.9 ± 1.4	179.0 ± 6.8	65.1 ± 8.0
YDP ²	U16	2	15.8 ± 0.3	9.3 ± 0.4	183.1 ± 3.0	70.3 ± 6.7	12	15.9 ± 0.2	10.0 ± 1.0	182.5 ± 5.2	72.1 ± 6.2
PDP	U18	21	17.0 ± 0.6	10.5 ± 1.7	180.7 ± 5.1	74.5 ± 7.6	23	17.0 ± 0.6	10.4 ± 1.8	181.4 ± 5.4	75.5 ± 7.8
PDP	U21	19	19.0 ± 1.0	13.3 ± 1.7	184.2 ± 7.1	78.1 ± 7.8	25	19.2 ± 1.0	13.3 ± 1.7	184.7 ± 6.8	79.0 ± 7.2
Total		80	15.8 ± 2.5	9.5 ± 2.9	177.4 ± 11.0	67.6 ± 14.1	125	15.6 ± 2.4	9.3 ± 2.7	175.8 ± 11.5	65.8 ± 14.0

Nb. Training age represents cumulative years of structured football training undertaken within professional and non-professional youth football teams. FP = Foundation Phase; YDP = Youth Development Phase; PDP = Professional Development Phase. Data are presented as mean ± SD.

Table 3.2 Sample characteristics by subsamples for the secondary (biological maturation) analyses.

Task	Sample	<i>n</i>	CA (years)	Training age (years)	Height (cm)	Body mass (kg)	%PAH	BA (years)	BA–CA (years)
CF	U13-U14	32	13.2 ± 0.6	7.0 ± 1.3	166.4 ± 10.4	52.9 ± 9.6	89.4 ± 3.4	13.7 ± 0.9	0.4 ± 0.7
CF	U14-U15	29	14.3 ± 0.6	8.2 ± 1.5	174.5 ± 11.3	61.6 ± 10.1	93.8 ± 3.5	15.0 ± 1.0	0.6 ± 0.8
WM	U13-U14	33	13.2 ± 0.6	7.0 ± 1.3	166.7 ± 10.9	53.1 ± 9.7	89.5 ± 3.7	13.8 ± 1.1	0.5 ± 0.7
WM	U14-U15	27	14.3 ± 0.6	8.3 ± 1.5	174.8 ± 11.0	61.3 ± 9.5	94.1 ± 3.4	15.1 ± 1.1	0.7 ± 0.9

Nb. CA = chronological age; BA = biological age; %PAH = percentage of predicted adult height. Training age represents cumulative years of structured football training undertaken within professional and non-professional youth football teams. Data are presented as mean ± SD.

3.3.2 Measures

3.3.2.1 Apparatus

All cognitive testing sessions were conducted using the SB360 system (see Section 2.8). Participants used age-appropriate football sizes throughout (i.e., U12–U13 = size 4; U14–U21 = size 5).

3.3.2.2 Cognitive Flexibility Test

In football, CF is considered particularly important, as it aligns with the sport's demands for continuous adaptation to changing tactical and situational constraints (see Section 2.3.2.3). The CF task employed a switching paradigm (Kiesel et al., 2010), adapted specifically for the SB360 system (Musculus et al., 2022). The task comprised a 2×2 quadrant arrangement of 90 cm $\times$ 90 cm squares (Q1–Q4), with a goal (222 cm wide $\times$ 97 cm high) featured on each side of the quadrant (Figure 3.1). The test commenced when participants passed the ball to a play button displayed on the SB360 screen. At the onset of the test, Q1 turned grey for 1,000 ms before the stimulus appeared, after which the stimulus was presented in a fixed clockwise sequence (Q1→Q2→Q3→Q4→Q1...) throughout the task. The stimulus consisted of a letter (e.g., 'A') and a digit (e.g., '6') and remained on the screen until the ball made contact with any panel. A 3,000 ms interval then occurred before a new character pair appeared in the next quadrant.

During the test, participants were required to perform a letter task when the character pair appeared in Q1 or Q2, and a number task when the pair appeared in Q3 or Q4. In the letter task, participants passed the ball to the left-side goal if the letter was a consonant, and to the right-side goal if the letter was a vowel, regardless of the digit displayed. Consonant letters were randomly selected from 'G', 'K', 'M', and 'R', while vowels were selected from 'A', 'E', 'I', and 'U'. In the number task, participants passed the ball to the left-side goal if the digit was even, and to the right-side goal if it was odd, regardless of the letter

displayed. Even digits were randomly selected from ‘2’, ‘4’, ‘6’, and ‘8’, and odd digits from ‘3’, ‘5’, ‘7’, and ‘9’.

All trials in Q1 (excluding the first trial) and Q3 were classified as switch-trials, where the type of task switched from the previous trial (i.e., letter-to-number task or number-to-letter task). Stimuli appearing in Q2 and Q4 were classified as non-switch-trials. Each participant completed 24 practice trials (8 letter tasks, 8 number tasks, and 8 mixed trials), followed by 56 test trials (29 non-switch and 27 switch-trials). Response time (RT) for switch- and non-switch-trials was measured from stimulus onset to the initiation of ball movement. Switch cost was calculated as the difference between mean switch-trial RT and mean non-switch-trial RT (i.e., switch RT – non-switch RT), with higher values indicating a greater additional RT cost associated with switching between task rules. Response accuracy was recorded for correct trials when the ball struck any panel on the correct side (left or right) from the middle of the quadrant, regardless of the distance from the displayed goal. Incorrect trials were recorded when the ball struck any panel on the incorrect side.

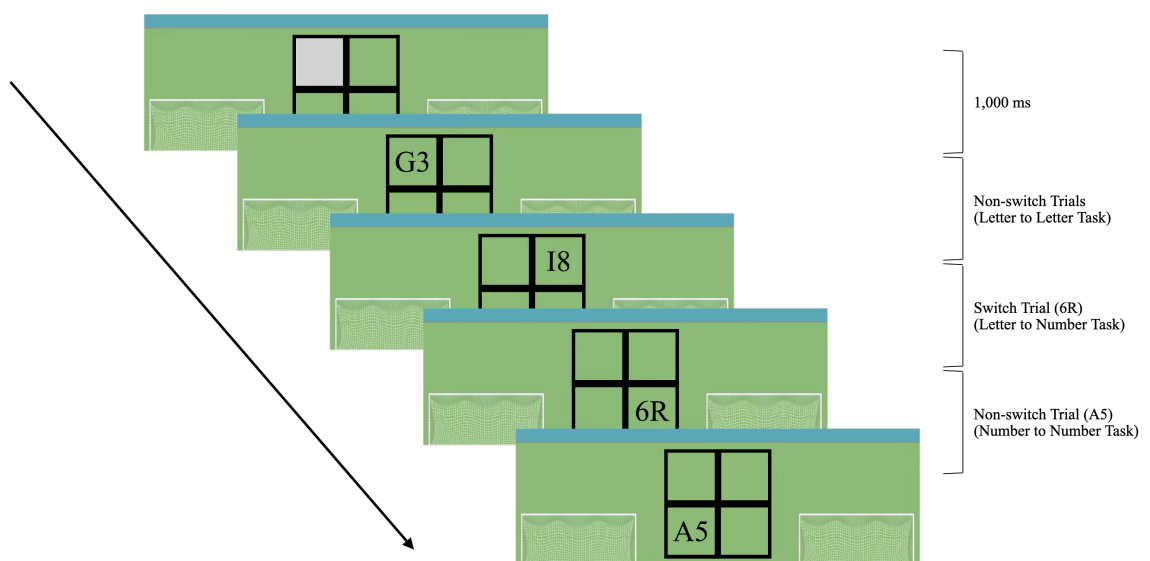


Figure 3.1 SoccerBot360 number-letter (cognitive flexibility) task.

Within the CF task, stimulus-response compatibility referred to whether the spatial location of the stimulus corresponded with the required response direction (Proctor & Vu, 2006). A compatible trial occurred when the stimulus was presented on the same side as the required response (e.g., a stimulus presented in the left-sided quadrant, Q4, requiring a pass to the left-side goal), whereas an incompatible trial occurred when the stimulus was presented on the opposite side to the required response (e.g., a stimulus presented in the left-sided quadrant, Q4, requiring a pass to the right-side goal). Across the 56 trials, 17 were compatible and 39 were incompatible, indicating that stimulus-response compatibility was not experimentally balanced. To evaluate whether this imbalance confounded task performance, additional linear and generalised linear mixed-effects model comparisons were conducted using the current CF sample (80 participants; 4,480 trials). After accounting for the fixed task structure (i.e., trial type [switch, non-switch] and stimulus quadrant [Q1, Q2, Q3, Q4]), adding stimulus-response compatibility did not improve model fit for either RT ($\chi^2(1) = 1.60, p = .21$) or accuracy ($\chi^2(1) < 0.001, p = .98$). These findings indicate that, although compatible and incompatible trials were unequally represented, stimulus-response compatibility did not explain additional variation in RT or response accuracy after accounting for trial type and stimulus quadrant.

3.3.2.3 Working Memory Test

WM has been linked to key football performance attributes, including technical-tactical abilities, situational awareness, and mental toughness (see Section 2.3.2.2). The *n*-back task, adapted specifically for the SB360 system with '*n*' set to '3' (Knöbel & Lautenbach, 2023), was utilised to assess WM. The task comprised a 100 cm × 100 cm white square, with a goal (222 cm wide × 97 cm high) positioned beneath the square (Figure 3.2). The test commenced when participants passed the ball to a play button displayed on the SB360 screen. From test onset, a sequence of stimuli (silhouettes of football-specific actions) was presented sequentially within the square. Each stimulus was displayed for 2,500 ms,

followed by a 1,500 ms inter-stimulus interval during which the square remained white (i.e., without a stimulus) before the next stimulus appeared.

During the test, participants were required to decide whether the current stimulus matched the stimulus presented three items earlier. If the stimulus was identical to that presented three trials before (i.e., target-trial), participants were instructed to pass the ball towards the goal as quickly as possible. If the stimulus did not match the stimulus presented three trials earlier (i.e., non-target-trial), participants were instructed to withhold their response and wait for the next stimulus. Each participant completed two sets of practice trials (first set: 4 target- and 13 non-target-trials, second set: 5 target- and 11 non-target-trials), followed by 50 test trials (15 target- and 35 non-target-trials). The RT window for each trial was 4,000 ms, comprising the 2,500 ms stimulus presentation and the subsequent 1,500 ms inter-stimulus interval. RT was measured from stimulus onset to the initiation of ball movement. Response accuracy was recorded as correct when the ball struck any panel during a target trial or when participants correctly withheld a response during a non-target trial. All other responses were classified as incorrect.

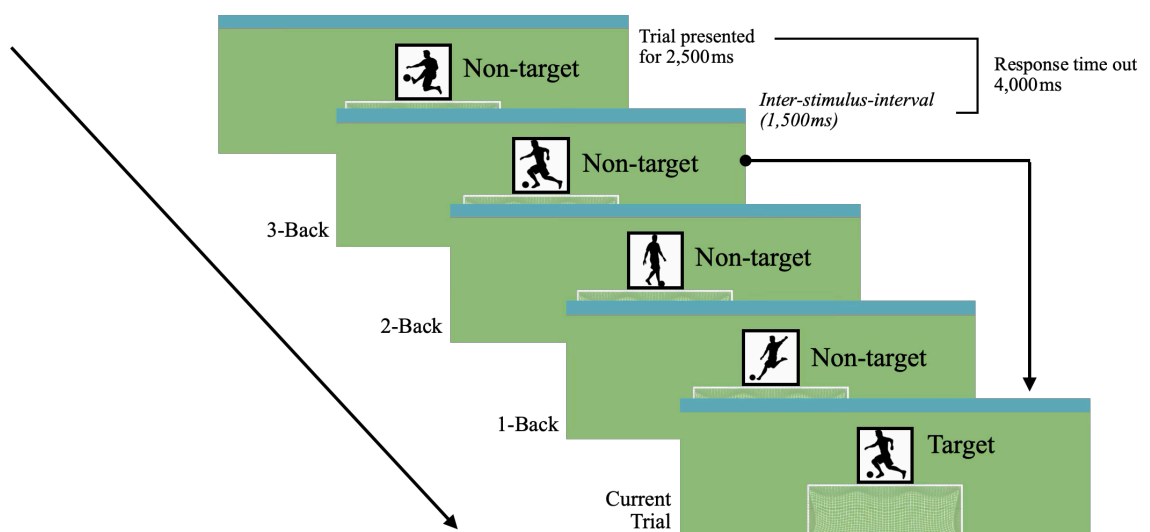


Figure 3.2 SoccerBot360 3-back (working memory) task.

For the WM task, accuracy was calculated using the scoring procedure described by Knöbel and Lautenbach (2023). First, the percentage of missed targets (i.e., target trials that did not receive a response) and the percentage of false alarms (i.e., responses made on non-target trials) were calculated. The percentage of correct target responses was then obtained as 100% minus the missed-target rate. The final accuracy score (ranged: 100% to 0%) was calculated by subtracting the false-alarm rate from the percentage of correct target responses. Thus, higher scores reflected both a greater proportion of correctly detected target stimuli and fewer inappropriate responses to non-target stimuli.

3.3.3 Procedures

Participants completed either a battery comprising both the CF and WM tests within a single session or only one of the two tests (i.e., CF or WM). Participants who completed only one cognitive test reported extenuating circumstances, such as changes to the team schedules, or were unfamiliar with the cognitive task stimuli (e.g., English consonants and vowels in the CF task), which prevented completion of the remaining test. For participants who completed both tests within a single session, the order of the tests was counterbalanced. Apart from the task-specific practice trials embedded within each test, no formal familiarisation sessions were conducted.

All testing was administered by the lead researcher (WC). Prior to each testing session, participants completed a 10 min warm-up supervised by academy physical performance coaches. At the beginning of each test, participants received standardised verbal and visual instructions outlining the testing rules, including images of actual testing scenes displayed via the SB360 software. During the tests, participants were required to pass the ball from a fixed distance of 5 m from the SB360 screen. For participants who completed both tests within one session, a 30 s rest period was provided between tests. Each test lasted approximately 20 min per participant.

3.3.4 Data Preparation

The data preparation procedures were adapted from previous applications of the SB360 version of number-letter and n -back tasks (Knöbel & Lautenbach, 2023; Musculus et al., 2022). The predefined filtering criteria, exclusion rationale, and retained data for the CF and WM tests are presented in Appendices 2 and 3, respectively.

3.3.5 Data Analysis

All analyses were conducted using R (version 4.4.1; R Core Team, 2025), and statistical significance was set at $p < .05$. Prior to inferential analyses, all outcome variables were screened to assess distributional assumptions and data suitability. Normality and linearity were evaluated using visual inspection of box plots and histograms, alongside Shapiro–Wilk tests. For group-based analyses, homogeneity of variances was assessed using Levene’s tests. Accuracy-related variables were expressed as percentages and converted to proportional values (0–1), where required for regression modelling. When proportional outcomes exhibited boundary inflation, appropriate beta-based modelling approaches with a logit link function were employed (Geissinger et al., 2022). Table 3.3 summarises all statistical tests performed for each outcome variable across the *exploratory*, *primary*, and *secondary* analyses.

Table 3.3 Statistical tests performed for each outcome variable across exploratory, primary, and secondary analyses.

Outcome	Exploratory (phase, team)	Primary (age)	Secondary (maturation)
CF Non-switch RT (ms)	ANOVA, Tukey’s HSD	Linear regression	Linear regression
CF Switch RT (ms)	ANOVA, Tukey’s HSD	Linear regression	Linear regression
CF Switch Cost (ms)	ANOVA, Tukey’s HSD	Linear regression	Linear regression
CF Accuracy (%)	KW, Holm-adj. Wilcoxon	ZOIB regression	Beta regression
WM RT (ms)	ANOVA, Tukey’s HSD	Linear regression	Linear regression
WM Accuracy (%)	ANOVA, Tukey’s HSD	Linear regression	Linear regression
WM False Alarm (%)	KW, Holm-adj. Wilcoxon	ZOIB regression	Beta regression
WM Missed Target (%)	KW, Holm-adj. Wilcoxon	Beta regression	Beta regression

Nb. RT variables for the CF task in the secondary analysis were log-transformed prior to regression analyses. KW = Kruskal–Wallis; ZOIB = zero-/one-inflated beta regression.

3.3.5.1 Exploratory Analysis (Academy Pathway Structure)

Group-based analyses of the English youth academy pathway structure were conducted first as an *exploratory* examination to determine whether the assessment is sensitive to developmental differences within highly skilled youth players. Grouping variables included developmental phase and team (see Table 3.1). For the CF task, the FP was excluded from phase-level analyses due to a small sample size ($n = 4$), while the U12 ($n = 4$) and U16 ($n = 2$) teams were excluded from team-level analyses for the same reason. For normally distributed outcomes, one-way analyses of variance (ANOVA) were conducted, with Tukey's Honestly Significant Difference (HSD) tests used for post-hoc comparisons following significant omnibus effects. For outcomes violating normality assumptions, Kruskal–Wallis tests were employed, with Holm-adjusted pairwise Wilcoxon rank-sum tests used where appropriate. Effect sizes for one-way ANOVA models were quantified using partial eta squared (η^2), while eta squared based on the Kruskal–Wallis H statistic (η^2H) was reported for non-parametric comparisons (Tomczak & Tomczak, 2014). Effect sizes were interpreted using conventional benchmarks adapted from Cohen (1988), with values of approximately 0.01, 0.06, and 0.14 representing small, medium, and large effects, respectively.

3.3.5.2 Primary Analysis (Chronological Age)

Following the exploratory analysis, regression-based approaches were used as the *primary* analysis to examine continuous age-related effects. CA was entered as a continuous predictor for each outcome variable. For models meeting parametric assumptions, simple linear regression models were fitted, with model assumptions evaluated via residual-versus-fitted plots and normal Q–Q plots. Effect sizes were quantified using R^2 values. For bounded proportional outcomes, beta regression models were applied, with model fit evaluated using pseudo- R^2 metrics where applicable. Where proportional outcomes demonstrated inflation at 0% or 100%, zero-/one-inflated beta

(ZOIB) regression models were fitted using the Generalised Additive Models for Location, Scale and Shape (GAMLSS) framework (Stasinopoulos & Rigby, 2007), allowing separate modelling of mean performance and boundary inflation processes (Cribari-Neto & Zeileis, 2010). For linear regression models, model explanatory power was quantified using R^2 and interpreted using Cohen's benchmarks for f^2 (Cohen, 1988), whereby values of approximately 0.02, 0.13, and 0.26 represent small, medium, and large effects, respectively. For beta and ZOIB regression models, pseudo- R^2 indices were reported to describe relative model fit. However, as these values do not represent explained variance and are not directly comparable to linear R^2 , they were interpreted descriptively to compare model adequacy rather than absolute effect magnitude (Ferrari & Cribari-Neto, 2004; Smithson & Verkuilen, 2006).

3.3.5.3 Secondary Analysis (Biological Maturation)

The *secondary* analysis extended the primary regression framework to examine the influence of biological maturation on SB360 cognitive-motor performance. Maturation-related predictors, including CA, BA, and maturity timing (BA–CA), were examined separately for each outcome variable. In the *secondary* analysis, proportional outcome variables were analysed using standard beta regression. Given the relatively small subsample sizes and the low frequency of boundary observations (0% or 100%), a ZOIB regression was not considered appropriate. To satisfy the assumptions of beta regression, boundary values were adjusted using a small epsilon transformation so that all observations fell within the open interval (0,1) prior to analysis, while preserving the original values of all non-boundary observations. For the CF task, RT outcomes (except for switch cost) were log-transformed prior to modelling to improve normality of residuals. Within each outcome and subsample, model fit across predictors was compared using Akaike's Information Criterion (AIC) (Burnham & Anderson, 2002), with lower values indicating better relative fit. For beta-based models, average marginal effects

(AME) were computed and reported both as proportions (prop) and percentage points (pp) to facilitate interpretation of maturational effect across models (Long & Freese, 2014).

3.3.6 Sample Size Estimation

To evaluate whether the study was sufficiently powered to detect age-related effects in the primary regression analyses, *a priori* sample size estimation was conducted. Power calculations were performed using G*Power (version 3.1), specifying an F-test for linear multiple regression with a fixed model and R^2 deviation from zero, corresponding to a simple regression framework with one tested predictor (Appendix 4). The analysis assumed a significance level of $\alpha = 0.05$, a desired statistical power of 0.80, and a small-to-moderate effect size of Cohen's $f^2 = 0.15$. Under these assumptions, the required minimum total sample size was 55 participants.

In the present study, 80 participants were included in the primary regression analyses for the CF task and 125 participants for the WM task, indicating that the primary analyses were adequately powered. However, caution is warranted when interpreting the secondary (biological maturation) analysis, as these were conducted on age-band subsamples in which individual CF and WM outcome variables were assessed using linear regression models with fewer than 55 participants, potentially limiting statistical power and increasing the risk of Type II error (Cohen, 1988; Maxwell et al., 2008).

3.4 Results

3.4.1 Exploratory Analysis (Academy Pathway Structure)

Descriptive statistics for CF and WM task outcomes across academy phases and teams are presented in Tables 3.4 and 3.5, respectively. Inferential statistics from exploratory group analyses are presented in Tables 3.6 and 3.7, respectively.

Table 3.4 Descriptive statistics for cognitive flexibility (CF) task performance by developmental phase and team.

Phase	<i>n</i>	Age (years)	Non-switch RT (ms)	Switch RT (ms)	Switch Cost (ms)	Accuracy (%)	Perfect (100%) accuracy (<i>n</i>)
FP [†]	4	11.9 ± 0.5	1,778 ± 206	1,892 ± 194	114 ± 74	91.8 ± 10.2	2
YDP ¹	21	13.2 ± 0.8	1,792 ± 278	1,870 ± 260	78 ± 163	91.9 ± 9.6	4
YDP ²	15	15.1 ± 0.5	1,638 ± 293	1,835 ± 294	197 ± 110	86.8 ± 12.0	1
PDP	40	17.9 ± 1.3	1,579 ± 320	1,682 ± 336	103 ± 169	91.8 ± 7.8	6
Total	80	15.8 ± 2.5	1,656 ± 309	1,771 ± 313	115 ± 158	90.9 ± 9.3	13
Team	<i>n</i>	Age (years)	Non-switch RT (ms)	Switch RT (ms)	Switch Cost (ms)	Accuracy (%)	Perfect (100%) accuracy (<i>n</i>)
U12 [†]	4	11.9 ± 0.5	1,778 ± 206	1,892 ± 194	114 ± 74	91.8 ± 10.2	2
U13	13	12.7 ± 0.5	1,829 ± 275	1,941 ± 243	112 ± 166	90.4 ± 11.6	3
U14	8	14.0 ± 0.3	1,732 ± 290	1,755 ± 260	23 ± 151	94.4 ± 4.6	1
U15	13	14.9 ± 0.4	1,671 ± 298	1,870 ± 301	198 ± 110	87.8 ± 11.9	1
U16 [†]	2	15.8 ± 0.3	1,420 ± 176	1,608 ± 20	188 ± 156	80.5 ± 14.8	0
U18	21	17.0 ± 0.6	1,676 ± 334	1,739 ± 350	63 ± 166	91.6 ± 9.0	5
U21	19	19.0 ± 1.0	1,472 ± 274	1,620 ± 317	147 ± 164	92.1 ± 6.6	1

Nb. [†] Indicates that the phase/team data were excluded from the exploratory analysis due to an inadequate sample size. Data are presented as mean ± SD, unless otherwise stated.

Table 3.5 Descriptive statistics for working memory (WM) task performance by developmental phase and team.

Phase	<i>n</i>	Age (years)	Overall RT (ms)	Accuracy (%)	Missed Target (%)	False Alarm (%)	Zero (0%) false alarm (<i>n</i>)
FP	6	12.0 ± 0.3	1,392 ± 209	54.8 ± 13.9	33.3 ± 16.3	11.9 ± 7.5	0
YDP ¹	39	13.2 ± 0.6	1,413 ± 220	50.9 ± 12.4	38.3 ± 11.9	10.8 ± 6.5	2
YDP ²	32	15.3 ± 0.6	1,477 ± 286	53.4 ± 19.2	36.0 ± 16.7	10.5 ± 7.5	4
PDP	48	18.1 ± 1.3	1,356 ± 228	53.5 ± 13.5	31.7 ± 13.8	14.9 ± 9.1	2
Total	125	15.6 ± 2.4	1,407 ± 243	52.7 ± 14.8	34.9 ± 14.3	12.3 ± 8.0	8
Team	<i>n</i>	Age (years)	Overall RT (ms)	Accuracy (%)	Missed Target (%)	False Alarm (%)	Zero (0%) false alarm (<i>n</i>)
U12	6	12.0 ± 0.3	1,392 ± 209	54.8 ± 13.9	33.3 ± 16.3	11.9 ± 7.5	0
U13	24	12.8 ± 0.3	1,477 ± 227	49.6 ± 12.6	37.8 ± 12.1	12.6 ± 5.8	0
U14	15	13.8 ± 0.4	1,311 ± 168	53.1 ± 12.3	39.1 ± 12.1	7.8 ± 6.6	2
U15	20	14.9 ± 0.5	1,527 ± 220	58.8 ± 14.2	30.7 ± 12.9	10.6 ± 6.8	1
U16	12	15.8 ± 0.2	1,394 ± 366	44.5 ± 23.5	45.0 ± 18.9	10.5 ± 8.9	3
U18	23	17.0 ± 0.6	1,350 ± 254	57.3 ± 11.2	32.2 ± 13.4	10.6 ± 8.3	2
U21	25	19.2 ± 1.0	1,361 ± 206	49.9 ± 14.7	31.2 ± 14.4	18.9 ± 8.0	0

Nb. Data are presented as mean ± SD, unless otherwise stated.

3.4.1.1 Cognitive Flexibility (Academy Pathway Structure)

The exploratory analysis indicated that pathway-related differences in CF were expressed primarily through RT performance, particularly at the upper end of the academy pathway, while accuracy remained stable across phases and teams (Table 3.6). At the phase level, significant main effects were observed for RT variables ($ps \leq .04$), with small-to-moderate effect sizes ($\eta p^2 = .09$). Post-hoc comparisons showed faster non-switch RT in the PDP players ($1,579 \pm 320$ ms) relative to the YDP¹ players ($1,792 \pm 278$ ms). No other phase-level contrasts reached statistical significance. CF accuracy did not differ across phases ($p = .47$).

At the team level, significant differences were again evident for RT outcomes ($ps \leq .05$). In both RT metrics, U21 players (non-switch: $1,472 \pm 274$ ms; switch: $1,620 \pm 317$ ms) responded significantly faster than U13 players (non-switch: $1,829 \pm 275$ ms, $p = .01$; switch: $1,941 \pm 243$ ms, $p = .04$). Switch cost showed a trend towards differences between teams ($p = .06$), although no post-hoc comparisons reached statistical significance following Tukey adjustment. CF accuracy did not differ across teams ($p = .78$).

Table 3.6 One-way ANOVA and Kruskal–Wallis tests comparing cognitive flexibility (CF) outcomes across academy phases and teams.

Group	Outcome	Test	df	Test statistic	<i>p</i> -value	Effect size	Post-hoc comparison
Phase	Non-switch RT	ANOVA	2, 71	$F = 3.36$	.04	$\eta p^2 = .09$	PDP < YDP ¹ ($p = .03$)
Phase	Switch RT	ANOVA	2, 71	$F = 3.38$	.04	$\eta p^2 = .09$	ns
Phase	Switch Cost	ANOVA	2, 71	$F = 2.48$	.09	$\eta p^2 = .07$	ns
Phase	Accuracy	KW	2	$\chi^2 = 1.53$	.47	$\eta^2 H = .02$	ns
Team	Non-switch RT	ANOVA	4, 69	$F = 3.05$	.02	$\eta p^2 = .15$	U21 < U13 ($p = .01$)
Team	Switch RT	ANOVA	4, 69	$F = 2.54$	.05	$\eta p^2 = .13$	U21 < U13 ($p = .04$)
Team	Switch Cost	ANOVA	4, 69	$F = 2.42$	.06	$\eta p^2 = .12$	ns
Team	Accuracy	KW	4	$\chi^2 = 1.76$	.78	$\eta^2 H = .03$	ns

Nb. KW = Kruskal–Wallis. Post-hoc contrasts are based on Tukey HSD (ANOVA) or Holm-adjusted pairwise Wilcoxon tests (Kruskal–Wallis; KW), and only statistically significant contrasts are reported. ηp^2 = partial eta squared; $\eta^2 H$ = eta squared based on Kruskal–Wallis ($\chi^2 / (N - 1)$); ns = not significant.

3.4.1.2 Working Memory (Academy Pathway Structure)

In contrast to the CF task, WM performance showed limited differentiation across academy pathway structure (Table 3.7). At the phase level, no significant effects were observed for overall RT, accuracy, false alarms, or missed targets ($ps > .05$). At the team level, RT and accuracy did not differ significantly across teams ($ps \geq .08$). However, a significant team-level effect emerged for false alarms ($p < .01$, $\eta^2H = .16$). Post-hoc comparisons indicated that the U21 ($18.9 \pm 8.0\%$) exhibited higher false-alarm rates than U14 ($7.8 \pm 6.6\%$, $p < .01$), U15 ($10.6 \pm 6.8\%$, $p = .02$), and U18 ($10.6 \pm 8.3\%$, $p = .02$) players. Missed targets approached a significant team-level effect but did not reach the threshold for statistical significance ($p = .06$, $\eta^2H = .09$).

Table 3.7 One-way ANOVA and Kruskal–Wallis tests comparing working memory (WM) outcomes across academy phases and teams.

Group	Outcome	Test	df	Test statistic	<i>p</i> -value	Effect size	Post-hoc comparison
Phase	RT	ANOVA	3, 121	$F = 1.64$	.18	$\eta p^2 = .04$	ns
Phase	Accuracy	ANOVA	3, 121	$F = 0.29$	.84	$\eta p^2 = .01$	ns
Phase	False Alarms	KW	3	$\chi^2 = 5.84$	.12	$\eta^2H = .05$	ns
Phase	Missed Targets	KW	3	$\chi^2 = 5.34$	.15	$\eta^2H = .04$	ns
Team	RT	ANOVA	6, 118	$F = 2.01$	.07	$\eta p^2 = .09$	ns
Team	Accuracy	ANOVA	6, 118	$F = 1.97$	.08	$\eta p^2 = .09$	ns
Team	False Alarms	KW	6	$\chi^2 = 22.98$	<.01	$\eta^2H = .16$	U21 > U14 ($p < .01$) U21 > U15 ($p = .02$) U21 > U18 ($p = .02$)
Team	Missed Targets	KW	6	$\chi^2 = 12.28$	.06	$\eta^2H = .09$	ns

Nb. KW = Kruskal–Wallis. Post-hoc contrasts are based on Tukey HSD (ANOVA) or Holm-adjusted pairwise Wilcoxon tests (Kruskal–Wallis; KW), and only statistically significant contrasts are reported. ηp^2 = partial eta squared; η^2H = eta squared based on Kruskal–Wallis ($\chi^2 / (N - 1)$); ns = not significant.

3.4.2 Primary Analysis (Chronological Age)

3.4.2.1 Cognitive Flexibility (Chronological Age)

Primary regression analyses demonstrated pronounced age-related improvements in CF RT outcomes (Table 3.8; Figure 3.3). Increasing CA was associated with faster non-switch RT ($b = -44.27 \text{ ms} \cdot \text{year}^{-1}$, $p < .01$, $R^2 = .11$) and switch RT ($b = -41.98 \text{ ms} \cdot \text{year}^{-1}$, $p < .01$, $R^2 = .12$). In contrast, switch cost was not associated with CA ($p = .75$), indicating that the additional time required to switch between task rules remained stable across the examined age range. CF accuracy, analysed using ZOIB regression, was not significantly associated with CA in either the mean component ($p = .39$) or the inflation component, indicating stable accuracy across the examined age range.

Table 3.8 Chronological age effects on cognitive flexibility (CF) task performance.

Outcome	Model	β (SE)	95% CI	Test statistic	p -value	Effect size
Non-switch RT (ms)	LM	-44.27 (13.39)	[-70.91, -17.62]	$t(78) = -3.31$	<.01	$R^2 = .12$
Switch RT (ms)	LM	-41.98 (13.64)	[-69.13, -14.82]	$t(78) = -3.08$	<.01	$R^2 = .11$
Switch Cost (ms)	LM	2.29 (7.28)	[-12.20, 16.78]	$t(78) = 0.32$	.75	$R^2 < .01$
Accuracy (prop)	ZOIB (BEINF)	0.033 (0.037)	[-0.041, 0.106]	$z = 0.87$	.39	-

Nb. Effect sizes are reported as R^2 where applicable. LM = linear model; ZOIB = zero-/one-inflated beta regression.

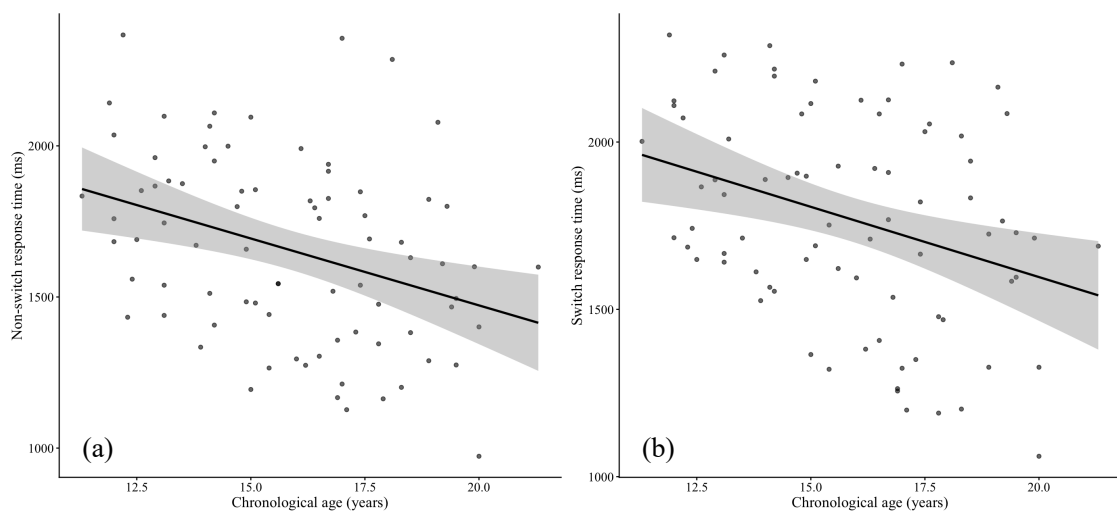


Figure 3.3 Association between chronological age (years) and response time (ms) outcomes in the cognitive flexibility (CF) task. Panels show (a) non-switch RT and (b) switch RT. Solid black lines represent fitted linear regression models, with shaded areas indicating 95% confidence intervals.

3.4.2.2 Working Memory (Chronological Age)

Similar to the exploratory analysis, WM performance showed limited sensitivity to CA (Table 3.9). CA was not significantly associated with RTs ($p = .10$) or accuracy ($p = .91$). CA also did not predict missed-target rates ($p = .16$). However, CA was positively associated with false-alarm rates in a zero-inflated beta regression model ($b = 0.064$, $p = .01$, $\text{pseudo-}R^2 \approx .23$), indicating an increase in false alarms with advancing age. The inflation component suggested a stable probability of zero false alarms across ages, with age-related effects driven by changes in the mean response process. Taken together, WM performance did not exhibit consistent age-related improvements in RT or accuracy. Age-related changes were restricted to false-alarm rates, suggesting subtle developmental shifts in response control or behaviour rather than global performance enhancement.

Table 3.9 Chronological age effects on working memory (WM) task performance.

Outcome	Model	β (SE)	95% CI	Test statistic	p -value	Effect size
RT (ms)	LM	-14.62 (8.91)	[-32.26, 3.02]	$t(123) = -1.64$	.10	$R^2 = .02$
Accuracy (ms)	LM	-0.07 (0.55)	[-1.15, 1.02]	$t(123) = -0.12$	.91	$R^2 < .01$
False Alarm (%)	ZIB (BEZI)	0.064 (0.023)	[0.018, 0.109]	$z = 2.75$	.01	-
Missed Target (%)	Beta	-0.033 (0.023)	[-0.079, 0.013]	$z = -1.42$	.16	$\text{pseudo-}R^2 = .02$

Nb. Effect sizes are reported as R^2 or $\text{pseudo-}R^2$ where applicable. LM = linear model; ZIB = zero-inflated beta regression.

3.4.3 Secondary Analysis (Biological Maturation)

The secondary analysis compared CA, BA, and BA–CA as predictors of CF and WM outcomes. Table 3.10 and 3.11 display the statistics of analysed models within the U13–U14 and U14–U15 subsamples, respectively.

Table 3.10 Comparison of regression models with chronological age (CA), biological age (BA), and maturity timing (BA–CA) as predictors in the early-adolescent subsample (U13-U14).

Task	Outcome	Predictor	Model	<i>n</i>	<i>b</i> (SE)	95% CI (<i>b</i>)	<i>t</i> / <i>z</i>	βstd	AIC	<i>p</i> -value	<i>R</i> ² / pseudo- <i>R</i> ²	adj_ <i>R</i> ²	logLik	AME (prop)	AME (pp)
CF	Non-switch RT_log	CA	LM	32	-0.114 (0.071)	[-0.259, 0.031]	-1.611	-0.282	1.997	.12	.08	.05	-	-	-
		BA*†	LM	32	-0.106 (0.043)	[-0.194, -0.018]	-2.472	-0.411	-1.280	.02	.17	.14	-	-	-
		BA-CA*	LM	32	-0.131 (0.062)	[-0.258, -0.005]	-2.120	-0.361	0.187	.04	.13	.10	-	-	-
	Switch RT_log	CA*	LM	32	-0.167 (0.060)	[-0.289, -0.045]	-2.790	-0.454	-8.896	.01	.21	.18	-	-	-
		BA*†	LM	32	-0.111 (0.038)	[-0.188, -0.034]	-2.930	-0.472	-9.569	.01	.22	.20	-	-	-
		BA-CA	LM	32	-0.093 (0.058)	[-0.212, 0.025]	-1.614	-0.283	-4.182	.12	.08	.05	-	-	-
	Switch Cost	CA†	LM	32	-111.15 (64.09)	[-242.03, 19.73]	-1.734	-0.302	437.53	.09	.09	.06	-	-	-
		BA	LM	32	-9.11 (42.83)	[-96.58, 78.37]	-0.213	-0.039	440.54	.83	.002	-.03	-	-	-
		BA-CA	LM	32	79.66 (58.54)	[-39.90, 199.23]	1.361	0.241	438.67	.18	.06	.03	-	-	-
	Accuracy	CA	Beta	32	0.199 (0.282)	[-0.355, 0.752]	0.703	-	-87.50	.48	.01	-	46.75	0.015	1.541
		BA	Beta	32	0.296 (0.181)	[-0.059, 0.651]	1.634	-	-89.48	.10	.05	-	47.74	0.022	2.205
		BA-CA*†	Beta	32	0.522 (0.245)	[0.040, 1.003]	2.124	-	-91.00	.03	.07	-	48.50	0.035	3.542

Table 3.10 Continued.

Task	Outcome	Predictor	Model	<i>n</i>	<i>b</i> (SE)	95% CI (<i>b</i>)	<i>t</i> / <i>z</i>	βstd	AIC	<i>p</i> -value	<i>R</i> ² / pseudo- <i>R</i> ²	adj_ <i>R</i> ²	logLik	AME (prop)	AME (pp)
WM	Overall RT	CA*†	LM	33	-140.6 (58.7)	[-260.2, -21.0]	-2.397	-0.395	451.8	.02	.16	.13	-	-	-
		BA	LM	33	-51.9 (37.3)	[-128.0, 24.2]	-1.392	-0.243	455.4	.17	.06	.03	-	-	-
		BA-CA	LM	33	-20.2 (56.6)	[-135.6, 95.2]	-0.357	-0.064	457.2	.72	.00	-.03	-	-	-
	Accuracy	CA	LM	33	2.45 (3.858)	[-5.42, 10.32]	0.635	0.113	272.1	.53	.01	-.02	-	-	-
		BA	LM	33	-0.90 (2.332)	[-5.66, 3.86]	-0.386	-0.069	272.4	.70	.01	-.03	-	-	-
		BA-CA †	LM	33	-3.43 (3.392)	[-10.35, 3.49]	-1.011	-0.179	271.5	.32	.03	.00	-	-	-
	False Alarm	CA*‡	Beta	33	-0.735 (0.182)	[-1.092, -0.379]	-4.041	-	-85.44	<.01	.23	-	45.72	-0.060	-5.970
		BA*‡	Beta	33	-0.473 (0.120)	[-0.708, -0.238]	-3.950	-	-85.16	<.01	.23	-	45.58	-0.042	-4.234
		BA-CA	Beta	33	-0.333 (0.181)	[-0.687, 0.022]	-1.839	-	-73.92	.07	.07	-	39.96	-0.032	-3.160
	Missed Target	CA	Beta	33	0.175 (0.137)	[-0.093, 0.443]	1.279	-	-41.15	.20	.05	-	23.58	0.042	4.235
		BA*†	Beta	33	0.170 (0.079)	[0.015, 0.325]	2.151	-	-43.90	.03	.12	-	24.95	0.041	4.088
		BA-CA	Beta	33	0.200 (0.120)	[-0.035, 0.435]	1.665	-	-42.14	.10	.07	-	24.07	0.048	4.838

Nb. Model fit was compared using AIC, with lower values indicating better relative model fit within each outcome. Linear regression outcomes report standardised coefficients (βstd). Beta regression outcomes report AME as proportions (prop; 0–1) and percentage points (pp; AME × 100). † Indicates the best-supported predictor for each outcome variable, irrespective of statistical significance. ‡ Indicates that the predictor demonstrated a model fit comparable to that of another predictor for the same outcome variable. **p* < .05.

Table 3.11 Comparison of regression models with chronological age (CA), biological age (BA), and maturity timing (BA–CA) as predictors in the mid-adolescent subsample (U14-U15).

Task	Outcome	Predictor	Model	<i>n</i>	<i>b</i> (SE)	95% CI (<i>b</i>)	t/z	βstd	AIC	<i>p</i> -value	<i>R</i> ² / pseudo- <i>R</i> ²	adj_ <i>R</i> ²	logLik	AME (prop)	AME (pp)
CF	Non-switch RT	CA	LM	29	0.016 (0.067)	[-0.122, 0.154]	0.236	0.045	-2.062	.82	.00	-.04	-	-	-
		BA	LM	29	-0.018 (0.040)	[-0.100, 0.063]	-0.460	-0.088	-2.228	.65	.01	-.03	-	-	-
		BA-CA†	LM	29	-0.030 (0.049)	[-0.131, 0.071]	-0.614	-0.117	-2.404	.54	.01	-.02	-	-	-
	Switch RT	CA†	LM	29	0.047 (0.055)	[-0.066, 0.161]	0.853	0.162	-13.42	.40	.03	-.01	-	-	-
		BA	LM	29	0.004 (0.033)	[-0.064, 0.072]	0.129	0.025	-12.67	.90	.00	-.04	-	-	-
		BA-CA	LM	29	-0.010 (0.041)	[-0.095, 0.074]	-0.249	-0.048	-12.71	.81	.00	-.04	-	-	-
	Switch Cost	CA	LM	29	52.88 (55.49)	[-60.98, 166.74]	0.953	0.180	387.40	.35	.03	-.00	-	-	-
		BA†	LM	29	45.50 (32.22)	[-20.61, 111.62]	1.412	0.262	386.29	.17	.07	.03	-	-	-
		BA-CA	LM	29	44.28 (40.59)	[-38.99, 127.56]	1.091	0.205	387.10	.28	.04	.01	-	-	-
	Accuracy	CA†	Beta	29	0.306 (0.275)	[-0.232, 0.844]	1.115	-	-86.70	.27	.03	-	46.35	0.020	1.951
		BA	Beta	29	0.138 (0.163)	[-0.181, 0.457]	0.850	-	-86.00	.40	.01	-	46.00	0.009	0.945
		BA-CA	Beta	29	0.017 (0.204)	[-0.383, 0.417]	0.083	-	-85.53	.93	.00	-	45.76	0.001	0.122

Table 3.11 Continued.

Task	Outcome	Predictor	Model	<i>n</i>	<i>b</i> (SE)	95% CI (<i>b</i>)	t/z	βstd	AIC	<i>p</i> -value	<i>R</i> ² / pseudo- <i>R</i> ²	adj_ <i>R</i> ²	logLik	AME (prop)	AME (pp)
WM	Overall RT	CA*†	LM	27	164.7 (63.3)	[34.1, 295.2]	2.598	0.461	361.0	.02	.21	.18	-	-	-
		BA	LM	27	67.7 (34.8)	[-4.0, 139.4]	1.945	0.363	363.7	.06	.13	.10	-	-	-
		BA-CA	LM	27	34.7 (46.1)	[-60.3, 129.6]	0.752	0.149	366.9	.46	.02	-.02	-	-	-
	Accuracy	CA	LM	27	1.12 (4.62)	[-8.38, 10.62]	0.243	0.049	219.6	.81	.00	-.04	-	-	-
		BA	LM	27	-1.07 (2.41)	[-6.02, 3.89]	-0.442	-0.088	219.4	.66	.01	-.03	-	-	-
		BA-CA†	LM	27	-2.35 (2.98)	[-8.48, 3.79]	-0.788	-0.156	219.0	.44	.02	-.02	-	-	-
	False Alarm	CA†	Beta	27	-0.192 (0.302)	[-0.784, 0.400]	-0.635	-	-71.28	.53	.01	-	38.64	-0.014	-1.438
		BA	Beta	27	0.055 (0.159)	[-0.258, 0.367]	0.343	-	-71.00	.73	.00	-	38.50	0.005	0.453
		BA-CA	Beta	27	0.094 (0.198)	[-0.294, 0.483]	0.477	-	-71.16	.63	.01	-	38.58	0.008	0.797
	Missed Target	CA†	Beta	27	-0.130 (0.170)	[-0.463, 0.203]	-0.764	-	-35.42	.45	.02	-	20.71	-0.030	-2.969
		BA	Beta	27	-0.000 (0.090)	[-0.176, 0.176]	-0.004	-	-34.84	.10	.00	-	20.42	-0.000	-0.008
		BA-CA	Beta	27	0.070 (0.112)	[-0.148, 0.289]	0.630	-	-35.23	.53	.01	-	20.61	0.017	1.651

Nb. Model fit was compared using AIC, with lower values indicating better relative model fit within each outcome. Linear regression outcomes report standardised coefficients (βstd). Beta regression outcomes report AME as proportions (prop; 0–1) and percentage points (pp; AME × 100). † Indicates the best-supported predictor for each outcome variable, irrespective of statistical significance. **p* < .05.

3.4.3.1 U13-U14 Subsample: Early Adolescence (Biological Maturation)

For the CF test, biological maturity predictors provided the most consistent explanation of RT measures (Table 3.10). For non-switch RT, BA ($b = -0.106$, $p = .02$, $R^2 = .17$) and BA-CA ($b = -0.131$, $p = .04$, $R^2 = .13$) were statistically strong predictors, whereas CA was not. For switch RT, both CA ($b = -0.167$, $p = .01$, $R^2 = .21$) and BA ($b = -0.111$, $p = .01$, $R^2 = .22$) were significant, with BA models demonstrating lower AIC values. In contrast, switch cost was not significantly associated with CA, BA, or BA-CA ($ps \geq .09$), indicating that neither age nor biological maturation strongly explained the additional time required to switch between task rules in this subsample. These findings suggest that while general age-related development contributed to improvements in RT measures, biological maturation meaningfully explained performance variability and provided the most robust explanation of CF response speed during early adolescence. For CF accuracy, maturity timing (BA-CA) was positively associated with accuracy ($b = 0.522$, $p = .03$), though the effect was small (pseudo- $R^2 = .07$; AME = 3.5 pp). For WM performance, CA best explained overall RT ($b = -140.61 \text{ ms} \cdot \text{year}^{-1}$, $p = .02$, $R^2 = .16$). For false alarms, both CA and BA showed strong negative associations ($ps < .01$; pseudo- $R^2 \approx .23$). BA was the best predictor of missed targets ($b = 0.170$, $p = .03$; pseudo- $R^2 = .12$; AME = 4.1 pp). No predictors were significantly associated with WM accuracy.

3.4.3.2 U14-U15 Subsample: Mid-Adolescence (Biological Maturation)

In contrast to the U13-U14 subsample, none of the CA, BA, or BA-CA predictors demonstrated statistically significant associations with CF testing outcomes in the U14-U15 group (Table 3.11), with all effects small and non-significant ($ps > .05$; $R^2 \leq .07$). For WM performance, CA was the best-fitting predictor for RT and was positively associated with slower responses ($b = 164.7 \text{ ms} \cdot \text{year}^{-1}$, $p = .02$, $R^2 = .21$). No maturity-related predictors were associated with WM accuracy, false alarms, or missed targets ($ps > .05$).

3.5 Discussion

This study examined developmental variation in SB360 cognitive-motor performance among skilled youth football players, with particular emphasis on the contributions of academy pathway structure, age, and biological maturation. Findings demonstrated that performance differences were primarily expressed in RT measures and were most evident across broad developmental spans rather than within adjacent age groups. Exploratory analyses showed limited differentiation between consecutive academy age bands, with differences emerging most clearly when comparing the youngest and oldest cohorts. Primary analyses indicated that increasing CA was associated with faster CF RT, whereas switch cost and accuracy remained stable across age. In contrast, WM outcomes demonstrated minimal age sensitivity, with effects confined to false-alarm behaviour. Secondary analyses further indicated that biological maturation contributed to performance during early-adolescence (U13-U14), particularly for RT measures, but these effects were attenuated in mid-adolescence (U14-U15). Collectively, these findings suggest that SB360 performance reflects an interaction between developmental, cognitive, and motor-execution processes rather than isolated cognitive development.

Exploratory analyses revealed that differences in cognitive-motor performance were primarily observed when comparing widely separated age groups (e.g., U13 vs. U21), whereas comparisons within consecutive age bands showed limited differentiation (Tables 3.6 and 3.7). This pattern aligns with previous research reporting pronounced age-related improvements in EF and perceptual-cognitive tasks across broad developmental spans in youth football players, but minimal differences within adjacent age groups (Beavan, Spielmann, et al., 2020; Ehmann et al., 2022; Heilmann et al., 2022; Paško et al., 2021; Schumacher et al., 2018). Such findings suggest that age-group classifications within academy structures may have limited sensitivity for cognitive benchmarking. Instead, observed differences across broader age ranges likely reflect general

developmental progression, biological maturation, and accumulated training exposure rather than football-specific cognitive differentiation. Consistent with previous work (Beavan, Chin, et al., 2020; Beavan, Spielmann, et al., 2020), the present findings indicate that variation in general EF performance among highly skilled youth players largely mirrors normative developmental trajectories observed in the general population.

In this study, these age effects were not uniform across outcomes and emerge selectively depending on task and performance metrics. Increasing CA was significantly associated with faster CF RT across non-switch and switch conditions (Figure 3.3), whereas switch cost and accuracy remained stable across age. In contrast, WM outcomes showed minimal age sensitivity (Table 3.9). As outlined in Chapter 2, CF has been consistently associated with football expertise and is widely regarded as the most complex of the core EFs, as it requires set shifting alongside successful updating in WM while suppressing previously relevant responses (Collins & Koechlin, 2012; Miyake et al., 2000). In contrast, although WM is theoretically relevant to football performance, its empirical association with football outcomes is mixed and may be less robust when examined as a standalone construct (see Section 2.3.2.2). This suggests that WM contributes to football behaviour through interactions with other cognitive processes rather than emerging as a strong independent discriminator of expertise. Collectively, this may partly explain why CF demonstrated greater developmental sensitivity than WM in the present sample.

From a methodological perspective, an important distinction between the present study and much of the existing literature relates to the integration of overt motor responses within SB360 tasks. Traditional cognitive assessments typically employ button-press responses to isolate cognitive processing demands (Foster et al., 2022), whereas the SB360 requires whole-body, football-specific actions such as kicking. These motor demands undergo substantial developmental change during adolescence, particularly in

relation to strength, coordination, and limb velocity (Cerrah et al., 2024), meaning that SB360 RT reflects both cognitive processing speed and motor-execution capacity. This distinction is further illustrated by differences between task characteristics. The CF task requires an overt motor response on every trial, making RT a continuous index of motor-execution speed, whereas the WM task involves response inhibition on most trials, substantially reducing the influence of motor demands. Likewise, accuracy and error-based measures primarily reflect response correctness rather than the precision or quality of movement execution. Consequently, developmental effects were most evident in outcomes requiring consistent motor output (i.e., CF RT), but not in accuracy measures that capture binary correctness.

In line with this interpretation, the absence of age-related differences in CF switch cost indicates that improvements in switch and non-switch RT occurred in parallel, suggesting that developmental changes across age primarily reflected faster overall response speeds rather than specific improvements in the executive control mechanisms required to resolve switching demands. For example, although the U21 players responded significantly faster than the U13 players during switch trials, the U13 players exhibited a lower switch cost (Table 3.4). Moreover, secondary analyses further demonstrated that biological maturation explained additional variance in CF RT during early adolescence, whereas switch cost was not associated with CA, BA, or BA–CA (Table 3.10). In the U13-U14 subsample, BA emerged as the most consistent predictor of RT, with non-switch RT identifying BA as the only significant predictor. These findings suggest that faster responses in the SB360 CF task may be closely related to biological maturation and physical development, particularly in cognitively less demanding conditions. In this context, the absence of maturation-related effects in the older cohort may be attributable to their more advanced maturity status (Table 3.2), with their %PAH approaching the

post-pubertal phase (approximately 95%), during which motor coordination becomes more stable (Cumming et al., 2017).

However, secondary analyses did not directly compare the three developmental predictors using a single multiple regression model and instead compared AIC values from three different simple linear regression models. The secondary analyses therefore indicate whether each developmental variable was independently associated with performance but do not permit direct comparison of the relative contributions of CA, BA, and BA–CA. In addition, evidence regarding age-related differences in switch cost is mixed, whereas RT performances in switching tasks generally align with the present findings (Ferguson et al., 2021; Reimers & Maylor, 2005; Schwarze et al., 2024; Wasylyshyn et al., 2011). Consequently, the absence of age-related differences in switch cost alone should not be interpreted as evidence that faster RT in older players was driven exclusively by motor-execution improvements. Rather, the present findings indicate that SB360 performance reflects the combined influence of cognitive processing and motor-execution, although their relative contributions cannot be disentangled within the current study design.

Collectively, findings suggest that developmental influences on SB360 performance depend on both task characteristics and the performance metric examined. Across the SB360 test battery, RT outcomes derived from tasks requiring consistent motor responses demonstrated greater developmental sensitivity, whereas switch cost, accuracy, and error-based outcomes showed limited differentiation. In the current test battery, accuracy-based measures primarily reflect response correctness rather than the technical precision of motor execution. Accordingly, RT metrics may be more suitable for cross-sectional developmental profiling, whereas accuracy outcomes may be better suited to longitudinal monitoring of within-player change. Given the apparent sensitivity of the SB360's overt motor-response modality to developmental variation, future task development may

benefit from incorporating motor precision-based measures (e.g., ball-placement absolute error) to better capture not only whether correct decisions are made, but also how effectively perceptual information is integrated into coordinated motor responses under time-constrained conditions.

Recent work by Knöbel et al. (2025), extending earlier SB360 validation research (Musculus et al., 2022), reported comparable developmental patterns in CF performance among professional academy players, with RT improvements plateauing in non-switch-trials around age 15 but continuing in switch-trials until age 16. While they questioned the prognostic value of SB360 EF tasks for talent identification, the convergence of findings across independent professional academies suggests that the SB360 is sensitive to developmental and maturational differences in motor-executed performance. This distinction indicates that limitations may relate less to measurement sensitivity and more to the applied relevance of domain-general EF paradigms within football contexts. Although prior SB360 validation studies adopted the term *football-specific*, their empirical emphasis has primarily been directed towards the domain-general cognitive constructs embedded within the paradigms. The motor-execution components introduced through the SB360 response modality have not been examined as independent performance dimensions. As such, *football-specific* elements have been incorporated at the level of response, but their functional contribution to performance has not been explicitly evaluated.

Despite incorporating *football-specific* motor responses, the perceptual and cognitive processes of SB360 tasks remain largely domain-general. In competitive football, perceptual processes involve continuous information extraction from multiple dynamic sources (Aksum et al., 2020), with actions shaping subsequent environmental constraints (Gibson, 1979; Passos et al., 2016). In contrast, SB360 tasks operate on discrete, trial-

based stimuli with fixed decision rules and binary response requirements. Although these stimuli may cue motor actions, they do not capture the range of action possibilities, spatiotemporal demands, or interaction dynamics present in match play (see Section 2.2). Moreover, the stationary-ball kicking required in the SB360 tasks may only partially represent the movement kinematics of competitive match play, thereby warranting further examination of response fidelities. Likewise, actions within the SB360 do not influence subsequent task states, limiting the representation of perception–action coupling. Accordingly, while the SB360 introduces some *football-specific* response modalities, its current task design may not fully achieve *ecological validity* from a perceptual-cognitive or perception–action perspective.

As noted earlier, careful consideration of task modality and assessment design is required to optimise the interpretability and applied value of such tools (Kalén et al., 2021). The present findings indicate that SB360 outcomes are sensitive to motor-execution demands and task characteristics, with developmental effects most evident in RT metrics. Importantly, performance outcomes are likely to reflect an interaction between domain-general cognitive processes and task design characteristics, rather than serving as direct measures of *football-specific* decision-making. Accordingly, while overt motor-response tasks may provide insight into developmental variation in cognitive-motor response speeds, the standalone utility of the currently implemented EF paradigms within professional football contexts remains unclear. Therefore, future work should prioritise the development and validation of domain-specific tasks that more directly reflect football-relevant performance demands (Kalén et al., 2021) and more sensitive performance metrics, particularly those capturing movement accuracy and execution quality. Such refinements may better leverage the system’s immersive and motor-integrated features to enhance its applied value for talent development and player evaluation in professional football environments.

Several limitations should be considered when interpreting these findings. First, the cross-sectional design limits causal inference and restricts the ability to disentangle the independent contributions of CA and biological maturity to SB360 performance. Moreover, secondary-analysis subsamples were based on reduced sample sizes and should be interpreted cautiously (Button et al., 2013). Second, the uneven distribution of players across age groups may have reduced statistical power for detecting effects within narrow age bands, increasing the likelihood of Type II error in cross-sectional comparisons (Cohen, 1988; Maxwell et al., 2008). Therefore, future longitudinal research with larger age-stratified samples would strengthen inferences regarding developmental trajectories in SB360 cognitive-motor performance. Finally, SB360 task outcomes reflect an interaction between cognitive processing and large motor execution, meaning that observed age-related effects cannot be attributed solely to general cognitive development.

3.6 Conclusion

This study provides a comprehensive evaluation of developmental influences on SB360 cognitive-motor performance in skilled youth football players. Across analyses, age-related effects were selective and task dependent, with robust developmental trends observed for CF RT but limited sensitivity for CF switch cost, accuracy, and WM outcomes. Biological maturity emerged as an important explanatory factor for CF RT performance during early adolescence, while these effects were attenuated in mid-adolescence. Collectively, the findings highlight that SB360 performance reflects an interaction between cognitive processing and motor-execution capacity that is shaped by age and maturation. From an applied perspective, findings underscore the importance of task- and outcome-specific interpretation, cautious use of cross-sectional benchmarks, and longitudinal monitoring to support meaningful player evaluation and development within professional football academies. Finally, the study also highlights that domain-specific response modalities alone may be insufficient to ensure the representativeness of

real-world performance. The use of the term *football-specific* in assessment tools warrants conceptual precision, particularly regarding which performance dimensions and task constraints the assessment is designed to capture.

**Chapter 4. How Do Perceived Readiness and Subjective Workload
Influence Performance in Cognitive-Motor Tasks? An Applied
Examination Within a Professional Football Academy**

4.1 Abstract

Purpose: This study examined the associations between pre-test perceived readiness, post-test perceived workload, and standardised SoccerBot360 (SB360) cognitive-motor performance in skilled youth football players. **Methods:** Prior to SB360 assessments, participants' readiness was assessed using ratings of perceived exertion (RPE) and motivation. Following these measures, participants completed a battery of assessments that comprised of cognitive flexibility (CF) and working memory (WM) tasks, followed by subjective workload measures (NASA-TLX; Hart & Staveland, 1988). **Results:** Multiple regression analyses indicated that pre-test RPE and motivation showed limited explanatory value for SB360 performance. In contrast, post-test perceived workload exhibited clearer and outcome-specific associations with performance. When outcomes were aggregated across the test battery (CF + WM), higher overall workload was associated with lower response accuracy and higher error-related metrics, whereas no association was observed with RT. Follow-up task-level analyses confirmed associations with reduced CF and WM accuracy and increased WM missed targets. Exploratory analyses further demonstrated an association between higher overall workload and lower CF switch cost. NASA-TLX subscale analyses revealed that perceived workload was predominantly characterised by mental demand and effort, with comparatively low physical demand. **Conclusion:** When compared with the findings in Chapter 3, the results indicate that SB360 outcome metrics are differentially sensitive to developmental versus state-dependent influences. Response correctness measures appear more responsive to perceived workload, whereas RT outcomes are more strongly constrained by age-related factors. Collectively, these findings support a more nuanced interpretation of SB360 performance and highlight the value of incorporating subjective workload alongside behavioural outcomes when interpreting cognitive-motor performance in applied academy settings.

4.2 Introduction

In professional football, there is increasing interest in the assessment of executive function (EF) using structured testing protocols, driven by efforts to advance talent development and identification processes through more objective evaluation of skills related to decision-making, which have been identified as being critical for elite performance (Huijgen et al., 2015; Sakamoto et al., 2018; Vestberg et al., 2017). Alongside laboratory-based paradigms, sport-specific cognitive-motor assessments have emerged with the aim of enhancing ecological relevance by embedding perceptual-cognitive demands within representative motor responses and task constraints (Beavan, Fransen, et al., 2019; Dolata et al., 2025; Knöbel & Lautenbach, 2023; Musculus et al., 2022; Rodrigues et al., 2024). However, as cognitive testing is increasingly implemented within applied sporting environments, performance outcomes are likely to reflect more than underlying cognitive capacity alone. Contemporary evidence demonstrates that executive functioning is influenced by a range of transient physiological and psychological states, including fatigue, motivation, emotional state, and perceived task demands, through their effects on attentional allocation, executive control, and information processing efficiency (Botvinick & Braver, 2015; Gantois et al., 2020; Hou & Cai, 2022; Pessoa, 2008). Consequently, understanding how these state-dependent influences contribute to cognitive-motor performance is important for the valid interpretation and applied use of cognitive assessments within real-world settings.

Despite extensive evidence linking transient physiological and psychological states to EF performance, their influence has predominantly been investigated under controlled laboratory conditions in which pre-test fatigue or motivation are experimentally manipulated (Marcora et al., 2009; Van Cutsem et al., 2017). In contrast, players within professional football academies may undertake benchmark testing following different combinations of training exposure, academic commitments, travel, recovery, and other

daily activities that may naturally influence their physical and psychological state prior to testing (Bishop, 2008; Russell et al., 2019). Likewise, pre-test conditions are inherently difficult to standardise in applied settings.

Traditionally, applied sport environments have focused on transient state factors, such as ratings of perceived exertion (RPE) or motivational state, at the time of assessment to identify conditions that may influence performance. These subjective measures, which have been used as indicators of athletes' physiological and psychological readiness, have demonstrated robust associations with physical performance outcomes (e.g., sprinting, jumping; Impellizzeri et al., 2004). From a cognitive perspective, self-reported RPE and motivation may also provide pragmatic indicators of athletes' immediate readiness by reflecting the cumulative effects of fatigue, motivation, and other state-dependent influences that have been shown to affect executive functioning (Botvinick & Braver, 2015; Marcora et al., 2009; Zhao et al., 2018). Despite its widespread use in monitoring physical performance readiness, the transfer of these relationships to cognitive-motor tasks remains equivocal. Two SB360 studies have measured and reported negligible or inconsistent associations between pre-test physical and motivational states and subsequent EF task performance (Knöbel & Lautenbach, 2023; Musculus et al., 2022). Nevertheless, these findings have not been examined across developmental stages in an applied football context. Therefore, the extent to which pre-test subjective readiness explains performance variability in football-specific cognitive-motor tasks remains unclear.

While perceived readiness reflects an athlete's state before task engagement, subjective workload provides complementary insight into the demands experienced by the performer during the task. Contemporary theories of cognitive control propose that the engagement of executive processes depends not only on task requirements but also on the perceived

effort required to maintain goal-directed behaviour, reflecting a continuous interaction between cognitive resources and task demands (Botvinick & Braver, 2015). Similarly, workload theory conceptualises subjective workload as the relationship between environmental demands and the cognitive and physical resources required to successfully accomplish a task (Hart, 2006; Matthews et al., 2015). Consequently, post-task perceived workload measures may provide valuable contextual information for interpreting behavioural performance beyond objective performance outcomes alone.

For example, the NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988) is the most widely used and extensively validated subjective workload instrument across applied performance domains (Longo et al., 2022). A key advantage of the NASA-TLX in the context of cognitive-motor testing is its ability to decompose subjective workload into distinct demand dimensions (i.e., mental, physical, temporal, effort, performance, and frustration), providing a multidimensional framework to characterise the sources of workload experienced during task execution (Hart, 2006; Hertzum, 2021). Recent applied football research has further suggested that subjective workload measures may capture performance-relevant information that is not consistently reflected by objective monitoring metrics alone (Montini et al., 2025). However, despite increasing application of workload measures within sport, little is currently known regarding how perceived workload relates to behavioural performance during cognitive-motor assessments in skilled athletes.

EF performance in standardised testing contexts is typically measured using a combination of RT, accuracy, and error-based metrics, each assumed to reflect different components of cognitive control, including processing speed, response selection, inhibitory regulation, and working memory (von Bastian et al., 2020). However, testing variables used to evaluate EF performance remain heterogeneous across the literature

(Löffler et al., 2024), and established scoring approaches can produce different performance distributions across populations (Wray et al., 2023). Furthermore, accumulating evidence suggests that behavioural metrics obtained from the same task may not reflect a unitary construct and can differ in their sensitivity to fatigue, stress, workload, or motivational state (Boksem et al., 2006; Eysenck et al., 2007; van der Linden et al., 2003).

These considerations are particularly relevant for integrated cognitive-motor assessments such as the SB360, where behavioural performance additionally incorporates football-specific motor execution. As demonstrated in Chapter 3, RT measures were most sensitive to developmental changes in tasks requiring consistent overt motor responses, suggesting that performance reflected improvements in both cognitive processing and motor-execution capacity. In contrast, switch cost, accuracy, and error-based outcomes appeared comparatively less influenced by age or biological maturity. These findings suggest that SB360 performance metrics are differentially sensitive to the cognitive and motor demands underpinning task performance. Consequently, examining athletes' perceived readiness and subjective workload may provide additional insight into the factors associated with each performance metric, as well as how the football-specific cognitive-motor demands of the task are experienced.

Collectively, existing evidence suggests that SB360 performance reflects a complex interaction between cognitive processing, motor-execution characteristics, and the specific demands of the assessment. While Chapter 3 demonstrated that different SB360 performance metrics are differentially sensitive to developmental and task-related factors, it remains unclear whether naturally occurring perceptions of readiness and workload are similarly associated with these performance outcomes under applied conditions. Building on the developmental findings in Chapter 3, the present study investigated whether these

subjective factors were associated with SB360 cognitive flexibility (CF) and working memory (WM) performance. Specifically, pre-test perceived readiness (RPE and motivation) and post-test perceived workload (NASA-TLX) were examined in relation to multiple SB360 performance outcomes. By integrating subjective readiness and workload measures with behavioural performance, this study sought to provide a more comprehensive framework for interpreting football-specific cognitive-motor assessment in professional youth football, where developmental, contextual, and state-dependent influences cannot be fully controlled but should be considered when evaluating performance.

4.3 Methods

4.3.1 Participants

The data of a total of 118 male youth football players (age: 15.7 ± 2.4 years; training age: 9.5 ± 2.7 years; height: 176.3 ± 11.3 cm; body mass: 66.3 ± 13.8 kg) from a Category One EPL academy, were analysed in this study. Table 4.1 outlines the participant characteristics. Ethical approval for this study was obtained from Liverpool John Moores University's Research Ethics Committee (Ref: 23/SPS/003; Appendix 1).

For the analysis of perceived readiness, protocol-specific subsamples were used to ensure that pre-test measures of perceived readiness corresponded directly to the cognitive task performed first within each testing session. Accordingly, analyses for the CF task included only participants who completed CF as the first task (Protocol 1; $n = 67$), while WM analyses were conducted on participants who completed WM first (Protocol 2; $n = 51$). Sample characteristics of the protocol-specific subsamples included in the perceived readiness analysis are presented in Table 4.2 and 4.3, respectively.

Table 4.1 Overall participant characteristics.

Team	<i>n</i>	Age (years)	Training age (years)	Height (cm)	Body mass (kg)
U12	3	12.1 ± 0.2	5.5 ± 0.5	159.2 ± 6.1	44.4 ± 5.9
U13	21	12.8 ± 0.4	7.0 ± 1.2	163.3 ± 8.4	48.9 ± 7.5
U14	16	13.8 ± 0.3	7.6 ± 1.2	167.9 ± 11.8	57.1 ± 10.1
U15	20	14.9 ± 0.4	8.7 ± 1.4	179.9 ± 7.5	65.4 ± 8.2
U16	11	15.9 ± 0.3	10.1 ± 1.0	183.3 ± 4.8	72.0 ± 6.5
U18	22	17.0 ± 0.6	10.3 ± 1.7	181.2 ± 5.4	75.5 ± 8.1
U21	25	19.3 ± 1.1	13.4 ± 1.8	184.3 ± 6.9	79.0 ± 7.0
Total	118	15.7 ± 2.4	9.5 ± 2.7	176.3 ± 11.3	66.3 ± 13.8

Table 4.2 Participant characteristics associated with perceived readiness for the cognitive flexibility task by team (Protocol 1; CF→WM).

Team	<i>n</i>	Age (years)	Training age (years)	Height (cm)	Body mass (kg)
U12	2	12.2 ± 0.3	5.7 ± 0.4	155.8 ± 2.4	41.0 ± 0.1
U13	15	12.9 ± 0.5	6.9 ± 1.3	165.2 ± 8.9	50.0 ± 7.5
U14	9	13.8 ± 0.3	7.9 ± 1.1	163.5 ± 13.1	53.0 ± 10.5
U15	10	14.8 ± 0.3	8.7 ± 1.3	177.6 ± 8.9	62.4 ± 9.5
U16	8	16.0 ± 0.2	10.2 ± 1.2	183.6 ± 5.6	73.2 ± 7.3
U18	12	17.1 ± 0.6	9.8 ± 1.8	181.6 ± 6.3	75.2 ± 5.5
U21	11	19.2 ± 1.2	13.0 ± 2.0	185.3 ± 6.3	77.4 ± 7.1
Total	67	15.4 ± 2.3	9.0 ± 2.5	175.1 ± 12.2	63.9 ± 14.0

Table 4.3 Participant characteristics associated with perceived readiness for the working memory task by team (Protocol 2; WM→CF).

Team	<i>n</i>	Age (years)	Training age (years)	Height (cm)	Body mass (kg)
U12	1	12.0 ± n/a	5.0 ± n/a	165.9 ± n/a	51.2 ± n/a
U13	6	12.8 ± 0.1	7.3 ± 0.9	158.7 ± 5.0	46.0 ± 7.3
U14	7	13.9 ± 0.4	7.1 ± 1.4	173.0 ± 8.0	61.8 ± 8.0
U15	10	14.9 ± 0.4	8.7 ± 1.6	182.2 ± 5.2	68.5 ± 5.5
U16	3	15.6 ± 0.2	9.6 ± 0.2	182.4 ± 1.8	68.9 ± 2.9
U18	10	17.0 ± 0.7	10.9 ± 1.3	180.7 ± 4.3	76.0 ± 10.8
U21	14	19.4 ± 1.0	13.7 ± 1.8	183.5 ± 7.4	80.2 ± 6.9
Total	51	16.1 ± 2.5	10.0 ± 2.9	177.9 ± 9.9	69.3 ± 13.2

4.3.2 Measures

4.3.2.1 Apparatus

All cognitive testing sessions were conducted using the SB360 system (see Section 2.8). Participants used age-appropriate football sizes throughout the SB360 testing sessions (i.e., U12–U13 = size 4; U14–U21 = size 5).

4.3.2.2 Cognitive Testing Battery

The current study utilised a battery of CF and WM tests. The CF test employed the SB360 version of number-letter task (Musculus et al., 2022), and the WM test employed the SB360 3-back task (Knöbel & Lautenbach, 2023). Detailed description of task and stimuli for the CF and WM tests are outlined in Chapter 3.

4.3.2.3 Perceived Readiness (*Pre-Test Physical State and Motivation*)

To assess perceived readiness for the SB360 cognitive-motor task, two self-reported pre-test measures were collected prior to testing (Figure 4.1a). Perceived physical state was measured using the 15-point Borg RPE scale (Borg, 1970), and motivation was assessed using a 20-point scale, adapted from NASA-TLX (Hart & Staveland, 1988). Participants responded to the questions: “*How physically exhausted are you at this moment?*” and “*How motivated are you to accomplish the test at this moment?*”, respectively (adapted from Knöbel & Lautenbach, 2023; Musculus et al., 2022). For analytical purposes, motivation scores were converted to 0–100 arbitrary unit (AU) by multiplying the original score by five (e.g., 14 points = 70 AU), consistent with the scoring convention commonly applied to TLX derived measures (Hart, 2006).

Prior to completing the questionnaires, participants were provided with brief verbal instructions regarding how to interpret and respond to the scales. No formal familiarisation or habituation procedures were conducted. However, participants were encouraged to ask questions if any item or scale anchor was unclear before providing their

responses. The RPE scale and TLX-derived rating formats are widely used in applied sport and human performance research, and their numerical anchors and descriptive labels are generally considered intuitive and easily interpretable by participants (Borg, 1970; Hart, 2006).

4.3.2.4 Perceived Workload (NASA-TLX)

To assess perceived workload of the testing battery, the 20-step NASA-TLX (Hart & Staveland, 1988) was administered following completion of the SB360 testing session (Figure 4.1b). The post-test TLX questionnaire comprised six subscales reflecting perceived task demands across multiple dimensions: mental demand (MD), physical demand (PD), temporal demand (TD), effort (EFF), performance (PE), and frustration (FR). An overall workload (OW) score was calculated as the mean of the six subscale scores (i.e., the sum of subscale scores divided by the number of subscales). An unweighted TLX approach was adopted, such that all subscales contributed equally to OW (Hart, 2006). All subscale and OW were converted to 0–100 AU for analyses, with higher values indicating greater perceived workload (e.g., higher PE scores reflect poorer perceived performance).

test TLX questionnaires to measure battery-level perceived workload. Each testing session, including pre- and post-test questionnaires, lasted approximately 40 min per participant. The sequence of cognitive tasks within each session was categorised into two protocols (Protocol 1: CF→WM; Protocol 2: WM→CF).

4.3.4 Data Preparation

Data preparation procedures followed identical participant-level and trial-level filtering procedures applied to the CF and WM tasks in Chapter 3. These procedures included standardised data screening, exclusion criteria, and RT filtering procedures applied consistently across all cognitive tasks.

4.3.5 Data Analysis

All statistical analyses were conducted using R (version 4.4.1; R Core Team, 2025), with statistical significance set at $p < .05$. Prior to inferential analyses, all outcome variables were assessed for distributional assumptions and data suitability using visual inspection of box plots and histograms, alongside Shapiro–Wilk tests. Multiple regression modelling was used throughout to examine associations between perceived readiness, perceived workload, and SB360 testing performance. Following model estimation, residual normality was evaluated using Q–Q plots and Shapiro–Wilk tests, homoscedasticity using Breusch–Pagan tests and scale-location plots, multicollinearity using variance inflation factors (VIF), and potential influential cases using leverage and Cook’s distance diagnostics.

For perceived readiness analyses, protocol-specific subsamples were used to ensure that pre-test measures of RPE and motivation corresponded directly to the cognitive task performed first within each testing session. CF analyses included only participants who completed the CF task first (Protocol 1; Table 4.2), whereas WM analyses included only participants who completed the WM task first (Protocol 2; Table 4.3). Separate regression

models were fitted for each task-specific outcome. The CF accuracy and WM false alarm outcomes, which were bounded between 0 and 100% and violating residual normality assumptions, were analysed using beta regression with a logit link function following conversion to proportional scores and adjustment to avoid boundary values (Smithson & Verkuilen, 2006). All remaining testing outcomes were analysed using multiple linear regression. In all perceived readiness models, RPE and motivation were entered as primary predictors, with chronological age included as a covariate to statistically control for developmental effects.

Perceived workload analyses examined post-battery subjective workload using TLX scores. Analyses were structured around two primary aims: (i) to examine perceived workload in relation to the testing protocol, and (ii) to examine associations between cognitive-motor performance and perceived workload. For protocol-related analyses, multiple linear regression models were fitted with testing protocol as the primary predictor, while age, pre-test RPE and motivation were included as covariates.

To examine associations between task performance and perceived workload, battery-level performance (i.e., aggregated performance across CF and WM tasks) indices were derived using z-standardised task outcomes to provide composite measures across the SB360 test battery. First, a battery RT index (Battery RT) was calculated as the mean of z-standardised overall CF and WM RT measures, with lower values reflecting faster response speed. Second, a battery accuracy index (Battery Accuracy) was calculated as the mean of z-standardised CF and WM accuracy scores, in which higher values reflected better overall accuracy-related performance. Third, a battery error index (Battery Error) was calculated as the mean of z-standardised WM false alarms and missed targets, with higher values reflecting poorer error-related performance.

These battery-level indices were analysed using multiple linear regression models with OW as the primary predictor, controlling for protocol, age, RPE, and motivation. Where statistically significant associations were observed at the battery level, follow-up task-level analyses were conducted to identify the individual cognitive task outcomes contributing to these associations. In addition, exploratory analyses examined associations between individual TLX subscales (MD, PD, TD, EFF, PE, and FR) and battery-level performance indices. CF switch cost was also examined separately in both the OW and TLX subscale models using multiple linear regression controlling for the same covariates, as it represents an executive-control measure that was not incorporated into the battery-level composite indices.

In addition to statistical significance testing, effect sizes were reported to quantify the magnitude of observed associations. For linear regression models, model-level effect sizes were expressed using R^2 and adjusted R^2 , reflecting the proportion of variance explained by the model. Based on conversions from Cohen's f^2 , R^2 values of approximately .02, .13, and .26 were interpreted as small, medium, and large effects, respectively (Cohen, 1988). Predictor-level effect sizes were quantified using standardised regression coefficients (β) and partial R^2 values to indicate the unique variance explained by each predictor while controlling for other variables in the model. Partial R^2 values were interpreted using the same benchmarks as R^2 , consistent with Cohen's f^2 conventions for multiple regression (Cohen, 1988; Cohen et al., 2003). For key categorical predictors (i.e., testing protocol), ΔR^2 from nested model comparisons was additionally reported to characterise their unique contribution at the model level (Field, 2018).

For beta regression models, overall model fit was summarised using pseudo- R^2 (Ferrari & Cribari-Neto, 2004; Smithson & Verkuilen, 2006). As no universally accepted

magnitude thresholds exist for pseudo- R^2 , values were interpreted descriptively and in relative terms. Changes in pseudo- R^2 from nested model comparisons were used to evaluate the unique contribution of individual predictors. Where applicable, average marginal effects (AME) were examined to aid interpretation of predictor effects on the probability scale, consistent with best practice for non-linear models (Long & Freese, 2014).

4.3.6 Sample Size Estimation

An *a priori* power analysis was conducted using G*Power (version 3.1) to estimate the minimum required sample size for multiple regression analyses examining the influence of pre-test readiness variables on SB360 performance. The analysis specified an F-test for linear multiple regression using a fixed model testing the deviation of R^2 from zero (Appendix 5). A small-to-moderate effect size was assumed ($f^2 = 0.15$), with $\alpha = 0.05$ and desired statistical power of 0.80. With three predictors included in the model (RPE, motivation, age), the required sample size was $n = 77$. In the present study, perceived readiness analyses were conducted separately for the CF ($n = 67$) and WM ($n = 51$) tasks due to protocol-specific participation. Both subsamples were below the *a priori* target of 77 participants. Accordingly, these regression models may have been underpowered to reliably detect small-to-moderate effects, and null findings should be interpreted cautiously, with consideration of potential Type II error (Cohen, 1988; Maxwell et al., 2008).

A separate *a priori* power analysis was conducted for the regression models examining post-battery perceived workload variables. Using the same statistical framework, a small-to-moderate effect size ($f^2 = 0.15$), $\alpha = 0.05$, and power of 0.80 were specified. With five predictors (TLX score, protocol, age, RPE, motivation), the required sample size was $n = 92$ (Appendix 6). The workload analyses were conducted on a battery-level sample of 118

players, exceeding the required minimum sample size. Therefore, these models were adequately powered to detect small-to-moderate effects.

4.4 Results

4.4.1 Perceived Readiness (Pre-Test RPE and Motivation)

Descriptive statistics for CF and WM pre-test measures are outlined in Tables 4.4 and 4.5, respectively. Inferential statistics from regression analyses for perceived readiness predictors are presented in Table 4.6.

For the CF task, perceived readiness predictors (RPE and motivation) showed no significant associations with any outcome variable. Likewise, age was not associated with CF accuracy or switch cost ($ps \geq .47$), but emerged as the only significant predictor for RT outcomes. Specifically, older age was associated with faster non-switch RT ($b = -51.1$ ms, $p = .02$, partial $R^2 = .09$) and switch RT ($b = -43.6$ ms, $p = .05$, partial $R^2 = .06$).

For the WM task, accuracy, RT, and false alarms were not predicted by RPE, motivation, or age ($ps > .10$). For missed targets, age was significantly associated with lower missed-target rates ($b = -1.630$, $p = .05$), explaining a modest proportion of unique variance (partial $R^2 = .08$, $\beta_{std} = -0.292$), whereas RPE and motivation were not associated with missed-target performance ($ps \geq .57$).

Table 4.4 Pre-test RPE, motivation, and cognitive flexibility task performance by participants in the Protocol 1 (CF→WM) subsample.

Team	<i>n</i>	RPE (6-15)	Motivation (0-100)	Accuracy (%)	Non-switch RT (ms)	Switch RT (ms)	Switch Cost (ms)
U12	2	7.5 ± 0.7	95.0 ± 7.1	89.3 ± 15.1	1,798 ± 338	1,949 ± 293	151 ± 45
U13	15	10.5 ± 2.5	80.0 ± 16.5	91.1 ± 8.4	1,743 ± 322	1,818 ± 244	75 ± 180
U14	9	8.9 ± 2.8	84.4 ± 11.0	91.8 ± 10.2	1,562 ± 379	1,582 ± 336	20 ± 72
U15	10	10.0 ± 2.4	91.0 ± 6.1	93.7 ± 6.0	1,625 ± 280	1,694 ± 319	69 ± 162
U16	8	12.6 ± 2.4	81.2 ± 11.9	91.5 ± 6.1	1,493 ± 427	1,657 ± 464	164 ± 190
U18	12	13.1 ± 2.2	80.0 ± 16.5	89.1 ± 10.1	1,562 ± 266	1,636 ± 352	74 ± 177
U21	11	13.5 ± 1.7	64.1 ± 22.6	91.4 ± 7.8	1,398 ± 266	1,521 ± 369	123 ± 141
Total	67	11.3 ± 2.8	80.2 ± 16.9	91.3 ± 8.2	1,584 ± 329	1,671 ± 344	87 ± 158

Nb. Data are presented as mean ± SD.

Table 4.5 Pre-test RPE, motivation, and working memory task performance by participants in the Protocol 2 (WM→CF) subsample.

Team	<i>n</i>	RPE (6-15)	Motivation (0-100)	Accuracy (%)	RT (ms)	False Alarm (%)	Missed Target (%)
U12	1	10.0 ± n/a	90.0 ± n/a	70.5 ± n/a	1,345 ± n/a	2.9 ± n/a	26.7 ± n/a
U13	6	11.5 ± 2.1	61.7 ± 13.3	51.1 ± 7.7	1,417 ± 259	10.0 ± 6.2	38.9 ± 11.5
U14	7	10.1 ± 2.6	85.0 ± 11.9	52.8 ± 4.9	1,277 ± 136	11.0 ± 7.4	36.2 ± 6.5
U15	10	10.4 ± 2.9	83.0 ± 16.4	55.6 ± 13.5	1,543 ± 216	9.7 ± 6.2	34.7 ± 14.3
U16	3	11.3 ± 0.6	71.7 ± 20.2	44.4 ± 24.5	1,471 ± 67	13.3 ± 4.3	42.2 ± 21.4
U18	10	12.1 ± 1.7	73.0 ± 12.5	58.7 ± 13.5	1,385 ± 236	8.0 ± 9.2	33.4 ± 18.3
U21	14	10.7 ± 2.8	66.4 ± 25.0	55.5 ± 15.0	1,318 ± 187	18.8 ± 8.7	25.7 ± 10.7
Total	51	11.0 ± 2.4	73.7 ± 19.0	54.9 ± 13.2	1,391 ± 212	12.2 ± 8.5	33.0 ± 13.8

Nb. Data are presented as mean ± SD.

Table 4.6 Associations between perceived readiness predictors (RPE and motivation) and SoccerBot360 assessment performance (CF and WM).

Task	Outcome	Predictor	<i>b</i> (SE)	β std	<i>p</i> -value	Partial R^2	Δ pseudo- R^2	AME (prop)	AME (pp)
CF	Accuracy (beta)	RPE	-0.03 (0.04)	-	.54	-	.00	-0.002	-0.224
		Motivation	0.001 (0.01)	-	.84	-	.00	0.000	0.011
		Age	-0.003 (0.05)	-	.95	-	.00	0.000	-0.026
	Non-switch RT (LM)	RPE	8.70 (16.86)	.075	.61	.00	-	-	-
		Motivation	0.20 (2.59)	.011	.94	.00	-	-	-
		Age *	-51.14 (20.35)	-.365	.02	.09	-	-	-
	Switch RT (LM)	RPE	8.78 (18.00)	.073	.63	.00	-	-	-
		Motivation	0.26 (2.77)	.013	.93	.00	-	-	-
		Age *	-43.65 (21.73)	-.298	.05	.06	-	-	-
	Switch Cost (LM)	RPE	0.08 (8.54)	.002	.99	.00	-	-	-
		Motivation	0.06 (1.31)	.006	.97	.00	-	-	-
		Age	7.49 (10.32)	.111	.47	.01	-	-	-
	Accuracy (LM)	RPE	0.88 (0.87)	.161	.32	.02	-	-	-
		Motivation	0.07 (0.11)	.100	.54	.01	-	-	-
		Age	0.37 (0.78)	.069	.64	.01	-	-	-
WM	RT (LM)	RPE	0.77 (13.60)	.009	.96	.00	-	-	-
		Motivation	-2.17 (1.76)	-.195	.22	.03	-	-	-
		Age	-19.44 (12.27)	-.227	.12	.05	-	-	-
	False Alarms (beta)	RPE	-0.05 (0.04)	-	.30	-	.02	-0.005	-0.506
		Motivation	0.004 (0.01)	-	.49	-	.00	0.000	0.044
		Age	0.07 (0.04)	-	.10	-	.03	0.007	0.735
	Missed Targets (LM)	RPE	-0.34 (0.88)	-.059	.70	.00	-	-	-
		Motivation	-0.07 (0.11)	-.090	.57	.01	-	-	-
		Age *	-1.63 (0.79)	-.292	.05	.08	-	-	-

Nb. Linear regression (LM) outcomes report standardised coefficients (β std) and partial R^2 . Beta regression (beta) outcomes report Δ pseudo- R^2 (drop-one comparisons) and AMEs are reported as proportions (prop; 0–1) and as percentage points (pp; $\text{AME} \times 100$). * $p < .05$.

4.4.2 Perceived Workload (Post-Battery TLX)

Descriptive statistics for the TLX scores are displayed in Table 4.7. Figure 4.2 illustrates the distribution of TLX subscales. In the primary model predicting OW, no effect of testing protocol was observed ($\Delta R^2 = .00$). In contrast, age showed a trend towards lower OW ($b = -0.832, p = .06$; partial $R^2 = .03$; Figure 4.3), while neither RPE nor motivation was associated with OW. TLX subscale analyses indicated selective effects. Motivation was positively associated with MD ($b = 0.21, p = .04$; partial $R^2 = .04$) and EFF ($b = 0.47, p < .01$; partial $R^2 = .12$), whereas age was negatively associated with PD ($b = -2.16, p < .01$; partial $R^2 = .08$) and TD ($b = -1.74, p = .05$; partial $R^2 = .04$). Motivation was also negatively associated with PE ($b = -0.17, p = .02$; partial $R^2 = .05$), indicating that higher pre-test motivation was associated with better post-test perceived performance. No meaningful effects were observed for FR, and protocol effects were negligible across all subscales ($\Delta R^2 \leq .01$). The analyses of TLX scores predicted by protocol and covariates are presented in Supplementary Table S4.3.

Table 4.7 Post-test perceived task load index (TLX) scores.

Team	<i>n</i>	OW	MD	PD	TD	EFF	PE	FR
U12	3	40.9 ± 10.4	73.3 ± 20.2	18.3 ± 7.6	45.0 ± 13.2	66.7 ± 7.6	23.3 ± 25.2	18.3 ± 20.2
U13	21	46.9 ± 8.3	77.9 ± 15.5	21.9 ± 15.1	44.0 ± 20.0	75.2 ± 18.3	31.0 ± 9.3	31.4 ± 21.8
U14	16	50.3 ± 12.0	79.7 ± 17.2	27.8 ± 17.9	55.3 ± 17.8	80.0 ± 20.7	28.4 ± 14.7	30.3 ± 24.9
U15	20	53.0 ± 10.2	81.0 ± 13.0	29.2 ± 20.5	52.8 ± 20.8	78.2 ± 18.2	30.0 ± 11.7	46.8 ± 26.5
U16	11	49.7 ± 7.1	79.1 ± 17.0	25.9 ± 20.8	45.0 ± 15.3	73.2 ± 17.9	34.5 ± 7.9	40.5 ± 23.3
U18	22	39.6 ± 9.5	75.0 ± 22.9	16.1 ± 12.6	29.5 ± 23.8	60.9 ± 25.6	29.1 ± 13.7	27.0 ± 24.8
U21	25	41.8 ± 9.9	75.6 ± 17.2	11.2 ± 8.3	38.2 ± 18.3	61.6 ± 26.7	35.8 ± 13.4	28.6 ± 23.3
Total	118	46.1 ± 10.6	77.6 ± 17.3	20.9 ± 16.6	43.2 ± 21.2	70.4 ± 22.8	31.3 ± 12.7	33.0 ± 24.6

Nb. OW = overall workload; MD = mental demand; PD = physical demand; TD = temporal demand; EFF = effort; PE = performance; FR = frustration. Data are presented as mean ± SD.

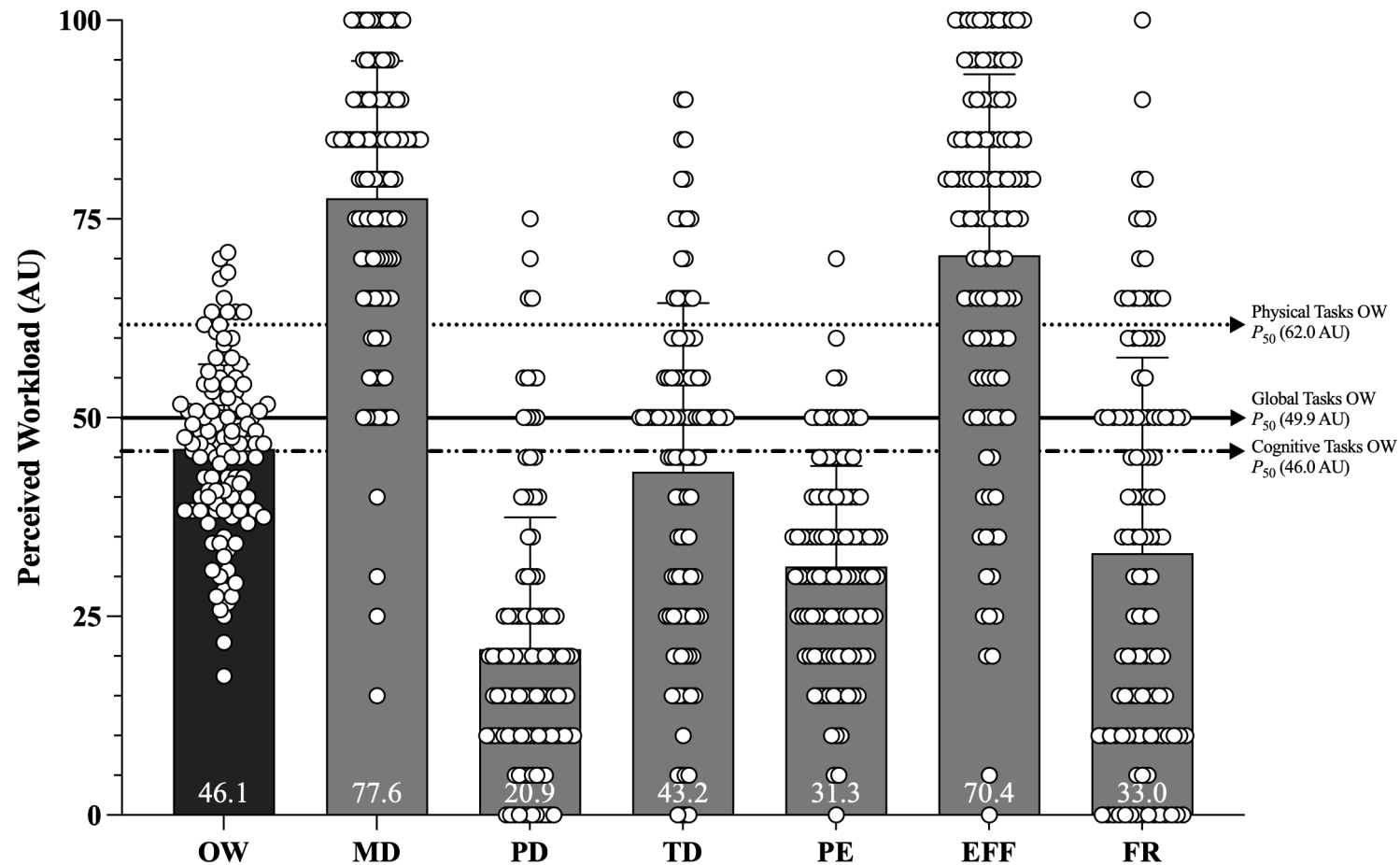


Figure 4.2 Post-test perceived workload across TLX subscales (AU). Scatter plots represent individual scores and bars represent group means. Horizontal lines indicate median (50th percentile) global NASA-TLX workload scores reported across task categories (global, cognitive, and physical) in a large-scale meta-analysis (Grier, 2015), included for contextual benchmarking.

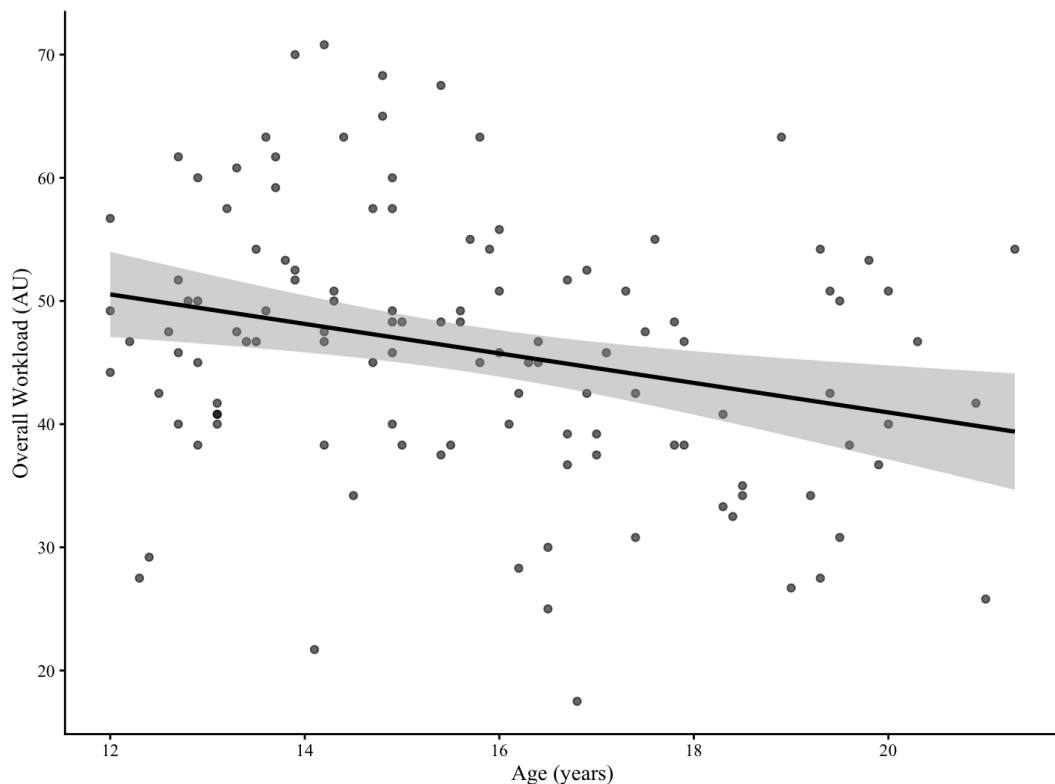


Figure 4.3 Association between overall workload (AU) and chronological age (years). Solid line represents fitted linear regression models, with shaded areas indicating the 95% confidence intervals of the fitted regression estimates.

When outcomes were aggregated across the SB360 test battery (at the battery-level task performance), OW was not associated with Battery RT ($b = 0.002, p = .82$), whereas age was negatively associated with RT, indicating faster responses with increasing age ($b = -0.085, p = .01$; partial $R^2 = .06$; Table 4.8). In contrast, higher OW was associated with poorer accuracy- and error-related performance, demonstrated by a negative association with Battery Accuracy ($b = -0.022, p < .01$; partial $R^2 = .08$) and a positive association with Battery Error ($b = 0.013, p = .02$; partial $R^2 = .05$). Protocol showed no meaningful associations across battery-level outcomes ($\Delta R^2 = .00$), while motivation demonstrated a trend-level positive association with Battery Accuracy ($b = .008, p = .06$; partial $R^2 = .03$).

Table 4.8 Battery-level performance indices predicted by overall workload (OW) and covariates.

Outcome	Predictor	<i>b</i>	SE	<i>t</i>	β_{std}	<i>p</i> -value	Partial R^2	R^2	Adj_ R^2	$\Delta R^2_{(protocol)}$
Battery RT	OW	0.002	0.007	0.229	.022	.82	.00	.07	.03	.00
	Protocol	0.070	0.152	0.461	-	.65	.00	.07	.03	.00
	Age **	-0.085	0.033	-2.549	-.260	.01	.06	.07	.03	.00
	RPE	0.002	0.031	0.058	.006	.954	.00	.07	.03	.00
	Motivation	-0.008	0.005	-1.649	-.173	.102	.02	.07	.03	.00
Battery Accuracy	OW **	-0.022	0.007	-3.214	-.305	.01	.08	.11	.07	.00
	Protocol	0.008	0.143	0.057	-	.95	.00	.11	.07	.00
	Age	0.021	0.032	0.656	.065	.51	.00	.11	.07	.00
	RPE	-0.015	0.029	-0.497	-.051	.62	.00	.11	.07	.00
	Motivation	0.008	0.004	1.907	.196	.06	.03	.11	.07	.00
Battery Error	OW *	0.013	0.006	2.341	.227	.02	.05	.07	.03	.00
	Protocol	-0.082	0.117	-0.701	-	.49	.00	.07	.03	.00
	Age	0.046	0.026	1.762	.180	.08	.03	.07	.03	.00
	RPE	-0.014	0.024	-0.565	-.059	.57	.00	.07	.03	.00
	Motivation	-0.003	0.004	-0.957	-.100	.34	.01	.07	.03	.00

Nb. Battery-level indices are *z*-standardised composites. Lower Battery RT reflects faster response speed; higher Battery Accuracy reflects better accuracy; higher Battery Error reflects poorer error-related performance. *b* = unstandardised coefficient; β_{std} = standardised coefficient. β_{std} is not reported for categorical predictors (protocol); partial R^2 reflects unique variance explained by each predictor; $\Delta R^2_{(protocol)}$ represents the change in model R^2 when protocol is removed. * $p < .05$, ** $p < .01$.

The task-level analyses focused on outcome variables that demonstrated statistically significant associations with OW at the battery level, with exploratory analyses additionally examining CF switch cost (Table 4.9). Higher OW was associated with lower CF accuracy ($b = -0.184$, $p = .02$; partial $R^2 = .05$; Figure 4.4a) and lower CF switch cost ($b = -3.306$, $p = .02$; partial $R^2 = .05$; Figure 4.4b). OW was also associated with lower WM accuracy ($b = -0.319$, $p = .02$; partial $R^2 = .05$; Figure 4.5a) and greater WM missed targets ($b = 0.261$, $p = .04$; partial $R^2 = .04$; Figure 4.5b), indicating poorer accuracy-related performance under higher perceived workload. However, OW was not significantly associated with WM false alarms (Figure 4.5c), whereas age showed a

positive association with false alarms ($b = 1.088, p < .01$; partial $R^2 = .09$). No protocol effects were observed across any task-level outcomes ($\Delta R^2 = .00$), and RPE and motivation showed no consistent associations at the task level beyond a positive association between motivation and CF accuracy ($b = 0.099, p = .05$).

Table 4.9 Task-level (CF and WM) outcomes predicted by perceived overall workload (OW) and covariates.

Outcome	Predictor	b	SE	t	β std	p -value	Partial R^2	R^2	Adj_ R^2
CF Accuracy	OW *	-0.184	0.077	-2.386	-.227	.02	.05	.11	.07
	Protocol	-0.871	1.620	-0.538	-	.59	.00	.11	.07
	Age	0.641	0.358	1.791	.179	.08	.03	.11	.07
	RPE	-0.337	0.332	-1.016	-.104	.31	.01	.11	.07
	Motivation *	0.099	0.049	2.017	.207	.05	.04	.11	.07
CF Switch Cost	OW *	-3.306	1.436	-2.302	-.224	.02	.05	.06	.02
	Protocol	13.205	30.098	0.439	-	.66	.00	.06	.02
	Age	2.441	6.648	0.367	.038	.71	.00	.06	.02
	RPE	2.355	6.160	0.382	.040	.70	.00	.06	.02
	Motivation	0.687	0.915	0.751	.079	.45	.01	.06	.02
WM Accuracy	OW *	-0.319	0.129	-2.469	-.241	.02	.05	.06	.02
	Protocol	1.648	2.705	0.609	-	.54	.00	.06	.02
	Age	-0.458	0.598	-0.767	-.079	.45	.01	.06	.02
	RPE	0.138	0.554	0.249	.026	.80	.00	.06	.02
	Motivation	0.072	0.082	0.879	.093	.38	.01	.06	.02
WM False Alarms	OW	0.057	0.071	0.806	.077	.42	.01	.10	.06
	Protocol	-0.863	1.490	-0.579	-	.56	.00	.10	.06
	Age **	1.088	0.329	3.305	.331	<.01	.09	.10	.06
	RPE	-0.325	0.305	-1.065	-.109	.29	.01	.10	.06
	Motivation	-0.030	0.045	-0.659	-.068	.51	.00	.10	.06
WM Missed Targets	OW *	0.261	0.126	2.071	.202	.04	.04	.06	.02
	Protocol	-0.765	2.642	-0.290	-	.77	.00	.06	.02
	Age	-0.631	0.583	-1.081	-.111	.28	.01	.06	.02
	RPE	0.190	0.541	0.351	.037	.73	.00	.06	.02
	Motivation	-0.042	0.080	-0.524	-.055	.60	.00	.06	.02

Nb. b = unstandardised coefficient; β std = standardised coefficient; partial R^2 reflects unique variance explained by each predictor. * $p < .05$, ** $p < .01$.

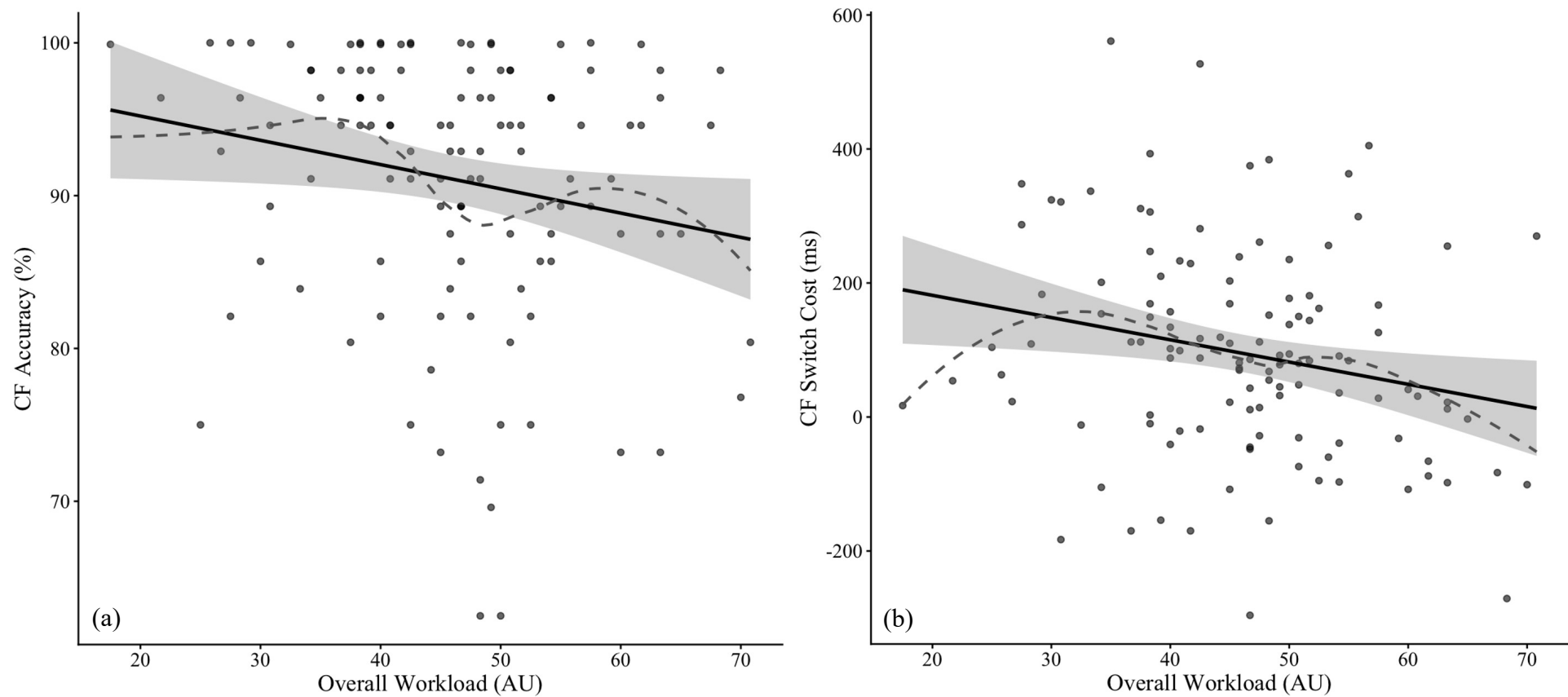


Figure 4.4 Associations between cognitive flexibility (CF) outcomes and perceived overall workload (OW; AU). Panels show (a) CF accuracy (% correct) and (b) CF switch cost (ms). Solid lines represent fitted linear regression models, with shaded areas indicating the 95% confidence intervals of the fitted regression estimates. Dashed lines represent locally weighted scatterplot smoothing (LOESS) curves shown for descriptive purposes only.

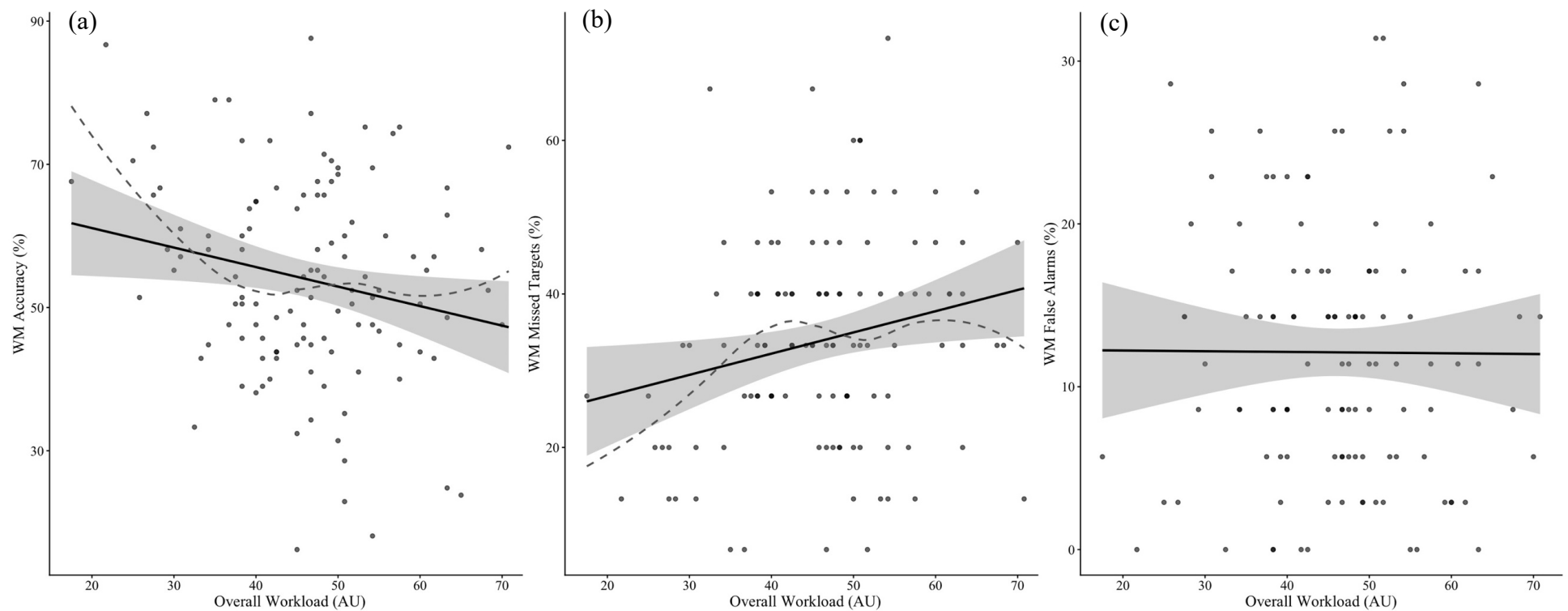


Figure 4.5 Associations between working memory (WM) outcomes and perceived overall workload (OW; AU). Panels show (a) WM accuracy (% correct), (b) WM missed targets (%), and (c) WM false alarms (%). Solid lines represent fitted linear regression models, with shaded areas indicating the 95% confidence intervals of the fitted regression estimates. Dashed lines represent locally weighted scatterplot smoothing (LOESS) curves shown for descriptive purposes only.

Finally, exploratory analyses examining TLX subscales in relation to battery-level performance and CF switch cost indicated selective and outcome-specific associations (Table 4.10). For RT, higher TD was associated with lower Battery RT ($b = -0.008$, $p = .02$; partial $R^2 = .05$), reflecting faster overall responses, whereas higher PE was associated with higher Battery RT ($b = 0.016$, $p = .01$; partial $R^2 = .06$). For accuracy, higher MD ($b = -0.011$, $p = .01$; partial $R^2 = .06$) and higher PE ($b = -0.017$, $p < .01$; partial $R^2 = .07$) were both associated with lower Battery Accuracy, reflecting poorer accuracy-related performance. For CF switch cost, only higher EFF was associated with lower switch cost ($b = -1.745$, $p = .02$; partial $R^2 = .05$). No TLX subscales were significantly associated with Battery Error ($ps > .10$). Across all subscale models, protocol effects were negligible, and age effects were limited to RT-related outcomes.

Table 4.10 Exploratory analyses examining associations between TLX subscales and battery-level performance indices and cognitive flexibility (CF) switch cost.

Outcome	Predictor	<i>b</i>	SE	<i>t</i>	β std	<i>p</i> -value	Partial R^2	R^2	Adj_ R^2
Battery RT	MD	0.006	0.004	1.349	.126	.18	.02	.09	.04
	PD	-0.003	0.005	-0.554	-.053	.58	.00	.07	.03
	TD *	-0.008	0.004	-2.343	-.219	.02	.05	.11	.07
	EFF	-0.002	0.004	-0.587	-.061	.56	.00	.07	.03
	PE **	0.016	0.006	2.727	.251	.01	.06	.13	.09
	FR	0.003	0.003	1.055	.096	.29	.01	.08	.04
Battery Accuracy	MD **	-0.011	0.004	-2.647	-.247	.01	.06	.08	.04
	PD	-0.007	0.004	-1.482	-.144	.14	.02	.05	.00
	TD	-0.003	0.004	-0.928	-.091	.36	.01	.03	-.01
	EFF	-0.005	0.004	-1.427	-.150	.16	.02	.04	.00
	PE **	-0.017	0.006	-2.908	-.273	<.01	.07	.10	.05
	FR	-0.005	0.003	-1.565	-.145	.12	.02	.05	.01
Battery Error	MD	0.004	0.003	1.288	.123	.20	.02	.04	-.01
	PD	0.003	0.004	0.922	.090	.36	.01	.03	-.01
	TD	0.004	0.003	1.469	.143	.15	.02	.04	.00
	EFF	0.003	0.003	0.950	.100	.34	.01	.03	-.01
	PE	0.008	0.005	1.661	.160	.10	.02	.05	.00
	FR	0.003	0.002	1.379	.129	.17	.02	.04	.00
CF Switch Cost	MD	-1.158	0.872	-1.328	-.127	.19	.02	.03	-.02
	PD	-1.122	0.927	-1.210	-.119	.23	.01	.03	-.02
	TD	-0.437	0.728	-0.600	-.059	.55	.00	.02	-.03
	EFF *	-1.745	0.715	-2.441	-.254	.02	.05	.06	.02
	PE	0.540	1.211	0.446	.044	.66	.00	.01	-.03
	FR	-0.974	0.596	-1.635	-.153	.11	.02	.04	-.01

Nb. Each TLX subscale was entered as a predictor in a separate model, controlling for protocol, age, RPE, and motivation. TLX subscales: MD = mental demand; PD = physical demand; TD = temporal demand; EFF = effort; PE = performance; FR = frustration. Battery-level indices are z-standardised composites. Lower Battery RT reflects faster response speed; higher Battery Accuracy reflects better accuracy-related performance; higher Battery Error reflects poorer error-related performance. *b* = unstandardised coefficient; β std = standardised coefficient; partial R^2 reflects the unique variance explained by each TLX subscale. $p < .05$, ** $p < .01$.

4.5 Discussion

This study examined the associations between pre-test perceived readiness (RPE and motivation), SB360 cognitive task performance (CF and WM), and post-test perceived workload (NASA-TLX) in skilled youth football players. Overall, perceived readiness demonstrated limited explanatory value for SB360 performance outcomes. Neither pre-test RPE nor motivation showed pronounced and consistent associations with CF or WM performance (Table 4.6), suggesting that subjective readiness states were largely unrelated to subsequent cognitive-motor performance within the testing battery. These results are consistent with findings from previous SB360 validation studies, in which the influence of pre-test RPE and motivation on both CF and WM performance was inconsistent (Knöbel & Lautenbach, 2023; Musculus et al., 2022). However, when a larger sample was analysed regardless of testing protocols, a significant positive effect of motivation was observed for CF accuracy (Table 4.9). Given that protocol effects were negligible across all analyses and that perceived readiness analyses may have been underpowered due to sample sizes, future research should further investigate pre-test motivational states with an adequate sample size.

The absence of protocol order effects across CF and WM tasks suggests that SB360 performance is robust to task sequencing within a single testing session, supporting flexible integration of the SB360 CF and WM tasks within academy testing schedules. Hence, practitioners may administer either task independently or as part of the full testing battery without concern that task order will systematically influence the interpretation of performance outcomes. The present findings also indicate that routine pre-test readiness measures, such as RPE or motivation, may have limited explanatory value when used as *primary* covariates for interpreting SB360 performance. The lack of consistent associations between these subjective readiness states and performance outcomes suggests that short-term fluctuations in perceived exertion or motivation are unlikely to

meaningfully account for variability in EF task performance within this testing battery. In youth populations, perceived exertion may also reflect broader aspects of mental fatigue rather than physical states alone (Knöbel & Lautenbach, 2023), further complicating its interpretation. Consequently, age and maturation-related characteristics may provide a more stable and interpretable proxy for physical state when evaluating cognitive-motor testing outcomes in youth athletes, while readiness measures may still serve a *supplementary* role within broader athlete monitoring systems.

Contrary to perceived readiness, post-test perceived workload exhibited clearer and more systematic associations with SB360 performance. At the battery level (CF + WM), higher OW was associated with poorer accuracy and error-related outcomes, whereas no association was observed with Battery RT (Table 4.8). Follow-up task-level analyses demonstrated that these associations were primarily explained by lower CF and WM accuracy and higher WM missed targets, whereas WM false alarms were primarily explained by age rather than workload (Table 4.9; Figures 4.4 and 4.5). Although CF switch cost was not included in the battery-level indices, exploratory analyses additionally demonstrated that higher OW was associated with lower switch cost. TLX subscale analyses further demonstrated that the workload–performance relationship was heterogeneous and outcome-specific. Participants perceived their performance (PE) as poorer when overall RT was slower or accuracy was lower, whereas higher TD was associated with faster RT and higher MD with poorer accuracy. Exploratory analyses further indicated that only perceived effort (EFF), rather than MD or other workload dimensions, was associated with CF switch cost (Table 4.10). No TLX subscales were significantly associated with Battery Error. Descriptively, perceived workload from SB360 testing was primarily characterised by MD and EFF, with comparatively lower contributions from PD (Figure 4.2). Advancing age was also associated with a trend towards lower OW (Figure 4.3). Collectively, these findings indicate a clear dissociation

between perceived readiness and perceived workload in their relationships with SB360 performance. Perceived workload was more strongly linked to response correctness, errors, and switch cost than to RT outcomes.

Notably, when considered alongside the cross-sectional findings reported in Chapter 3, the present results indicate that SB360 outcome metrics are differentially sensitive to developmental and state-dependent influences. Previously, CF RT and WM false alarms were strongly associated with age-related factors, whereas accuracy (i.e., response correctness), switch cost, and missed-target outcomes of these tasks demonstrated weak or non-significant developmental associations. In contrast, the present study showed that these latter outcomes were systematically related to post-test perceived workload, while RT-based indices were largely unaffected by subjective workload. This complementary pattern reinforces that SB360 metrics in the current test battery do not reflect a unitary construct of cognitive performance but instead index distinct performance components with different underlying constraints.

From a cognitive perspective, this pattern is consistent with theoretical accounts suggesting that workload-related performance decrements emerge when task demands approach or exceed available executive resources, resulting in selective impairments rather than uniform degradation across all performance indices (Kahneman, 1973; Wickens, 2008). Accuracy- and error-based outcomes may therefore function as more proximal behavioural indicators of cognitive resource depletion or control instability, while RT may be partially preserved through compensatory control processes, with more global performance breakdown emerging when such compensatory mechanisms can no longer be sustained (Hockey, 1997; Matthews et al., 2015). In EF tasks that require rapid but discrete motor responses, such as those implemented in the SB360, performance under increased workload may be characterised by preserved response speed alongside

reduced response accuracy in skilled youth football players, reflecting adaptive or compensatory control processes rather than uniform performance slowing.

The present findings also align with prior work indicating that RT and accuracy do not necessarily index the same underlying cognitive processes and can be differentially influenced by fatigue, stress, or workload manipulations (Boksem et al., 2006; van der Linden et al., 2003). In applied sport and motor-cognitive testing contexts, RT outcomes are often constrained by biomechanical and neuromuscular factors, particularly in youth populations where maturation-related changes in movement speed and coordination are pronounced (Cerrah et al., 2024; Lloyd et al., 2014; Radnor et al., 2021). Collectively, alongside the findings from Chapter 3, the current data may help explain why RT outcomes were more closely aligned with age-related factors, whereas accuracy and errors, which place greater demands on executive control and attentional regulation, were more sensitive to perceived workload states (Eysenck et al., 2007; Wickens, 2008).

In relation to the characteristics of perceived workload, OW derived from the current SB360 test battery fell within the range of global OW values reported for cognitively demanding tasks in the broader literature, while remaining lower than those typically observed for physically demanding tasks (Figure 4.2; Grier, 2015). This contextualisation suggests that, at a global level, subjective workload imposed by the current test battery was comparable to other laboratory-based cognitive tasks, rather than to physically intensive sport or exercise tasks. Examination of TLX subscale profiles provides further insight into the nature of perceived workload during SB360 testing. Across the sample, workload was predominantly characterised by MD and EFF, with comparatively low PD, indicating that players primarily experienced the testing as cognitively demanding rather than physically strenuous.

This TLX subscale profile contrasts with previous syntheses of sport-related TLX data, where average MD and PD scores tend to be more closely aligned across competitive sporting tasks (e.g., cycling, swimming, rugby, table tennis; Hertzum, 2021). In the present study, the marked divergence between MD and PD suggests that, despite the football-specific motor-response requirements, the subjective workload profile was characterised predominantly by cognitive rather than physical demands. Such low PD may be attributable to the stationary-ball kicking response modality within the SB360 tasks. As noted in Chapter 3, these discrete responses may allow participants to partially isolate perceptual-cognitive processing from motor execution, thereby reducing physical load while reinforcing concerns regarding action fidelity, given that perceptual-cognitive processes and motor actions are tightly coupled in competitive football.

However, these findings should be interpreted with appropriate caution. Associations between individual NASA-TLX subscales and performance outcomes were examined using separate regression models rather than within a single multivariable model. Consequently, the relative strength or importance of individual workload dimensions cannot be directly compared, as each subscale was evaluated independently while controlling for the same covariates. Likewise, comparisons of OW and TLX subscale profiles with previous studies should be considered descriptive rather than direct, as differences in methodological and statistical approaches may have influenced the observed workload ratings and their associations with performance. These methodological differences cannot be fully accounted for and may therefore limit direct comparisons across studies (Grier, 2015).

Overall, these findings suggest that incorporating NASA-TLX ratings alongside SB360 performance metrics provides an additional interpretive layer for understanding performance variability across different workload dimensions that are not directly

observable from behavioural outcomes alone (Montini et al., 2025). Rather than serving as evidence of task fidelity or representativeness of match demands, the TLX profile offers descriptive context regarding the subjective demands imposed by the testing protocol. However, the direction of the observed associations between perceived workload and EF performance cannot be determined from the present study. Higher perceived workload may reflect increased cognitive demands contributing to reduced performance, but it is equally plausible that players with lower EF performance retrospectively perceived the tasks as more demanding. Consequently, the present findings should be interpreted as demonstrating associations rather than causal relationships. Nevertheless, the selective associations observed between different workload dimensions and specific performance outcomes support the value of considering subjective workload alongside behavioural performance when interpreting SB360 assessments.

From an applied perspective, findings have practical implications for the scheduling and implementation of SB360 testing within academy environments. Despite a broad range of pre-test RPE scores (Tables 4.4 and 4.5), the absence of consistent associations between pre-test RPE and performance, combined with the lack of protocol order effects, suggests that SB360 assessments are relatively robust to variations in testing conditions, including preceding activities and time of day. In the present study, testing was conducted under typical academy conditions without strict standardisation of prior training exposure or precise testing timing. Within this context, performance outcomes appeared to be more strongly influenced by perceived workload and developmental factors than by pre-test readiness states. This indicates that the current SB360 test battery can be integrated flexibly alongside conventional football training without requiring tight control of pre-test physical load or scheduling constraints.

However, despite participants reporting relatively low PD for the SB360 tasks, practitioners should exercise caution when administering the SB360 test to players returning from musculoskeletal injury. Although these tasks may be perceived primarily as cognitive assessments, they still require repeated kicking actions and, as demonstrated in Chapter 3, RT performance is likely influenced by neuromuscular function. While self-reported RPE may not meaningfully influence test score interpretation, objective indicators of a player's current physical status should be considered, particularly during rehabilitation phases or when injury risk is elevated, to avoid misinterpretation of performance or unintended loading.

Several methodological limitations should be considered when interpreting the present findings. First, the study relied exclusively on subjective measures of perceived readiness and workload, without concurrent assessment of internal or external physical outputs such as heart rate, ball release velocity, or repetitive tissue loading (Dixon et al., 2026). Consequently, it was not possible to directly evaluate the correspondence between PD and objective physical stress beyond task-related RT measures, highlighting the need for future research to incorporate complementary physiological and biomechanical assessments. Second, workload was assessed retrospectively following completion of the SB360 test battery, which may be influenced by recency effects or performance outcomes, rather than reflecting moment-to-moment workload fluctuations during task execution. Third, structural constraints related to scheduling, age-group routines, and player availability limited experimental control and precluded causal inference (Fullagar et al., 2019). Finally, all measures were captured at a single time point per participant, restricting insight into within-player variability and limiting interpretation of how workload–performance relationships may evolve across repeated exposures. Accordingly, longitudinal designs are required to better characterise the stability, sensitivity, and practical utility of subjective measures in relation to SB360 performance across contexts.

4.6 Conclusion

This study provides a critical evaluation of how perceived readiness and perceived workload relate to SB360 cognitive-motor performance in youth football players. Pre-test readiness measures demonstrated limited explanatory value, whereas post-test perceived workload demonstrated selective associations with accuracy, switch cost, and error-based performance outcomes. However, given the observed association between pre-test motivation and accuracy in larger samples, further research is warranted to clarify the role of motivational states in shaping performance, particularly for outcome measures related to response correctness. When integrated with the cross-sectional developmental findings in Chapter 3, the results indicate that SB360 outcome metrics are differentially sensitive to state-dependent and age-related influences, reflecting distinct performance components rather than a unitary construct of cognitive ability. Incorporating NASA-TLX ratings alongside behavioural outcomes may provide a valuable interpretive framework for understanding cognitive-motor performance variability. Collectively, findings support a more nuanced, dimension-specific interpretation of SB360 data in both research and applied settings and emphasise the importance of contextualising cognitive-motor performance within the subjective demands imposed by the assessment protocol.

4.9 Supplementary Tables

Supplementary Table S4.1 Battery-level perceived workload (TLX) predicted by protocol and covariates.

Outcome	Predictor	<i>b</i>	SE	<i>t</i>	β_{std}	<i>p</i> -value	Partial R^2	R^2	Adj_ R^2	$\Delta R^2_{(protocol)}$
OW	Protocol	-1.26	1.97	-0.642	-	.52	.00	.12	.08	.00
	Age	-0.83	0.43	-1.943	-.19	.06	.03	.12	.08	.00
	RPE	-0.20	0.40	-0.498	-.05	.62	.00	.12	.08	.00
	Motivation	0.11	0.06	1.779	.18	.08	.03	.12	.08	.00
MD	Protocol	-1.64	3.29	-0.497	-	.62	.00	.06	.03	.00
	Age	-0.49	0.72	-0.677	-.07	.50	.00	.06	.03	.00
	RPE	0.66	0.67	0.975	.10	.33	.01	.06	.03	.00
	Motivation *	0.21	0.10	2.121	.22	.04	.04	.06	.03	.00
PD	Protocol	3.38	3.10	1.091	-	.28	.01	.09	.06	.01
	Age **	-2.16	0.68	-3.196	-.32	<.01	.08	.09	.06	.01
	RPE	0.77	0.64	1.219	.12	.23	.01	.09	.06	.01
	Motivation	0.05	0.09	0.561	.06	.58	.00	.09	.06	.01
TD	Protocol	-1.10	3.97	-0.278	-	.78	.00	.09	.06	.00
	Age *	-1.74	0.86	-2.017	-.20	.05	.04	.09	.06	.00
	RPE	-1.57	0.81	-1.931	-.20	.06	.03	.09	.06	.00
	Motivation	-0.07	0.12	-0.558	-.06	.58	.00	.09	.06	.00
EFF	Protocol	-4.99	3.94	-1.266	-	.21	.01	.23	.20	.01
	Age	-1.26	0.86	-1.467	-.13	.15	.02	.23	.20	.01
	RPE	-0.18	0.81	-0.224	-.02	.82	.00	.23	.20	.01
	Motivation **	0.47	0.12	3.930	.37	<.01	.12	.23	.20	.01
PE	Protocol	-1.81	2.39	-0.760	-	.45	.01	.08	.05	.01
	Age	0.79	0.52	1.514	.15	.13	.02	.08	.05	.01
	RPE	-0.81	0.49	-1.665	-.17	.10	.02	.08	.05	.01
	Motivation *	-0.17	0.07	-2.410	-.25	.02	.05	.08	.05	.01
FR	Protocol	-1.48	4.80	-0.308	-	.76	.00	.02	-.02	.00
	Age	-0.13	1.04	-0.121	-.01	.90	.00	.02	-.02	.00
	RPE	-0.08	0.98	-0.080	-.01	.94	.00	.02	-.02	.00
	Motivation	0.14	0.14	0.984	.10	.33	.01	.02	-.02	.00

Nb. *b* = unstandardised coefficient; β_{std} = standardised coefficient; partial R^2 reflects unique variance explained by each predictor; $\Delta R^2_{(protocol)}$ represents the change in model R^2 when protocol is removed. β_{std} is not reported for categorical predictors (protocol). * $p < .05$, ** $p < .01$.

**Chapter 5. Effects of Standardised Perceptual-Cognitive Training
Using an Immersive Football-Specific Technology Within a
Professional Academy**

5.1 Abstract

Purpose: Despite the increasing adoption of football-specific cognitive training technologies within applied settings, there remains limited evidence regarding their effectiveness in improving cognitive functions. Accordingly, this study aimed to provide a longitudinal evaluation of a standardised SoccerBot360 (SB360) training intervention within a professional youth academy context. **Methods:** Thirty-one male youth academy players (age: 13.7 ± 0.9 years) completed a six-week SB360 intervention within a crossover design, involving one training session per week using two target-hitting SB360 training games. Cognitive-motor performance was assessed at baseline, mid-point, and post-crossover using SB360 assessments of choice response time, cognitive flexibility, anticipation, and inhibition. Linear mixed-effects models were employed to examine time and group effects, while accounting for inter-individual variability. **Results:** Significant improvements were observed across most outcome variables over time. However, no between-group differences were detected at any time point, indicating that the observed performance gains likely reflected task familiarisation, although the intervention may also have had limited efficacy in producing measurable cognitive adaptations. Effect size analyses further demonstrated that inter-individual variability accounted for a substantially greater proportion of variance (ES: 0.54–0.80) than fixed effects of time or group (ES: 0.00–0.13), highlighting considerable differences in individual response trajectories. A significant age effect was observed for choice response time only, with no consistent age-related differences across higher-order cognitive tasks. **Conclusion:** Findings indicate that the six-week standardised SB360 intervention did not produce group-level cognitive adaptations. Collectively, the observed findings are likely explained by multiple interacting factors, including limited intervention efficacy, training volume, challenge point optimisation, task familiarisation, training-assessment specificity, and the degree of intervention individualisation.

5.2 Introduction

During competition, football players have to rapidly perceive and process relevant information in order to make quick decisions that outperform opponents (Williams et al., 2023). A growing body of research has demonstrated that cognitive functions, commonly referred to as perceptual-cognitive skills (PCS) or executive function (EF), are associated with tactical awareness, adaptability, and technical consistency under pressure in football players (Haugan et al., 2025; Huijgen et al., 2015; Roca et al., 2013; Sakamoto et al., 2018), and that these functions distinguish players across skill or competition levels (Hope et al., 2024; Vestberg et al., 2012) and performance outcomes (Vestberg et al., 2017). Similarly, a meta-analysis reported that superior cognitive functions are associated with expert and elite athletes (Scharfen & Memmert, 2019a). Given the link between PCS and expertise, interest in cognitive training and assessment has increased in recent years, particularly in relation to talent identification, development, and (de)selection (Altmann et al., 2024; Scharfen & Memmert, 2019a; Triggs et al., 2025).

In response, cognitive training and assessment tools that integrate training and/or testing features have been developed by commercial providers for applied practitioners and athletes (Harris et al., 2018), with the intention of systematically replicating the perceptual demands of the game. For example, virtual reality, 360° simulation environments, and video-based systems enable players to experience complex perceptual challenges in controlled yet sport-specific contexts (Gray, 2019). Furthermore, these technologies provide opportunities to develop standardised assessments of tactical knowledge that better reflect competitive match contexts (Kelly et al., 2024). Collectively, such approaches aim to enhance PCS and decision-making without imposing excessive physical load, while supporting the principle of representative design in game-specific contexts (Thatcher et al., 2021).

Recent advances have focused on more football-specific immersive technologies that explicitly couple perceptual-cognitive demands with representative motor execution (Beavan, 2019). For example, the SB360 training protocols combine physical execution with perceptual-cognitive stimuli presented via a 360° projection system (Heilmann et al., 2021). Players perform passing, receiving, and dribbling actions while responding to dynamic visual cues that target cognitive processes, such as inhibition (INH), working memory (WM), and cognitive flexibility (CF). This integrated approach addresses limitations of other cognitive training tools, such as virtual reality systems, that often decouple perception from representative motor actions (Beavan, 2019). Furthermore, the adoption of these football-specific technologies by professional football clubs suggests that their integrated training and testing formats are valued by high-level practitioners (Beavan, Fransen, et al., 2019; Dolata et al., 2025; Rodrigues et al., 2024).

Despite their growing adoption within professional football settings, independent scientific evaluation of football-specific immersive technologies within cognitive training domains remains limited. Several studies have examined the reliability and validity of assessment protocols embedded within these technologies (Beavan, Fransen, et al., 2019; Dolata et al., 2025; Knöbel & Lautenbach, 2023; Musculus et al., 2022; Rodrigues et al., 2024). However, this work has largely focused on measurement properties rather than the effects of training interventions implemented using these systems. To date, only one study has investigated training effectiveness of the SB360 (Heilmann et al., 2021).

Heilmann et al. (2021) explored the effects of 12-month SB360 use on cognitive-motor tasks in German professional male academy players. They employed a broad cognitive testing battery, including choice response time (CRT), anticipation (ANT), INH, and WM, allowing cross-domain comparisons across age groups. This initial examination of SB360-based training and assessments reported that standardised cognitive tasks

differentiated cognitive-motor performance between age groups and that improvements in cognitive testing performance were observed across age following long-term exposure. However, they did not include a control group, and the intervention design lacked specification and standardisation, with SB360 exposure described as 1–2 sessions per week over a 12-month period without specifying the training dose, task difficulty, or content progression. These factors constrain reproducibility and limit the interpretation (Ross & Zaidi, 2019). In addition, within- and between-subject effects were examined primarily through pre-post comparisons and between-age-group mean differences. While this approach provided an initial indication of developmental trends and temporal change, repeated observations were treated at the group level, and the nested structure of longitudinal data was not formally modelled. Thus, within-player change and between-player variability were not examined simultaneously, limiting insight into individual performance trajectories over time (Owen et al., 2022).

More broadly, there is a scarcity of longitudinal studies in sport talent development research (Till & Baker, 2020), a pattern that extends to work examining cognitive skill development in football (Haugan et al., 2025). As a result, support for the effectiveness of cognitive training interventions remains largely subjective. This limited evidence base has led to heavy reliance on claims from commercial providers, which often lack rigorous objective scientific validation (Walton et al., 2018) and may be subject to reporting bias (Harris et al., 2018). Furthermore, existing intervention studies have predominantly evaluated training effects at the group level, despite the importance of inter-individual variability in talent identification and development processes in football (Bergkamp et al., 2019; Williams & Reilly, 2000).

Accordingly, this study aimed to evaluate the effects of a six-week standardised SB360 training intervention on cognitive-motor task performance in youth academy football

players. In addition, subject-level variability in cognitive performance trajectories following the intervention were examined. Based on previous intervention studies, it was hypothesised that players undertaking SB360 training would demonstrate greater improvements in response accuracy and response time (RT) on SB360 cognitive assessments following the intervention period compared with control players (Heilmann et al., 2021; Rodrigues et al., 2024). This study sought to provide a transparent and empirically grounded evaluation of the immersive cognitive-motor training technology within the challenges of a professional youth academy context.

5.3 Methods

5.3.1 Participants

Thirty-one male youth football players from a Category One EPL Academy participated in this study during the 2022-23 and 2023-24 seasons. Participants were enrolled in the U13–U15 teams, and their demographic characteristics and experience participating in formalised youth training programmes are presented in Table 5.1. None of the participants had prior experience of SB360 training before study commencement. Ethical approval was obtained from the lead institute’s Research Ethics Committee (Ref: 23/SPS/003; Appendix 1).

5.3.2 Study Design

A longitudinal crossover design was employed (Figure 5.1). Participants were randomly assigned to two groups (A and B) matched according to chronological age. Following a familiarisation test (FT) conducted four weeks before baseline testing, three cognitive testing sessions were completed: baseline (T1), mid-point at 6 weeks (T2), and post-crossover at 12 weeks (T3). Group A completed a six-week SB360 training intervention between T1 and T2, while Group B remained in a control phase continuing their regular

academy training without the SB360. The groups then crossed over, with Group B completing the intervention between T2 and T3.

Table 5.1 Participants information

Demographic, football-specific information	Total	U15	U14	U13
Total Participants				
<i>n</i>	31	10	6	15
Age (years)	13.7 ± 0.9	14.9 ± 0.1	13.9 ± 0.2	12.9 ± 0.3
Height (cm)	168.0 ± 12.2	180.0 ± 7.2	171.7 ± 7.6	158.3 ± 8.7
Body mass (kg)	54.4 ± 10.2	64.7 ± 4.6	55.9 ± 9.7	46.8 ± 6.0
Training age (years)	7.8 ± 1.2	8.8 ± 0.7	8.3 ± 1.1	7.0 ± 0.9
Weekly football practice time (hours)	5.9 ± 0.5	6.5 ± 0.0	6.0 ± 0.0	5.5 ± 0.0
Intervention Group A				
<i>n</i>	15	5	4	6
Age (years)	13.8 ± 0.9	14.9 ± 0.1	13.9 ± 0.2	12.9 ± 0.2
Height (cm)	171.6 ± 13.6	185.6 ± 5.9	173.6 ± 6.7	158.5 ± 7.7
Body mass (kg)	55.7 ± 13.6	67.4 ± 3.2	54.8 ± 10.4	46.5 ± 7.5
Training age (years)	8.0 ± 1.0	8.7 ± 0.8	8.2 ± 1.4	7.6 ± 0.7
Weekly football practice time (hours)	6.0 ± 0.4	6.5 ± 0.0	6.0 ± 0.0	5.5 ± 0.0
Intervention Group B				
<i>n</i>	16	5	2	9
Age (years)	13.7 ± 0.9	14.9 ± 0.1	14.0 ± 0.2	12.9 ± 0.3
Height (cm)	164.4 ± 10.8	174.3 ± 1.6	167.7 ± 10.1	158.1 ± 9.8
Body mass (kg)	53.1 ± 9.0	62.0 ± 4.4	58.2 ± 11.3	47.0 ± 5.3
Training age (years)	7.6 ± 1.3	8.8 ± 0.8	8.5 ± 0.9	6.8 ± 1.0
Weekly football practice time (hours)	5.9 ± 0.5	6.5 ± 0.0	6.0 ± 0.0	5.5 ± 0.0

Nb. Training age represents cumulative years of structured football training undertaken within professional and non-professional youth football teams. Weekly football practice includes academy football training and fixture.

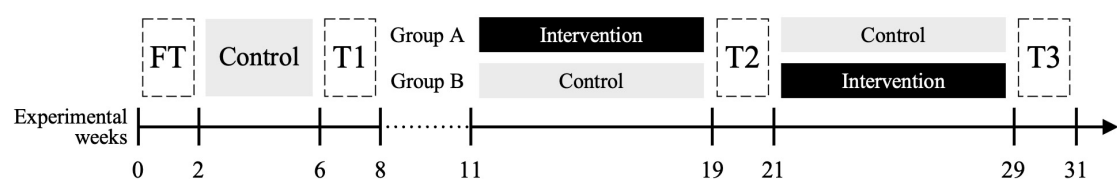


Figure 5.1 Study design. FT = familiarisation test; T1–T3 = cognitive testing sessions.

5.3.3 Measures

5.3.3.1 Apparatus

All cognitive testing sessions were conducted using the SB360 system (see Section 2.8). Participants used age-appropriate football sizes throughout all SB360 training and testing sessions (i.e., U12–U13 = size 4; U14–U21 = size 5).

5.3.3.2 Cognitive Testing Sessions

The test battery comprised of four standardised SB360 cognitive-motor tasks: CF, CRT, ANT, INH, and WM. These tasks were selected based on previous research demonstrating associations between respective cognitive functions and successful performance in football (Glavaš, 2020; Gonçalves et al., 2015; Huijgen et al., 2015; Sakamoto et al., 2018; Vestberg et al., 2012).

Cognitive Flexibility: The CF test employed the SB360 version of the number-letter task (Musculus et al., 2022). Response accuracy (CF_ACC), response time for switch-trials (CF_SRT) and non-switch-trials (CF_NSRT), and switch cost (CF_SC) were measured as outcome variables. A detailed description of the task rules and stimuli for the CF test is provided in Chapter 3, Section 3.3.2.2.

Choice Response Time: During the CRT test, three white panels were presented in the horizontal plane on the SB360 screen, with one panel turning red and displaying a semi-circular target between 2,500 ms and 4,000 ms into each trial (Figure 5.2). Participants were instructed to pass the ball to the semi-circular target on the red panel as quickly and accurately as possible. Each trial ended when the ball struck the screen. Each participant completed four familiarisation trials, followed by ten test trials. Task response time (CRT_RT) was measured from stimulus onset to the initial ball movement. Response accuracy was recorded for correct trials when the ball struck the semi-circular target on the red panel. Incorrect trials were recorded when the ball struck any other panel.

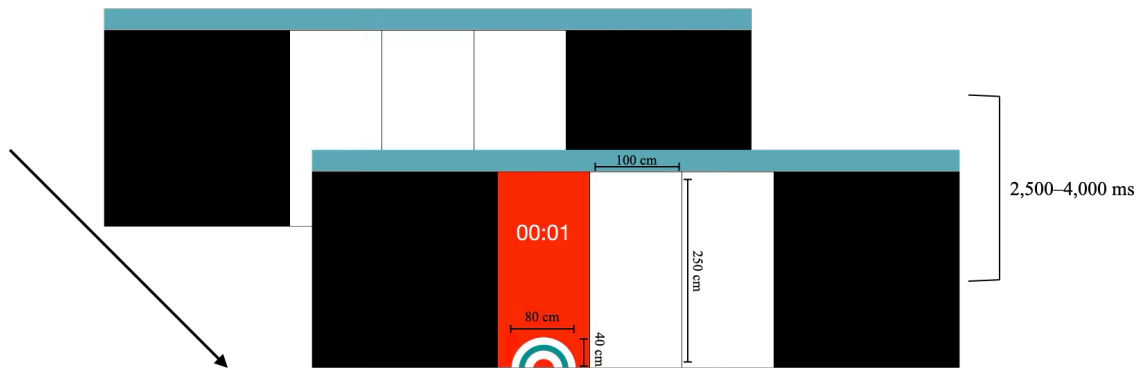


Figure 5.2 Choice response time task.

Anticipation: At the start of the test, all panels surrounding the 360° screen were coloured white. At 1,000 ms into each trial, a round object (30 cm in diameter) descended diagonally from the top to the bottom of the screen (Figure 5.3). Concurrent with the onset of the stimulus (i.e., the falling round object), an audio tone played for 3,200 ms, increasing in frequency as the object approached the bottom of the screen. The object became invisible when the audio ceased at 3,200 ms, marking the end of the trial. Participants were required to anticipate the landing point of the object and pass the ball as quickly and accurately as possible to strike that point on the panel. A trial was recorded as incorrect if the participant failed to pass within the 3,200 ms time limit. The object alternated between falling from the top of the play button panel towards the right and left sides of the screen, with varying speeds (0.55 m/s to 0.75 m/s), and angles (-72° to 70°) for each trial. Each participant completed two practice trials, followed by ten test trials. Task response time (ANT_RT) was measured from stimulus onset to the initial ball movement, and response accuracy (ANT_ACC) was measured as the horizontal distance (metres [m]) between the participant's pass and the point where the object touched the ground.

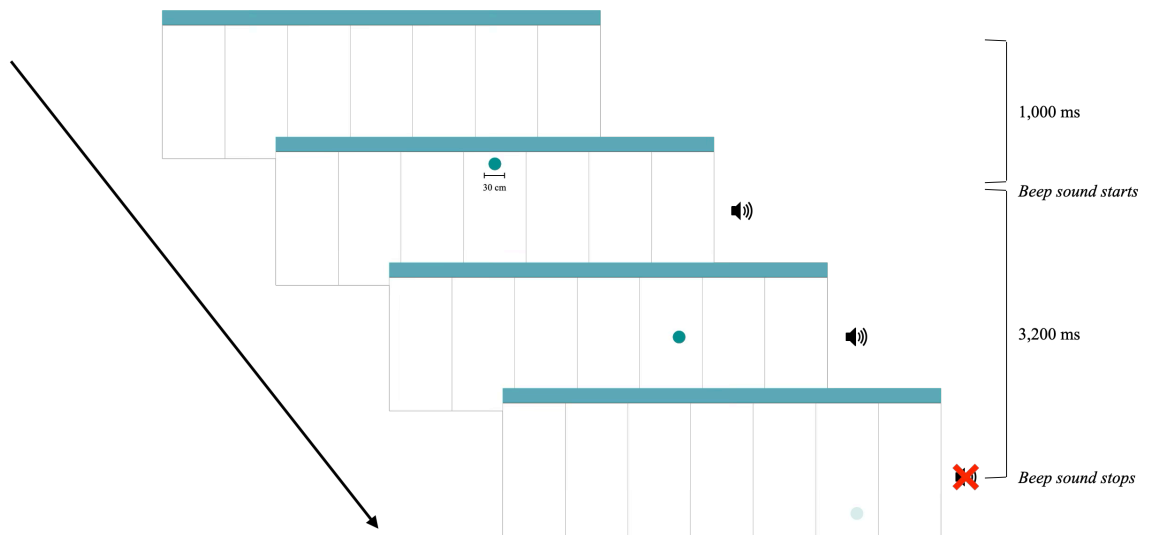


Figure 5.3 Anticipation task.

Inhibition: The Stroop Number task, adapted from Henik and Tzelgov (1982), was utilised in the INH task. Three white panels were presented horizontally on the SB360 screen for 3,000 ms, after which the left and right panels turned red (Figure 5.4). The red panels contained stimulus circles displaying numbers that varied in both font size and numerical value, randomly selected between ‘1’ and ‘9’. A trial was classified as congruent when one panel displayed a larger numerical value in a larger font size, or a smaller numerical value in a smaller font size, compared with the other panel. Conversely, a trial was classified as incongruent when one panel displayed a smaller numerical value in a larger font size, or a larger numerical value in a smaller font size, than the other panel.

During the test, participants were required to pass the ball to a semi-circular target at ground level on the panel displaying either the larger or smaller numerical value, depending on the experimental block. Each experimental block consisted of five trials (two congruent and three incongruent), and participants completed four test blocks following two familiarisation trials (one congruent and one incongruent). In the first and third blocks, passing to the panel with the larger numerical value was considered correct, whereas in the second and fourth blocks, passing to the panel with the smaller numerical

value was correct. Response time for congruent (INH_CRT) and incongruent (INH_ICRT) trials was measured from stimulus onset to the initial ball movement. The Stroop effect (INH_SE; response time cost between experimental conditions) was calculated as the difference between mean incongruent-trial RT and mean congruent-trial RT (i.e., incongruent RT – congruent RT), with higher values indicating a greater additional RT cost associated with resolving stimulus–response interference. Response accuracy (INH_ACC) was recorded as correct when the semi-circular target on the correct panel was struck, and incorrect when the ball struck any other area on the screen.

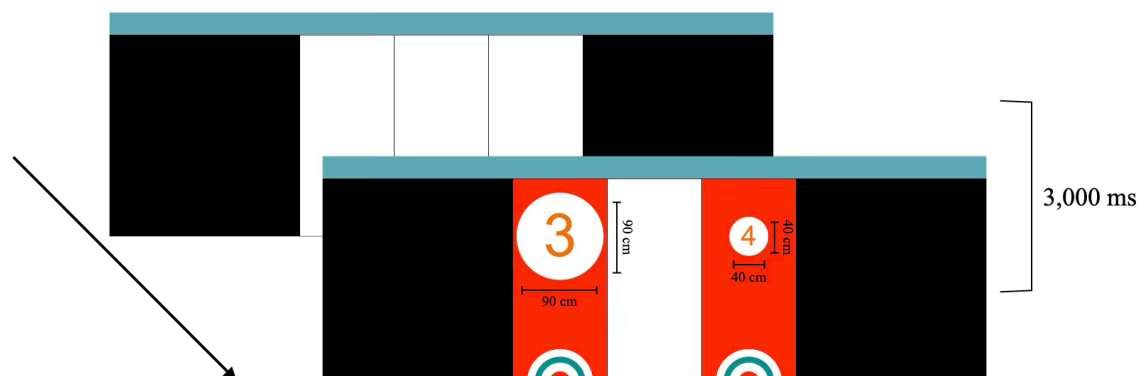


Figure 5.4 Inhibition test.

Working Memory: The Corsi Block Test (Corsi, 1972) adapted specifically for the SB360 system, was utilised for the WM assessment (Figure 5.5). Initially, participants were presented with a football pitch within a stadium displayed on the surround of the 360° screen, containing nine traffic cones. A yellow arrow sequentially pointed to the cones in a specific order before each trial to indicate the sequence. This was followed by a 1,000 ms audio tone, during which the yellow arrow disappeared from the screen. After the tone, participants were instructed to pass the ball to each cone in the exact order indicated by the yellow arrow, using a single ball that rebounded. No time limit was imposed during the test. The test began with sequences of two cones, progressively increasing linearly up to sequences of nine cones. If participants successfully executed

the sequence, a new trial with one additional cone was presented. If a participant failed to strike a cone or struck the wrong cone in the sequence, the trial was recorded as an error trial, and the subsequent trial presented the same number of cones as the previous one. The test concluded after two consecutive error trials. The highest number of cones in a sequence that the participant successfully replicated was recorded, along with the total number of errors (i.e., incorrect passes) and the average number of errors per sequence (i.e., the total number of errors divided by the longest correct sequence).

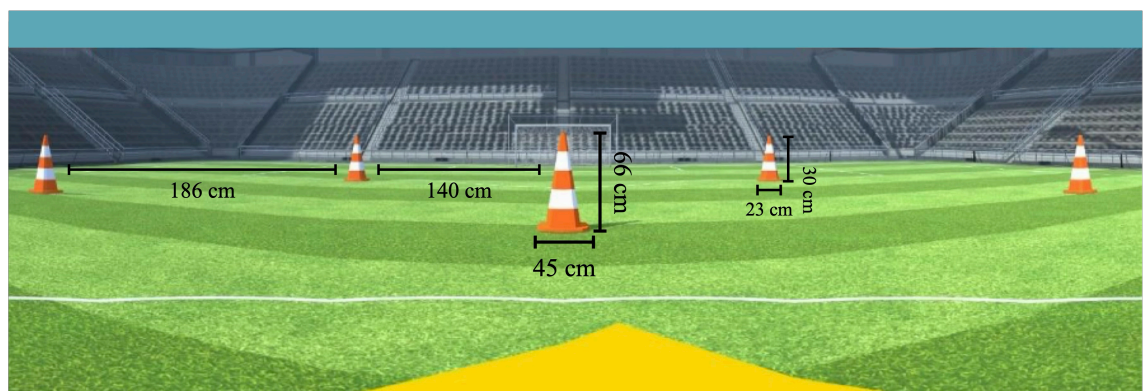


Figure 5.5 Working memory test.

5.3.3.3 Cognitive Training Intervention

The SB360 system provides multiple training-mode games designed to engage domain-general cognitive skills alongside football-specific motor actions. According to the game developer (Umbrella Software Development GmbH), each training mode was designed to target specific cognitive functions through distinct task characteristics. Based on task relevance, coach consultation, session feasibility (i.e., game time), and the combined coverage of all five cognitive functions included in the current test battery, two training games were selected: Mini Goals (MG) and Moving Targets (MT). Each game was performed across three difficulty levels, with difficulty progressively increased every two sessions.

Mini Goals: MG involved goals that alternately opened and closed on the 360° screen (Figure 5.6a). The objective of MG was for participants to score as many goals as possible into the open goals within a 30 s timeframe. MG was designed to target INH and CRT. The continuously changing open goals are hypothesised to require participants to inhibit planned passing actions when a previously selected goal closes and rapidly identify an alternative open target, thereby placing demands on inhibitory control. In addition, participants are required to perceive the changing visual information, select an appropriate target, and execute the pass as quickly as possible within the fixed time period, which is hypothesised to train CRT. Appendix 7 outlines the detailed MG game parameters across difficulty levels.

Moving Targets: MT involved various moving objects of different shapes (square, circle, and triangle) and colours (blue, purple, green, yellow, and red) presented on the 360° screen (Figure 5.6b). The objective of MT was for participants to achieve a predetermined score as quickly as possible by repeatedly striking the ball at the moving objects. During the pre-orientation (Pre-O) levels, the SB360 system displayed the shape and colour of the target to be hit, indicating which target would follow next, along with the target scores from the onset of the game. MT was designed to target ANT, CF, and WM. The target-hitting task with moving objects is hypothesised to place demands on anticipatory skills by requiring participants to predict a target's future location to execute an accurate pass. CF is hypothesised to be engaged through the variable scoring system, whereby different target characteristics (e.g., colour, size, speed, height) are assigned different point values, requiring participants to continually adapt their target selection strategies according to the task demands. In the Pre-O levels, displaying the current and subsequent target information is hypothesised to place demands on WM, as retaining the upcoming target information while completing the current action may facilitate a more efficient transition to the next target. Each trial concluded once the participant successfully scored the

required points for that game level. Appendix 8 outlines the detailed MT game parameters across difficulty levels.

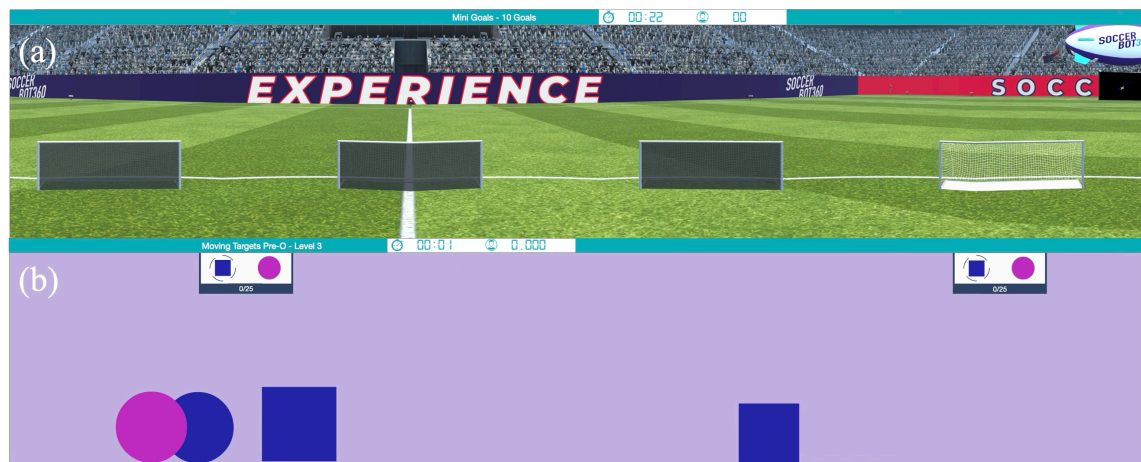


Figure 5.6 Image of SocerBot360 training-mode tasks. (a) Mini Goals (MG) and (b) Moving Targets (MT).

5.3.4 Procedures

5.3.4.1 Testing Sessions

All testing was administered by the lead researcher (WC). At the beginning of each testing session, participants completed an individual warm-up lasting 5–10 min within the SB360. Prior to each test, participants received standardised verbal and visual instructions outlining testing rules, including images of actual testing scenes displayed via the SB360 software. During the tests, participants were required to pass the ball from a fixed distance of 5 m from the SB360 screen. A 30 s rest period was provided between tests, and each testing session lasted approximately 30–40 min. The order of the tests was counterbalanced across participants to control for order effects.

5.3.4.2 Training Sessions

All SB360 training was administered by the lead researcher (WC). Before each training session, participants completed a 15 min group warm-up led by physical performance coaches. During each session, participants played the two SB360 training-mode games,

completing four trials for each mode and resulting in a total of eight trials per session. Standardised verbal and visual instructions on the game rules were provided through the SB360 software and by operating staff. While participants could monitor their game scores on the screen, no individualised feedback was provided by staff during or after the games. Each SB360 training session lasted approximately 45 min, during which each participant was actively engaged for approximately 10–15 min. The playing order of participants, and the selection of games, were counterbalanced in each session to ensure an equitable distribution of task order and game exposure. Each group trained for one session per week across their respective six-week intervention.

5.3.4.3 Control Blocks

During the control block, participants followed their regular academy training programme, which was individually prescribed through players' Individual Development Plan (IDP). The IDP sessions were delivered on the pitch or in the gym in small units (2–5 players) and supervised by relevant staff. On-pitch sessions primarily targeted technical skill development, whereas gym-based sessions focused on individual physical development needs. The inclusion of a control block was intended to provide a practical comparator to the intervention while maintaining ecologically valid training exposure. This design also ensured that all participants continued to receive developmentally appropriate training in line with academy practice, addressing ethical considerations associated with withholding training from youth academy players.

5.3.5 Data Preparation

Following data collection, the WM testing results were excluded from the final analysis in this study. This decision was based on several factors. First, several participants reported that the positions of the traffic cones on the screen closely resembled a football formation, enabling them to memorise the sequences as a series of digits by assigning

specific numbers to each cone according to its position (e.g., assigning number 8 to a cone in a central midfielder position). Consequently, the scores may have been influenced by participants' memorisation strategies linked to football playing formations and standard positions, rather than by visuospatial attention and working memory capacity. Moreover, although Corsi Block testing scores are not always directly comparable due to differing scoring systems across studies, the total errors and average errors per sequence are not commonly used methods for this test (Arce & McMullen, 2021). This discrepancy further limits the comparability and interpretability of the findings.

For the remaining four cognitive tasks, incorrect trials (i.e., false responses) were excluded from RT analyses. Task-specific RT thresholds and outlier handling procedures were applied based on previous literature (Musculus et al., 2022). Following data preparation, final sample sizes included in the analysis were CF = 27, INH = 29, CRT = 31, and ANT = 31. Full filtering criteria, exclusion rationale, and final sample information for each cognitive task are detailed in Appendix 9.

5.3.6 Data Analysis

All statistical tests were conducted in R (version 4.4.1; R Core Team, 2025). To assess SB360 training effects while accounting for inter-individual variability, linear mixed-effects models (LMM) were employed for each testing variable (Iannaccone et al., 2021). Model selection followed a stepwise procedure to identify the most parsimonious model for each testing variable (Bates et al., 2015; Frank, 2015). Players were first included as a random intercept, and the resulting model was compared with a base intercept-only model using model-fit criteria. When inclusion of the random intercept improved model fit, the random-intercept model was retained as a null model for the respective outcome variable. Following selection of the random-intercept null model, a series of candidate models incorporating different fixed-effect structures was evaluated. Specifically, models

including age (years), time (T1, T2, T3), group (A, B), and the time $\times$ group interaction were fitted and compared using the predefined stepwise model-selection procedure to identify the most parsimonious model for each outcome variable. Given the crossover design and the primary research interest in whether changes over time differed between groups, the time $\times$ group interaction was examined and reported for each testing variable irrespective of whether the interaction model was retained as the best-fitting final model.

Candidate models were compared using the Akaike Information Criterion (AIC) and chi-square likelihood ratio tests. Lower AIC values indicated better relative model fit, whereas likelihood ratio tests assessed whether the inclusion of additional model terms significantly improved fit ($p < .05$). Maximum likelihood (ML) estimation was used for comparisons between models with differing fixed-effects structures, and restricted maximum likelihood (REML) estimation was applied to the final model of each testing variable (Field, 2024). Marginal and conditional R^2 values were reported as measures of explained variance attributable to the fixed effects and to the combined fixed and random effects, respectively (Nakagawa & Schielzeth, 2013).

When a random-intercept null model was not supported for an outcome variable, alternative exploratory analyses were conducted based on the distributional characteristics of the data. For the INH Stroop effect (INH_SE), which was the only outcome requiring a non-parametric approach, differences across time points were assessed using a Friedman test, with Kendall's coefficient of concordance (W) calculated as a measure of effect size. To assess the robustness of these findings and examine potential intervention-related effects accounting for group allocation, an LMM including the time $\times$ group interaction was also conducted as a secondary sensitivity analysis. This model was not treated as a primary inferential analysis because the random-intercept structure was unsupported.

Accordingly, ten outcome variables were included in the mixed-effects models: CRT_RT, CF_ACC, CF_SRT, CF_NSRT, CF_SC, ANT_ACC, ANT_RT, INH_CRT, INH_ICRT, and INH_SE. The INH_ACC variable was excluded from further analysis due to pronounced ceiling effects across time in both Group A ($97.9 \pm 2.7\%$) and Group B ($98.4 \pm 2.2\%$).

5.3.7 Sample Size Estimation

Due to the applied professional academy context, participant availability determined the sample size. To contextualise the achieved sample, simulation-based sensitivity analyses were conducted in R for the primary contrast of interest (Ditroilo et al., 2025), defined as the between-group difference in change from T1 to T2, corresponding to the group-by-time interaction in LMM with a random intercept for player. Using the final samples following data-filtering and assuming two-tailed $\alpha = 0.05$ and $1 - \beta = 0.80$, analyses indicated that the study was sensitive to detect minimum between-group differences in T1–T2 change of approximately 60 ms for CRT_RT; 250 ms for CF overall RT, 220 ms for CF_SC, and 7 pp for CF_ACC; 200 ms for ANT_RT and 0.10 m for ANT_ACC; 50 ms for INH overall RT and 80 ms for INH_SE. Interpretation of the intervention effects should be considered in relation to these sensitivity thresholds, with RT outcomes generally falling within minimum detectable ranges, whereas accuracy-based outcomes and CRT_RT warrant more cautious interpretation.

5.4 Results

Eight models were retained to analyse the contribution of fixed and random effects to performance on cognitive tasks across testing blocks and groups. Table 5.2 presents the polynomial regression analyses for each testing variable.

Table 5.2 Retained models that indicate the effect of age, time, group, and interaction on the standardised SoccerBot360 cognitive-motor training intervention.

Polynomial Regressions	AIC	<i>p</i> -value	χ^2	$R^2_{(m)}$	$R^2_{(c)}$
Choice Response Time Test: Response Time					
^a Final model: lmer (CRT_RT ~ Age + Time + (1 Player))					
Base model without random effects: lm (CRT_RT ~ 1, data = data)	-173.4				
Null model with random effects: CRT_RT ~ 1 + (1 Player)	-214.9	<.01		.00	.69
Random intercepts model: Age	-226.1	<.01	13.15	.25	.78
^a Random intercepts model: Age + Time	-242.0	<.01	19.92	.19	.80
Random intercepts model: Age + Time + Group	-240.1	.85	0.03	.19	.81
Random intercepts model: Time * Group	-234.2	1.00	<0.01	.08	.81
Cognitive Flexibility Test: Accuracy					
^a Final model: lmer (CF_ACC ~ Time + (1 Player))					
Base model without random effects: lm (CF_ACC ~ 1, data = data)	591.2				
Null model with random effects: CF_ACC ~ 1 + (1 Player)	539.5	<.01		.00	.77
Random intercepts model: Age	540.1	.23	1.45	.04	.79
^a Random intercepts model: Time	538.6	.09	4.90	.01	.79
Random intercepts model: Group	540.6	.36	0.93	.03	.77
Random intercepts model: Time * Group	543.4	.75	1.21	.04	.79
Cognitive Flexibility Test: Switch Response Time					
^a Final model: lmer (CF_SRT ~ Time + (1 Player))					
Base model without random effects: lm (CF_SRT ~ 1, data = data)	80.8				
Null model with random effects: CF_SRT ~ 1 + (1 Player)	54.4	<.01		.00	.60
Random intercepts model: Age	55.9	.47	0.52	.02	.66
^a Random intercepts model: Time	33.2	<.01	25.20	.10	.75
Random intercepts model: Time + Group	32.7	.12	2.47	.16	.75
Random intercepts model: Time * Group	36.1	.37	3.12	.17	.75
Cognitive Flexibility Test: Non-Switch Response Time					
^a Final model: lmer (CF_NSRT ~ Time + (1 Player))					
Base model without random effects: lm (CF_NSRT ~ 1, data = data)	70.5				
Null model with random effects: CF_NSRT ~ 1 + (1 Player)	36.3	<.01		.00	.67
Random intercepts model: Age	38.2	.83	0.04	.00	.65
^a Random intercepts model: Time	12.0	<.01	28.27	.09	.80
Random intercepts model: Time + Group	11.9	.14	2.14	.15	.80
Random intercepts model: Time * Group	13.5	.21	4.15	.16	.81
Cognitive Flexibility Test: Switch Cost					
^a Final model: lmer (CF_SC ~ 1 + (1 Player))					
Base model without random effects: lm (CF_SC ~ 1, data = data)	-94.0				
^a Null model with random effects: CF_SC ~ 1 + (1 Player)	-102.1	<.01		.00	.37
Random intercepts model: Age	-100.5	.55	0.37	.01	.37
Random intercepts model: Time	-99.8	.44	1.64	.01	.39
Random intercepts model: Group	-100.4	.61	0.26	.01	.37
Random intercepts model: Time * Group	-95.0	.72	2.84	.03	.40

Table 5.2 Continued.

Polynomial Regressions	AIC	<i>p</i> -value	χ^2	$R^2_{(m)}$	$R^2_{(c)}$
Anticipation Test: Accuracy					
^a Final model: lmer (ANT_ACC ~ Time + (1 Player))					
Base model without random effects: lm (ANT_ACC ~ 1, data = data)	46.0				
Null model with random effects: ANT_ACC ~ 1 + (1 Player)	29.3	<.01		.00	.47
Random intercepts model: Age	31.2	.75	0.10	.00	.46
^a Random intercepts model: Time	24.8	.01	8.56	.05	.54
Random intercepts model: Time + Group	26.6	.67	0.18	.05	.54
Random intercepts model: Time * Group	25.5	.15	5.32	.07	.57
Anticipation Test: Response Time					
^a Final model: lmer (ANT_RT ~ Time + (1 Player))					
Base model without random effects: lm (ANT_RT ~ 1, data = data)	61.1				
Null model with random effects: ANT_RT ~ 1 + (1 Player)	24.1	<.01		.00	.65
Random intercepts model: Age	23.8	.12	2.39	.01	.69
^a Random intercepts model: Time	11.6	<.01	16.56	.06	.73
Random intercepts model: Time + Group	13.1	.48	0.49	.07	.73
Random intercepts model: Time * Group	13.3	.23	4.28	.01	.75
Inhibition Test: Congruent Response Time					
^a Final model: lmer (INH_CRT ~ Time + (1 Player))					
Base model without random effects: lm (INH_CRT ~ 1, data = data)	-78.4				
Null model with random effects: INH_CRT ~ 1 + (1 Player)	-95.2	<.01		.00	.49
Random intercepts model: Age	-94.4	.28	1.16	.02	.52
^a Random intercepts model: Time	-109.9	<.01	18.63	.10	.63
Random intercepts model: Time + Group	-107.9	.84	0.04	.10	.63
Random intercepts model: Time * Group	-108.7	.19	4.79	.16	.66
Inhibition Test: Incongruent Response Time					
^a Final model: lmer (INH_ICRT ~ Time + (1 Player))					
Base model without random effects: lm (INH_ICRT ~ 1, data = data)	-76.5				
Null model with random effects: INH_ICRT ~ 1 + (1 Player)	-96.0	<.01		.00	.52
Random intercepts model: Age	-94.6	.43	0.61	.01	.55
^a Random intercepts model: Time	-112.5	<.01	20.55	.10	.66
Random intercepts model: Time + Group	-110.5	.95	<0.01	.10	.66
Random intercepts model: Time * Group	-108.7	.54	2.15	.16	.66
Inhibition Test: Stroop Effect					
Final model: a Friedman test was performed as an alternative approach.					
Base model without random effects: lm (INH_SE ~ 1, data = data)	-277.2				
Null model with random effects: INH_SE ~ 1 + (1 Player)	-275.4	.61		.00	.02
Random intercepts model: Time * Group	-266.0	.99	0.60	.01	.06
Friedman test: INH_SE (Time)	χ^2	df	<i>p</i> -value	Kendall's <i>W</i>	
	0.62	2	.73	.01	

Nb. ^a indicates the best fitting model based on AIC and *p*-value.

5.4.1 Age

Age significantly improved model fit only for CRT_RT ($p < .01$). In the final model (CRT_RT ~ age + time), age remained a significant predictor of CRT_RT ($p = .04$). No significant age effects were observed for the remaining cognitive outcomes ($ps > .05$).

5.4.2 Time

Table 5.3 displays the analyses of time effects across the retained models. Time significantly contributed to RT outcomes. Participants exhibited significant reductions in RT outcomes at both T2 and T3, compared to baseline (T1) across tests ($ps \leq .02$), except for CRT_RT, where participants reported significant improvements at T3 only (-51 ± 11 ms) compared to T1 ($p < .01$). However, no time effects were observed for the CF switch cost (CF_SC; $p = .44$). Similarly, a Friedman test indicated no significant differences in the Stroop effect (INH_SE) across time points ($\chi^2(2) = 0.62, p = .73$, Kendall's $W = .01$).

For accuracy outcomes, the ANT_ACC model showed significant effects of time ($p = .01$), reflected by a reduction in mean error distance of 0.15 m at T3 compared with T1 ($p = .01$). In contrast, although CF_ACC demonstrated a trend towards greater accuracy across time, this effect did not reach statistical significance for model fit compared to the null model ($p = .09$; Table 5.2). Given that the time model for CF_ACC had lower AIC values than the null model, time was therefore added to the final model. The final model reported that CF accuracy scores were significantly improved at T3 ($92.2 \pm 1.2\%$) compared to T1 ($89.6 \pm 1.8\%$) ($p = .03$; Table 5.3).

Table 5.3 Final mixed-effects models for outcome variables.

Fixed effects	CRT_RT (ms)				CF_ACC (%)			
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value	β (SE)	95% CI	<i>t</i>	<i>p</i> -value
Intercept	1221 (213)	[805, 1638]	5.747	<.01 **	90.94 (1.64)	[87.73, 94.15]	55.59	<.01 **
age	-33 (15)	[-63, -3]	-2.148	.04 *				
Time (T2)	-14 (11)	[-36, 7]	-1.322	.19	1.46 (1.16)	[-0.81, 3.73]	1.258	.21
Time (T3)	-51 (11)	[-74, -29]	-4.481	<.01 **	2.57 (1.16)	[0.30, 4.84]	2.216	.03 *
Random effects	Estimate	SD			Estimate	SD		
Player	5384	73.37			65.88	8.117		
Residual	1649	40.61			19.15	4.376		
$R^2_{(m)}$	.18				.00			
$R^2_{(c)}$	.81				.77			
Fixed effects	CF_SRT (ms)				CF_NSRT (ms)			
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value	β (SE)	95% CI	<i>t</i>	<i>p</i> -value
Intercept	1834 (72)	[1692, 1976]	25.342	<.01 **	1722 (68)	[1589, 1856]	25.243	<.01 **
Time (T2)	-245 (54)	[-351, -140]	-4.556	<.01 **	-209 (45)	[-298, -121]	-4.645	<.01 **
Time (T3)	-271 (54)	[-377, -166]	-5.039	<.01 **	-252 (45)	[-340, -163]	-5.586	<.01 **
Random effects	Estimate	SD			Estimate	SD		
Player	102227	319.7			98294	313.5		
Residual	39180	197.9			27403	165.5		
$R^2_{(m)}$	.10				.09			
$R^2_{(c)}$	.75				.80			
Fixed effects	CF_SC (ms)				ANT_ACC (m)			
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value	β (SE)	95% CI	<i>t</i>	<i>p</i> -value
Intercept	93 (20)	[54, 132]	4.709	<.01 **	1.157 (0.054)	[1.051, 1.263]	21.395	<.01 **
Time (T2)					-0.022 (0.053)	[-0.127, 0.082]	-0.416	.68
Time (T3)					-0.147 (0.053)	[-0.252, -0.043]	-2.764	.01 **
Random effects	Estimate	SD			Estimate	SD		
Player	6877	82.93			0.047	0.216		
Residual	10968	104.73			0.044	0.210		
$R^2_{(m)}$	.00				.04			
$R^2_{(c)}$	.39				.54			
Fixed effects	ANT_RT (ms)				INH_CRT (ms)			
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value	β (SE)	95% CI	<i>t</i>	<i>p</i> -value
Intercept	1750 (58)	[1635, 1864]	29.966	<.01 **	1055 (27)	[1002, 1108]	38.922	<.01 **
Time (T2)	-161 (44)	[-247, -74]	-3.646	<.01 **	-61 (25)	[-110, -13]	-2.499	.02 *
Time (T3)	-166 (44)	[-253, -80]	-3.773	<.01 **	-113 (25)	[-161, -65]	-4.599	<.01 **
Random effects	Estimate	SD			Estimate	SD		
Player	75537	274.8			12533	112.0		
Residual	30134	173.6			8780	93.7		
$R^2_{(m)}$	.05				.09			
$R^2_{(c)}$	.73				.63			
Fixed effects	INH_ICRT (ms)							
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value				
Intercept	1086 (27)	[1033, 1140]	39.693	<.01 **				
Time (T2)	-61 (24)	[-108, -15]	-2.574	.01 **				
Time (T3)	-116 (24)	[-162, -69]	-4.877	<.01 **				
Random effects	Estimate	SD						
Player	13545	116.38						
Residual	8177	90.43						
$R^2_{(m)}$	.09							
$R^2_{(c)}$	.66							

Nb. * p <.05; ** p <.01.

5.4.3 Group

Polynomial regression analyses indicated that group was not a significant contributor to variance in any of the eight retained models ($ps > .05$), including T2 where between-group differences were expected. Figure 5.7 displays between-group comparisons across experimental blocks.

5.4.4 Time $\times$ Group Interaction

Table 5.4 summarises the time $\times$ group interaction analyses examining whether changes in performance over time differed between groups. These models are reported as secondary analyses because none were retained during the predefined model-selection procedure as the final models (see Table 5.2). No significant time $\times$ group interactions were observed for CRT_RT, CF_ACC, CF_SRT, CF_NSRT, CF_SC, ANT_ACC, and INH_SE ($ps \geq .11$). For ANT_RT, the T3 $\times$ group interaction approached statistical significance ($p = .053$), whereas the T2 $\times$ group interaction was not significant ($p = .33$). For the inhibition task, significant T2 $\times$ group interaction terms were identified for both INH congruent RT (INH_CRT; $p = .03$) and incongruent RT (INH_ICRT; $p = .04$); however, the corresponding T3 $\times$ group interaction terms were not significant ($ps \geq .24$).

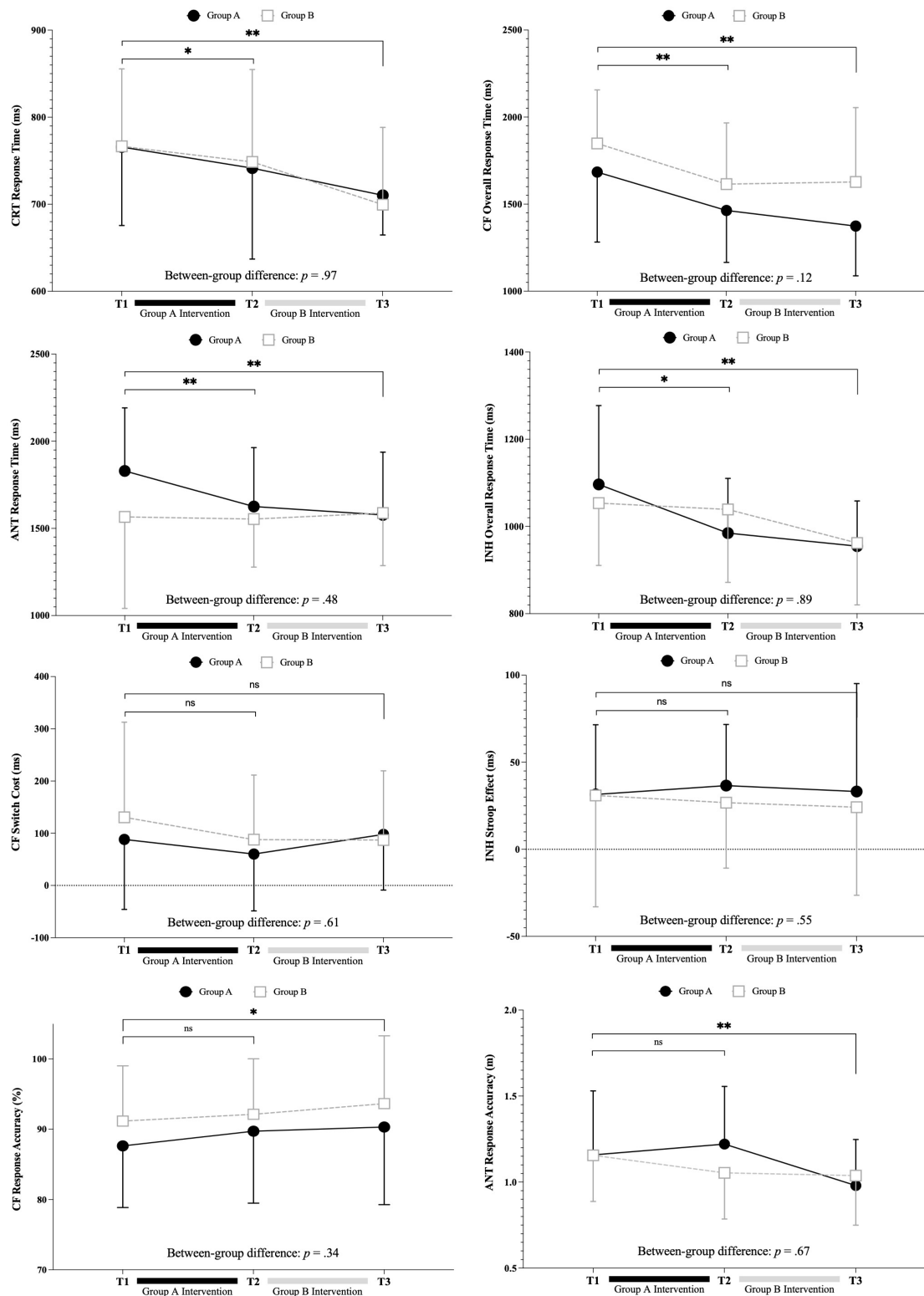


Figure 5.7 Group performance trajectories across testing variables. The CF and INH response times are presented as overall response time. ‘ns’ = non-significant p -value ($p > .05$); * $p < .05$; ** $p < .01$.

Table 5.4 Time $\times$ group interaction mixed-effects models for outcome variables.

Fixed effects	CRT_RT (ms)				CF_ACC (%)			
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value	β (SE)	95% CI	<i>t</i>	<i>p</i> -value
Intercept	766 (22)	[722, 810]	34.25	<.01 **	87.6 (2.6)	[82.6, 92.7]	34.191	<.01 **
timeT2	-24 (14)	[-53, 4]	-1.675	.10	2.1 (1.7)	[-1.3, 5.4]	1.223	.23
timeT3	-56 (14)	[-84, -27]	-3.834	<.01 **	2.7 (1.7)	[-0.7, 6.0]	1.576	.12
GroupB	1 (31)	[-61, 63]	0.023	.98	3.5 (3.4)	[-3.2, 10.3]	1.028	.31
T2:GroupB	6 (20)	[-34, 47]	0.31	.76	-1.1 (2.3)	[-5.6, 3.4]	-0.492	.63
T3:GroupB	-11 (20)	[-52, 29]	-0.56	.58	-0.2 (2.3)	[-4.7, 4.3]	-0.089	.93
Random effects	Estimate	SD			Estimate	SD		
Player	5925	76.98			61.4	7.8		
Residual	1573	39.67			17.4	4.2		
$R^2_{(m)}$	.08				.04			
$R^2_{(c)}$	.81				.79			
Fixed effects	CF_SRT (ms)				CF_NSRT (ms)			
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value	β (SE)	95% CI	<i>t</i>	<i>p</i> -value
Intercept	1732 (103)	[1531, 1933]	16.889	<.01 **	1644 (97)	[1454, 1833]	16.982	<.01 **
timeT2	-235 (79)	[-389, -80]	-2.977	<.01 **	-207 (65)	[-334, -80]	-3.187	<.01 **
timeT3	-306 (79)	[-460, -151]	-3.881	<.01 **	-316 (65)	[-433, -188]	-4.864	<.01 **
GroupB	184 (138)	[-85, 454]	1.339	.19	142 (130)	[-113, 396]	1.093	.28
T2:GroupB	-19 (106)	[-227, 188]	-0.183	.86	-5 (87)	[-175, 166]	-0.053	.96
T3:GroupB	62 (106)	[-145, 269]	0.586	.56	115 (87)	[-56, 286]	1.322	.19
Random effects	Estimate	SD			Estimate	SD		
Player	88871	298.1			87145	295.2		
Residual	37282	193.1			25253	158.9		
$R^2_{(m)}$	.17				.16			
$R^2_{(c)}$	.75				.81			
Fixed effects	CF_SC (ms)				ANT_ACC (m)			
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value	β (SE)	95% CI	<i>t</i>	<i>p</i> -value
Intercept	88 (38)	[14, 162]	2.341	.02 *	1.158 (0.075)	[1.010, 1.306]	15.373	<.01 **
timeT2	-28 (42)	[-110, 54]	-0.669	.51	0.063 (0.072)	[-0.079, 0.205]	0.871	.39
timeT3	10 (42)	[-72, 91]	0.232	.82	-0.178 (0.072)	[-0.320, -0.037]	-2.466	.02 *
GroupB	42 (50)	[-57, 141]	0.837	.41	-0.002 (0.105)	[-0.208, 0.203]	-0.020	.98
T2:GroupB	-14 (56)	[-145, 95]	-0.265	.79	-0.165 (0.101)	[-0.362, 0.032]	-1.639	.11
T3:GroupB	-53 (56)	[-163, 57]	-0.948	.35	0.060 (0.101)	[-0.137, 0.257]	0.596	.55
Random effects	Estimate	SD			Estimate	SD		
Player	6563	81.01			0.046	0.214		
Residual	10455	102.25			0.039	0.198		
$R^2_{(m)}$	.03				.07			
$R^2_{(c)}$	.40				.57			
Fixed effects	ANT_RT (ms)				INH_CRT (ms)			
	β (SE)	95% CI	<i>t</i>	<i>p</i> -value	β (SE)	95% CI	<i>t</i>	<i>p</i> -value
Intercept	1830 (82)	[1670, 1990]	22.432	<.01 **	1078 (38)	[1003, 1152]	28.433	<.01 **
timeT2	-204 (60)	[-322, -85]	-3.370	<.01 **	-115 (33)	[-180, -49]	-3.438	<.01 **
timeT3	-252 (60)	[-371, -134]	-4.170	<.01 **	-142 (33)	[-207, -76]	-4.249	<.01 **
GroupB	-155 (114)	[-378, 67]	-1.369	.18	-44 (53)	[-147, 60]	-0.826	.41
T2:GroupB	83 (84)	[-82, 248]	0.990	.33	103 (46)	[12, 194]	2.222	.03 *
T3:GroupB	166 (84)	[1, 331]	1.976	.053 *	56 (46)	[-35, 147]	1.197	.24
Random effects	Estimate	SD			Estimate	SD		
Player	72372	269.0			12301	110.91		
Residual	27434	165.6			7811	88.38		
$R^2_{(m)}$	.08				.12			
$R^2_{(c)}$	.75				.66			

Table 5.4 Continued.

Fixed effects	INH_ICRT (ms)				INH_SE (ms)			
	β (SE)	95% CI	<i>t</i>	p-value	β (SE)	95% CI	<i>t</i>	p-value
Intercept	1109 (38)	[1034, 1184]	28.912	<.01 **	32 (13)	[6, 57]	2.460	.02 *
timeT2	-110 (32)	[-173, -46]	-3.387	<.01 **	5 (18)	[-29, 40]	0.292	.77
timeT3	-140 (32)	[-204, -77]	-4.329	<.01 **	2 (18)	[-33, 36]	0.097	.92
GroupB	-44 (53)	[-149, 60]	-0.826	.41	-1 (18)	[-35, 34]	-0.032	.97
T2:GroupB	93 (45)	[6, 182]	2.085	.04 *	-9 (25)	[-57, 39]	-0.379	.71
T3:GroupB	47 (45)	[-41, 135]	1.047	.30	-8 (25)	[-56, 40]	-0.345	.73
Random effects	Estimate	SD			Estimate	SD		
Player	13259	115.1			121.3	11.01		
Residual	7345	85.7			2174.2	46.63		
$R^2_{(m)}$	.11				.09			
$R^2_{(c)}$	.68				.66			

Nb. Time $\times$ group interaction models are reported as secondary analyses. None of these interaction models were retained during the predefined model-selection procedure and therefore were not treated as the primary inferential models. * $p < .05$; ** $p < .01$.

5.4.4 Effect Sizes

Despite progressive improvements over time in all retained models, except for EF cost-related variables (i.e., switch cost, Stroop effect), marginal R^2 values (variance explained by fixed effects only) indicated that time explained a small proportion of variance across the high-level cognitive tasks (CF, ANT, INH), with $R^2_{(m)}$ values ranging from 0.00 to 0.10 (Table 5.3). For the CRT_RT model, fixed effects (age + time) explained a greater proportion of the variance ($R^2_{(m)} = 0.19$).

In contrast, conditional R^2 values (variance explained by both fixed and random effects) ranged between 0.54–0.80 across all retained models, indicating moderate to strong within-subject variability (Table 5.3). This suggests that the individuality exerted a stronger influence on cognitive task performance than the effects of the six-week SB360 training intervention. In fact, individual-level observations demonstrated that participants had different performance trajectories in overall RT and accuracy outcomes within the same group and time (Figure 5.8).

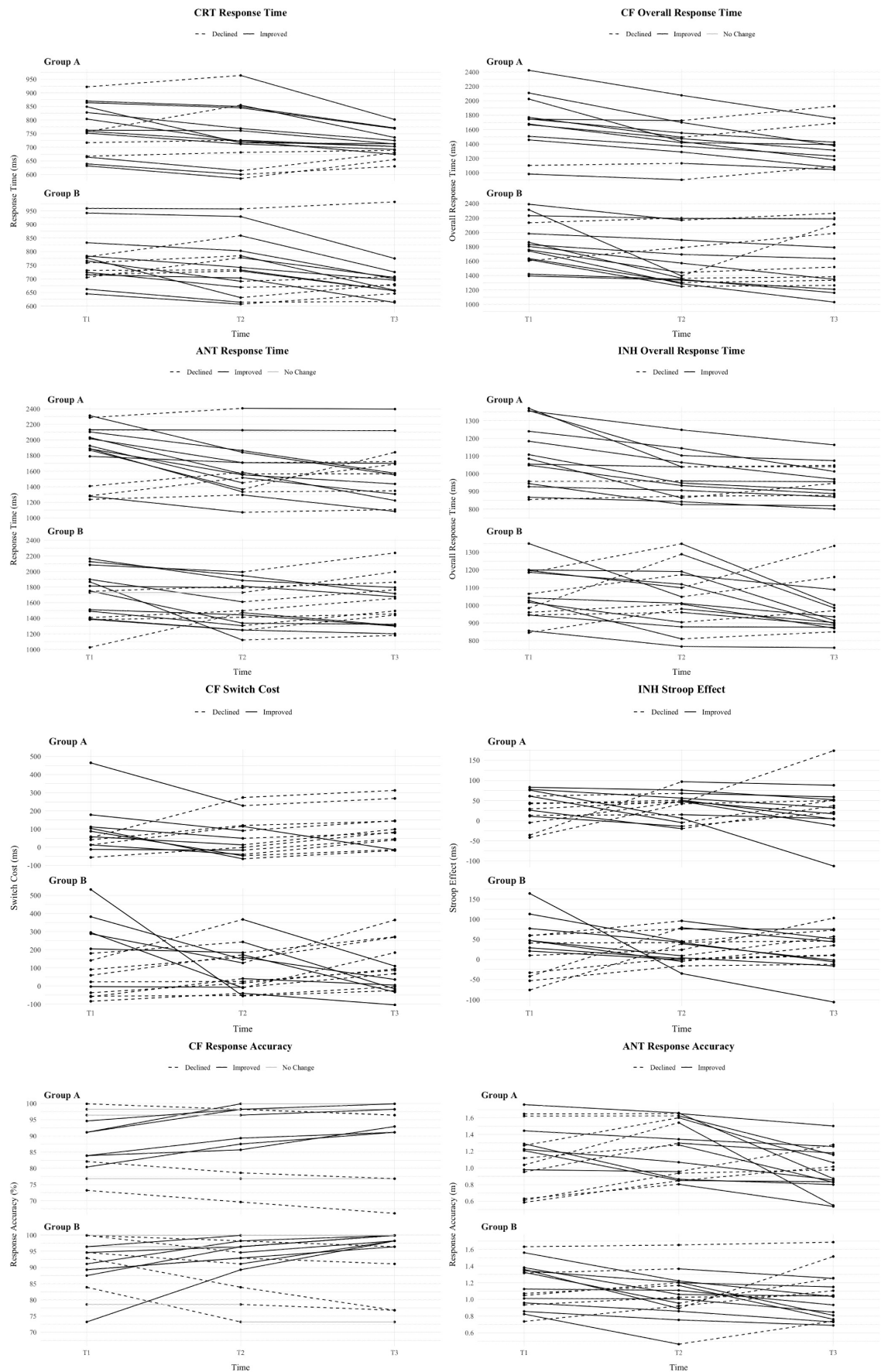


Figure 5.8 Individual performance trajectories across testing variables. The CF and INH response times are presented as overall response time. Black solid lines indicate improved performance; grey solid lines indicate no changes in performance; and black dotted lines indicate declined performance between timepoints.

5.5 Discussion

This study evaluated the effects of a six-week standardised SB360 training intervention on cognitive-motor performance in skilled youth football players using a longitudinal crossover design and linear mixed-effects modelling. Although participants demonstrated improvements over time across most cognitive outcomes, neither group allocation nor the time $\times$ group interaction consistently explained performance changes, indicating little evidence that the intervention produced improvements beyond repeated task exposure. Age significantly predicted only CRT_RT, while effect-size analyses demonstrated that inter-individual variability explained substantially more variance than the fixed effects of time or group. Collectively, these findings suggest that the observed improvements primarily reflected task familiarisation rather than intervention-induced cognitive adaptation and highlight the importance of individual variability when evaluating cognitive training interventions.

Previously, Heilmann et al. (2021) reported significant improvements in four of five SB360 cognitive tasks following SB360 training conducted over a 12-month period (1–2 sessions per week). However, the absence of a familiarisation test, standardised training, and control players limited interpretation of those findings, with the authors acknowledging that improvements may have been driven by task familiarity or general cognitive development. When these methodological limitations were addressed in the present study, participants in both intervention and control conditions demonstrated comparable improvements in the same outcome variables, with no evidence of between-group intervention differences. Given the relatively short test-retest interval (8–12 weeks), these time gains are likely attributable to task familiarisation rather than intervention-specific cognitive enhancement.

Furthermore, secondary time $\times$ group interaction analyses provided little additional evidence for intervention-specific effects. Although isolated T2 $\times$ group interaction terms were identified for both congruent and incongruent INH RTs, these effects were not maintained at T3 (Table 5.4), and both groups demonstrated largely parallel performance trajectories with substantial overlap in variability throughout the study period (Figure 5.7). Similarly, although the T3 $\times$ group interaction for ANT_RT approached statistical significance, the observed pattern was primarily driven by improvements within Group A, whereas Group B showed no corresponding improvement following the intervention. Moreover, no significant time $\times$ group interactions were identified for any of the remaining outcome variables, and none of the interaction models were retained during the predefined model-selection procedure. Collectively, these findings do not provide convincing evidence that the SB360 intervention produced systematic changes in performance beyond the general improvements observed over time. An equally plausible explanation is that the SB360 training intervention itself had limited efficacy in producing measurable cognitive adaptations under the present training conditions.

This broader interpretation is also consistent with the absence of improvements in CF_SC and INH_SE. Switch cost and Stroop effect are designed to minimise the influence of general processing speed by quantifying the additional cognitive demands associated with task switching and response inhibition, respectively. Consequently, the present pattern may indicate that repeated task exposure primarily enhanced general response efficiency and familiarity with the testing procedures rather than the executive-control mechanisms underlying CF and INH. However, because CF_SC and INH_SE were secondary outcome measures and no direct manipulation of EF was undertaken, this interpretation warrants caution.

Regarding task familiarisation, Musculus et al. (2022) examined the convergent validity of the SB360 number-letter (CF) and Flanker (INH) tasks and reported similar patterns. Players completed computerised versions of the cognitive tasks prior to SB360 equivalents to familiarise them with task rules. Both CF and INH performance accuracy were higher and CF switch RT was faster in the respective SB360 tasks despite greater motor demands, indicating that familiarity with task structure and response requirements can meaningfully influence performance. Together, these findings suggest that pre-post comparisons in SB360-based cognitive intervention studies may be substantially influenced by familiarisation effects, particularly when participants have limited prior exposure to the assessment tasks. Therefore, future research should incorporate sufficient task familiarisation and, where feasible, separate baseline and pre-intervention assessments to better isolate training-related change.

The absence of interaction and group effects may also reflect limited training-assessment specificity, whereby training and testing tasks do not engage identical underlying cognitive processes despite being described using similar construct labels. For example, Heilmann, Formenti, et al. (2023) employed a domain-general visuomotor training task but evaluated outcomes using laboratory-based EF tests that differed in stimulus properties, response modalities, and rule structures, yielding no intervention effects. Similar discrepancies between training and assessment tasks have been reported elsewhere and interpreted considering repeated testing, task familiarisation, and developmental factors (Abernethy & Wood, 2001; Heilmann et al., 2024; Theofilou et al., 2022). Likewise, Moen et al. (2018) demonstrated substantial improvements on a trained multiple object tracking task but no transfer to untrained EF measures, concluding that observed gains were confined to the trained skill and did not generalise to broader cognitive functions.

Across cognitive intervention studies, standardised cognitive tasks have consistently demonstrated sensitivity to practice-related improvements, as evidenced by within-group gains following repeated testing, yet limited sensitivity to changes induced by sport-based or visually oriented training interventions (Abernethy & Wood, 2001; Heilmann et al., 2024; Theofilou et al., 2022). This distinction suggests that such assessments may be insufficiently sensitive to detect adaptations that are specific to the training modality. Consequently, SB360 assessment tasks that more closely resemble the demands of training-mode games (e.g., ANT and MT tasks) may improve sensitivity to training-related change. However, the use of visually representative testing-mode tasks within the SB360 is currently constrained by methodological limitations, most notably the low number of test trials (e.g., 10 trials in the ANT task), which may reduce the robustness and reliability of the derived outcome measures (Musculus et al., 2022). Therefore, SB360 training-mode games with semi-standardised stimulus sequences may offer an alternative approach for evaluating training efficacy under controlled conditions. Nevertheless, whether improvements in these training-mode tasks transfer to domain-specific cognitive performance in football remains an open empirical question (Fransen, 2024; Kalén et al., 2021).

In this study, players completed one SB360 training session per week, equating to approximately 10-min of individual exposure each week over the six-week training period. While this dosage was pragmatically determined by the applied academy environment, it is plausible that such a limited training volume may have been insufficient to elicit measurable group-level adaptations. Designing longitudinal intervention studies with control conditions in elite academy settings presents ethical and logistical challenges, particularly where unequal access to training resources may conflict with player development priorities. The crossover design employed intended to maximise total intervention exposure, while ensuring equitable access. However, the resulting training

dose was constrained by competing demands on player time, such as team and IDP football training, gym-based physical training, match preparation, and recovery.

Evidence from higher-dose interventions suggests that training volume is a critical determinant of learning. For example, compared with matched controls, professional adult players demonstrated marked improvements on visuomotor tasks following a six-week intervention comprising two 30-min football-specific visuomotor training sessions per week, equating to approximately six to twelve times the weekly exposure of the present study (Rodrigues et al., 2024). Previous literature suggests that cognitive performance enhancements with potential transfer to athletic performance may require higher training frequencies and longer session durations (e.g., two to three supervised training sessions of 40–60 min per week; Walton et al., 2018). Moreover, a meta-analysis examining dose-response relationships in cognitive interventions for individuals with mild cognitive impairment reported that intervention effectiveness was strongly dependent on training duration, frequency, and total exposure, with significant improvements observed following one to two sessions per week, 60–120-min per session, over periods of ≥ 12 weeks in supervised settings (Shao et al., 2022). These findings suggest that the absence of between-group effects in the present study may partially reflect the relatively low training volume and the lack of augmented, individualised feedback compared with higher-dose interventions.

Findings from this study and previous literature indicate that core training principles, including volume, frequency, duration, and the provision of appropriate challenge points, are central to the effective implementation of cognitive training interventions. Taken together, we recommend that future research should examine cognitive interventions comprising a minimum of 20–30 min per session, delivered across two to three sessions per week, and over periods of 6–12 weeks, to evaluate whether higher training doses

facilitate measurable group-level adaptations. However, it is important to note that many dosage recommendations underpinning effective cognitive intervention designs have been derived from non-athlete populations, investigating cognitive decline prevention in older adults (≥ 65 years) (e.g., Shao et al., 2022; Walton et al., 2018). Accordingly, while dosage recommendations may guide the design of training interventions, further research is required to clarify the mechanisms underpinning perceptual-cognitive processes in football and to inform the development of pragmatic, evidence-based cognitive practice frameworks that demonstrate meaningful transfer to match performance.

In professional football environments, where player time is constrained and repeated exposure to technology-based training may be limited, more specialised applications of cognitive training that prioritise sport-specific performance enhancement over general cognitive development, such as technical skill development (Scharfen & Memmert, 2019b) or player rehabilitation (Chaput et al., 2024), may facilitate the provision of more concentrated training doses using such technologies. Moreover, the substantial individual differences observed in this study, alongside the absence of meaningful age-related differences across most cognitive tasks, underscore the importance of individualised challenge point optimisation rather than relying on standardised training prescriptions in skilled youth players. From this perspective, the applied value of cognitive training technologies is likely to depend on their capacity to deliver sufficiently challenging and adaptable training stimuli within realistic time constraints, and on their targeted use in contexts where added value is most plausible. Likewise, when analysing cognitive intervention data, analytical frameworks that simultaneously model within-player change and between-player variability (e.g., LMM) are recommended to better characterise developmental trends at the population level, while enabling meaningful interpretation of individual player responses.

Several limitations should be acknowledged. First, cognitive-motor performance was examined within a single-club cohort of elite academy football players, which may introduce selection bias and limit generalisability (Kalén et al., 2021). Second, participants from multiple age groups were analysed together due to imbalanced group sizes, and although age effects were largely absent, caution is warranted when interpreting findings (Beavan, Spielmann, Mayer, et al., 2019). Third, control blocks consisted of regular academy activities that were not designed to control perceptual-cognitive engagement and instead reflected routine developmental programmes. Finally, all SB360 activities were conducted following school attendance, which may have increased mental and physical fatigue and influenced task performance (Dong et al., 2022; Smith et al., 2017).

5.6 Conclusion

This study examined the effects of a six-week standardised SB360 training intervention on cognitive-motor performance in youth academy football players using a longitudinal crossover design that accounted for individual variability. Although performance improved across most cognitive outcomes over time, neither group allocation nor time $\times$ group interactions provided convincing evidence of intervention-specific effects. These findings suggest that the observed improvements primarily reflected task familiarisation, although the SB360 intervention may also have had limited efficacy in producing measurable group-level cognitive adaptations under the present training conditions. Inter-individual variability accounted for a substantial proportion of the observed variance, highlighting the limitations of relying solely on group-level comparisons when evaluating cognitive interventions. Collectively, findings indicate that future SB360-based interventions should carefully consider training dose, duration, and challenge point optimisation, alongside individualisation of training intervention, assessment specificity, and adequate task familiarisation.

Chapter 6. General Discussion

6.1 Accomplishment of Aims and Objectives

The primary aim of this thesis was to evaluate the methodological and applied utility of the SoccerBot360 (SB360) as a football-specific cognitive-motor assessment and training system within a professional youth academy context. To address this aim, a series of interrelated objectives were developed, focusing on (i) the performance characteristics and developmental sensitivity of the SB360 assessment, (ii) the influence of contextual and state-related factors on SB360 assessment protocols, and (iii) the effectiveness of SB360 as a cognitive training tool. These objectives were addressed through three empirical studies conducted within an English Premier League Category One football academy.

The first objective was to examine whether SB360 cognitive assessments are sensitive to developmental differences and capable of capturing meaningful variation in cognitive-motor performance across age groups. This was addressed in Chapter 3 through cross-sectional analyses of validated executive function (EF) tasks implemented within the SB360. The findings demonstrated that certain performance metrics, particularly response time (RT), showed systematic variation with chronological age (CA) and biological maturation, while accuracy-based measures were less sensitive. However, these effects were attenuated when analyses were restricted to consecutive age groups, indicating that SB360 performance reflects broader developmental differences rather than fine-grained variation within homogeneous cohorts. As such, this objective was partially achieved, providing evidence for developmental sensitivity in specific metrics while highlighting limitations in the interpretability of SB360-derived outcomes as general indicators of cognitive ability.

The second objective was to investigate the extent to which SB360 testing performance is influenced by contextual and state-related factors, including perceived readiness and subjective workload. This was examined in Chapter 4 using self-reported measures of pre-test readiness (RPE and motivation) and post-test workload (NASA-TLX) in relation to SB360 performance outcomes. The findings indicated that perceived workload, rather than readiness, was more consistently associated with performance, particularly for accuracy and error-based metrics. In contrast, RT measures were less sensitive to these contextual factors. These results demonstrate that SB360 performance is not solely reflective of stable cognitive characteristics but is also influenced by transient task-related demands. This objective was therefore achieved by establishing the contextual dependency of SB360 performance and identifying differential sensitivity across performance metrics.

The third objective was to evaluate the effectiveness of SB360 as a cognitive-motor training intervention. This was addressed in Chapter 5 through a longitudinal intervention study, examining performance changes following a standardised 6-week SB360 training programme. The findings indicated that, although performance improved over time across all measures, these changes were not significantly different between intervention and control conditions, suggesting that they were likely attributable to learning effects or repeated exposure rather than the training itself. In addition, the relatively low training dosage and limited training–assessment specificity may have constrained the potential for observable transfer effects. Thus, this objective was only partially achieved, demonstrating that SB360 training can be implemented within an applied academy environment but providing limited evidence that this specific intervention design, particularly the standardised and low training dosage, produces significant improvements in cognitive performance.

Collectively, findings across these studies address the overarching aim of the thesis by providing a systematic evaluation of the SB360 from both methodological and applied perspectives. While the system demonstrates potential as a structured football-specific assessment and training tool, the results highlight important limitations in relation to measurement sensitivity, contextual dependency, and training effectiveness. Nevertheless, this thesis represents an important initial step towards the structured integration of the SB360, and more broadly cognitive assessment and training protocols, within an elite football academy environment. By embedding the system within real-world player development processes, establishing standardised testing procedures, and critically evaluating its outputs, the present work provides a practical and methodological foundation for its applied use. Accordingly, these findings offer a basis for refining how such technologies are integrated within academy systems, providing a direct link to the theoretical and practical implications discussed in the following sections.

6.2 Synthesis of Findings

6.2.1 Developmental Effects of the SoccerBot360 Assessment

In Chapter 3, the cross-sectional investigation analysed SB360 performance across the academy pathway (age groups and developmental phases) using cognitive flexibility (CF) and working memory (WM) tasks, providing insight into the developmental sensitivity of the SB360 assessments. Clear age-related improvements were observed in RT, particularly within the CF task, whereas CF switch cost and accuracy-based measures demonstrated limited differentiation across age groups. This divergence suggests that temporal metrics may be more sensitive to developmental progression than response accuracy outcomes, which is consistent with broader cognitive literature indicating that response speed often reflects maturation-related changes more reliably than accuracy in adolescence (Camerota et al., 2020; Cromer et al., 2015; Luna et al., 2004). In contrast, WM performance showed weaker age-related trends, suggesting that developmental

sensitivity differed across SB360 outcome measures rather than being evident across all assessed variables.

Moreover, developmental effects were not uniform across the academy pathway. Age-related differences were more pronounced when comparing distant age bands (e.g., U13 vs. U21), while analyses within consecutive age groups or developmental phases revealed attenuated or non-significant differences. A similar pattern was observed in the intervention test battery (Chapter 5), including CF, inhibition (INH), anticipation (ANT), and choice response time (CRT), where age effects were largely absent within the U13–U15 sample, with the exception of CRT performance. These findings reflect previous work, where differences in EF performance were relatively subtle between adjacent age groups despite broader developmental trends across the professional youth academy pathway (Beavan, Chin, et al., 2020; Beavan, Spielmann, et al., 2020). Notably, these patterns were observed across both computerised general EF paradigms and assessment tools that are labelled as football-specific, such as the Helix and the Footbonaut, suggesting that immersive presentation or sport-specific response modalities do not necessarily capture elite-specific developmental trajectories in EFs.

Collectively, this pattern reflects broader developmental trajectories rather than clear distinctions within relatively homogeneous cohorts, aligning with evidence that EF development follows non-linear trajectories during adolescence (Tervo-Clemmens et al., 2023). However, age-related effects in the SB360 were outcome-dependent, with CF switch cost, WM, and accuracy-based measures showing limited developmental differentiation. This contrasts with previous research reporting pronounced improvements in WM performance across childhood and adolescence in the general population (Luna et al., 2004). Furthermore, analyses of biological maturation (Chapter 3) demonstrated similar patterns, with older biological age (BA) associated with faster RT in CF tasks,

while no clear maturation effects were observed in other performance outcomes. These maturation effects were confined to early adolescence (U13-U14) and diminished in older age groups, consistent with evidence that the relative contribution of biological maturation declines as athletes progress through later developmental stages (Wenger & Csapo, 2025).

Taken together, these findings suggest that SB360 performance reflects not only cognitive processes but also the motor demands embedded within each task, particularly in outcomes requiring rapid and consistent motor responses. Accordingly, developmental sensitivity differed across performance metrics, with RT outcomes demonstrating greater sensitivity than executive-control cost, accuracy, or WM measures. This further supports the notion that SB360 performance is shaped by an interaction between cognitive and motor components rather than purely reflecting domain-general cognitive development.

6.2.2 Differential Sensitivity of SoccerBot360 Diagnostic Performance Metrics

A key finding across Chapters 3 and 4 was the differential sensitivity of validated SB360 test metrics to developmental and contextual factors. RT measures were more strongly associated with CA and biological maturation, with these effects particularly pronounced in the CF task, whereas WM performance showed limited developmental sensitivity (Chapter 3). Importantly, this discrepancy was primarily observed in RT measures, as CF switch cost, accuracy and error-based outcomes from both tasks demonstrated no clear age- or maturation-related effects. One potential explanation for this pattern lies in the differing response requirements of the tasks: CF requires a consistent overt motor response on every trial, whereas WM involves intermittent responses with elements of response inhibition on most trials.

An important methodological consideration underlying this pattern relates to how RT and accuracy are operationalised within the SB360 compared to conventional computerised

cognitive paradigms. In laboratory-based tasks, response modalities are typically simplified (e.g., button-press) to minimise motor demands, allowing RT to more directly reflect stimulus evaluation and response preparation processes, and in some cases to be decomposed into subcomponents, such as initiation time and movement time (Foster et al., 2022; Houlihan et al., 1994; also see Section 2.4.2). In contrast, SB360 tasks require full-body motor actions, such as kicking, meaning that recorded RT reflects not only cognitive processing time but also movement execution time. Importantly, the SB360 measurement system does not distinguish between these temporal components, instead capturing a single aggregated RT measure. Accordingly, SB360 RT represents an integrated measure of cognitive-motor performance rather than a purely cognitive index.

While broader cognitive literature has reported positive associations between processing speed and maturation during childhood and adolescence (Camerota et al., 2020; Cromer et al., 2015; Luna et al., 2004), these findings are largely derived from paradigms incorporating minimal motor demands and are typically interpreted in relation to neural (brain) development (Baker et al., 2025; Larsen & Luna, 2018). Conversely, within the SB360 context, RT reflects a combination of neurocognitive processing and neuromuscular execution, given the requirement for larger motor actions. This interpretation is supported by the finding that BA was the strongest predictor of CF RT during early-adolescence. Specifically, BA was the only significant predictor of RT in non-switch-trials, which impose lower cognitive demands, whereas CA also emerged as a significant predictor in trials that require rule updating and task-set reconfiguration. This pattern suggests that RT in SB360 tasks is primarily constrained by neuromuscular function under lower cognitive demands, while broader developmental factors associated with CA, such as accumulated social experience and exposure, may become more influential as domain-general task complexity increases (Baker et al., 2025; Best et al., 2009).

This interpretation is further supported by findings from the intervention study (Chapter 5), where age effects were pronounced only in the CRT task while higher-order cognitive tasks showed negligible effects. Given that SB360 CRT performance is more directly dependent on rapid motor execution than perceptual-cognitive processes, this provides additional support for the interpretation that RT measures within the SB360 are influenced by neuromuscular development. Together, these findings reinforce the view that RT within the SB360 reflects integrated cognitive-motor functioning, with the relative contribution of cognitive versus motor factors varying as a function of task demands. However, caution is warranted when interpreting these findings, as both the maturation analyses (Chapter 3) and the intervention sample (Chapter 5) were based on relatively small and restricted cohorts, which may limit the generalisability of these effects.

In contrast, accuracy and error-based metrics of the CF and WM tasks demonstrated greater sensitivity to cognitive demands and state-related factors, particularly perceived workload (Chapter 4). It is important to note that these outcomes reflect decision accuracy (i.e., binary correctness) rather than motor-execution precision, distinguishing them from technical performance measures. Higher perceived workload was consistently associated with reduced accuracy and increased error rates, indicating that these outcomes are more reflective of transient cognitive states than stable developmental characteristics. Exploratory analyses further demonstrated selective associations across individual workload dimensions, suggesting that different aspects of perceived workload relate to different components of cognitive-motor performance.

This distinction aligns with the literature indicating that accuracy-based measures are more susceptible to fluctuations in attentional control, mental effort, and task demands, particularly in complex or cognitively demanding tasks (Boksem et al., 2005; Engle, 2002). Notably, these metrics showed limited differentiation across age groups in Chapter

3, further supporting the interpretation that they are more responsive to situational constraints and less indicative of maturational progression. This contextual dependency may explain why the current SB360 findings diverge from the paradigms established by traditional computerised cognitive tasks. In assessments with minimal motor demands, accuracy is often viewed as a blunt metric prone to ceiling effects (Camerota et al., 2020; Cromer et al., 2015), leaving RT as the primary indicator of attentional lapses (Kofler et al., 2013; MacDonald et al., 2006; Whelan, 2008). However, within the SB360, RT appears to be more strongly influenced by neuromuscular demand than in conventional computerised paradigms, which may increase the relative sensitivity of accuracy as an indicator of cognitive control under varying task demands.

Collectively, these findings indicate that validated SB360 performance metrics do not uniformly reflect underlying cognitive constructs. Instead, they capture different aspects of performance emerging from an interaction between cognitive demands, motor response characteristics, and the developmental stage of the athlete. RT appears to reflect developmental and motor-related characteristics, whereas executive-control cost and accuracy-based measures were comparatively less sensitive to age but showed greater responsiveness to contextual factors such as perceived workload. This dissociation highlights the importance of carefully selecting and interpreting performance metrics in both research and applied settings, as different SB360 outcomes may reflect fundamentally different underlying processes.

6.2.3 Cognitive versus Motor Demands in SoccerBot360 Task Performance

Findings from Chapter 4 provide insight into the perceived workload characteristics of SB360 tasks, particularly in relation to their cognitive and motor demands within the CF and WM test battery. The average overall workload (OW) observed in the present study (AU: 46.1 ± 10.6) was comparable to values reported in cognitively demanding tasks (AU

≈ 46) and substantially lower than those reported in physically demanding contexts ($AU \approx 62$) (Grier, 2015). This pattern suggests that SB360 assessments are perceived similarly to tasks involving minimal motor demands, such as computerised or screen-based cognitive paradigms. A comparable pattern was observed when contrasted with football training environments, where OW following low-intensity technical drills ($AU_{\text{weighted}} \approx 39$) was similar, but substantially higher values were reported for passing-and-shooting drills ($AU_{\text{weighted}} \approx 64$) and small-sided games (SSG) ($AU_{\text{weighted}} \approx 70$) in well-trained male adult armature players (Montini et al., 2025). Despite differences in NASA-TLX weighting approaches, the sensitivity of weighted and unweighted scales has been shown to be comparable (Hart, 2006). Collectively, these findings indicate that SB360 tasks are experienced as cognitively demanding but may not replicate the physical demands typically associated with football performance contexts.

This interpretation is further supported by the distribution of TLX subscales. Although overall workload reflected contributions from multiple workload dimensions, MD was rated highest ($AU: 77.6 \pm 17.3$), whereas physical demand (PD) was the lowest rated subscale ($AU: 20.9 \pm 16.6$). This pattern contrasts with other sport-specific NASA-TLX studies, including cycling, swimming, rugby, and table tennis, where PD values are substantially higher ($AU: 44 \pm 18$) and MD values comparatively lower ($AU: 43 \pm 16$) (Hertzum, 2021). Similarly, football training tasks, such as SSG and opposed-possession drills, consistently demonstrate higher PD values than those observed in the SB360, even under varying coaching conditions (Díaz-García et al., 2021). These comparisons reinforce the interpretation that the SB360 assessment imposes relatively low perceived physical demands compared with football-specific training tasks.

Accordingly, despite the integration of perception–action coupling and the requirement for full-body motor responses, SB360 assessment tasks were consistently experienced by

players as cognitively demanding rather than physically taxing. For example, the absence of significant relationships between pre-test RPE and SB360 performance outcomes suggests that acute physical state has limited influence on task performance. While earlier sections demonstrated that RT, particularly in overt motor-response tasks, is influenced by developmental factors related to the neuromuscular function, these effects do not appear to translate into increased PD during task execution. Together, these findings suggest that although motor responses contribute to performance outcomes, they are not perceived by players as a major source of workload during SB360 testing. Instead, the tasks are primarily experienced as cognitively demanding assessments.

6.2.4 Motivation and Cognitive Task Engagement

Findings from Chapter 4 also indicated that pre-test motivation showed limited association with SB360 performance when analysed within protocol-specific subsamples, where readiness measures were aligned with the first task in the testing sequence (i.e., CF→WM or WM→CF). Specifically, motivation was not significantly related to CF or WM outcomes under these conditions. However, when analyses were conducted across the full sample irrespective of testing protocol, a small positive association emerged between motivation and CF accuracy ($p = .05$; partial $R^2 = .04$). In addition, higher perceived effort (EFF) was associated with lower CF switch cost ($p = .02$; partial $R^2 = .05$), suggesting that players who perceived investing greater effort tended to demonstrate smaller switching costs during task performance. Although this finding should be interpreted cautiously, it suggests that motivational influences may become more detectable when statistical power is increased.

As reviewed in Section 2.5.4, the literature has demonstrated clear relationships between motivation and cognitive performance. Moreover, theoretical accounts suggest that cognitive performance under mental fatigue reflects not only executive resource depletion

but also shifts in motivational processes (Boksem et al., 2006), whereby individuals are less willing to continue task engagement when effort outweighs anticipated benefits (Tops et al., 2004). From this perspective, fluctuations in cognitive performance under fatigue can be partly explained by changes in motivation rather than solely by capacity limitations (Chaudhuri & Behan, 2000). Given that task sequencing did not influence performance and that accuracy-based measures were strongly associated with MD, further research incorporating larger samples and direct measures of mental fatigue, alongside RPE, may help to better characterise the role of motivation and its interaction with cognitive workload in shaping performance within cognitive-motor tasks.

6.2.5 SoccerBot360 Cognitive Training Intervention Effectiveness

Transitioning from the assessment-focused findings of Chapters 3 and 4 to the training intervention examined in Chapter 5, the results demonstrated limited evidence for the effectiveness of the SB360 training programme in producing meaningful improvements in cognitive-motor performance beyond expected learning or developmental effects. Although performance improvements were observed across RT and accuracy outcomes over time, RT cost measures (CF switch cost and INH Stroop effect) remained unchanged. Moreover, improvements occurred similarly in both intervention and control conditions, indicating that they were more likely attributable to repeated task exposure, familiarisation, or maturation rather than the intervention itself. This interpretation is supported by the absence of time $\times$ group interactions across performance metrics, suggesting that the six-week training exposure did not provide an additional benefit beyond regular academy training.

Several factors may explain the absence of clear intervention effects. First, the *training dosage* was comparatively low, with participants completing one session per week for six weeks and engaging in approximately 10–15 min of active SB360 training per session.

This level of exposure appears lower than that typically reported in cognitive training literature, where repeated and intensive practice is often required to elicit measurable adaptations (Walton et al., 2018). Second, the standardised nature of the training protocol, including fixed task formats and limited *individualisation*, may have constrained the alignment between task difficulty and individual challenge points, which is considered critical for skill acquisition and learning (Guadagnoli & Lee, 2004). Third, the *specificity* between training tasks and assessment measures may have been insufficient to produce detectable transfer, particularly given the use of disparate perceptual stimuli and task rules between the training- and testing-modes.

Importantly, linear mixed-effects models (LMM) indicated that inter-individual variability accounted for a substantially greater proportion of variance in performance than fixed effects of time or group. This finding reinforces the importance of considering individual response patterns in cognitive training research and suggests that group-level analyses may obscure meaningful variation in training responsiveness (see Section 2.7.6). Accordingly, under the current intervention design, the SB360 training protocol provided limited evidence of effectiveness as a cognitive training tool. Importantly, this interpretation should be contextualised within the specific characteristics of the intervention, including training dosage, task design, and measurement sensitivity, rather than being generalised to the SB360 system as a whole.

6.3 Implications for Theory and Research

6.3.1 Rethinking ‘Football-Specific’ Cognitive Assessment and Training Tools

Findings of this thesis raise important theoretical questions regarding the *ecological validity* and *football-specificity* of cognitive assessment and training systems, such as the SB360. As discussed in Chapter 2, *ecological validity* within sport contexts extends beyond surface-level resemblance to real-world environments and instead concerns the

extent to which tasks preserve the functional relationships between perceptual information, decision-making processes, and action execution. In this context, the differential sensitivity of SB360 performance metrics suggests that the system does not uniformly capture underlying cognitive processes but rather reflects an interaction between cognitive demands and response characteristics. This challenges the assumption that embedding a sport-specific response modality is sufficient to create a more functionally representative assessment of football cognition.

A key issue concerns the structure of the SB360 tasks themselves. While the response modality (i.e., kicking) is *football-specific*, the perceptual stimuli and decision-making processes remain largely domain-general. Decision-making in football is characterised by continuously evolving spatial-temporal constraints, dynamic affordances, and uncertainty in both action outcomes and opponent behaviour. In contrast, SB360 assessment tasks operate on a trial-by-trial basis with fixed decisional values and predefined response options. This divergence suggests that the system may lack critical components of *football-specific* perception–action coupling, particularly in relation to how players attune to context-dependent informational sources during match play and perceive corresponding action affordances. Furthermore, the absence of embedded risk–reward trade-offs, which are central to decision-making in football, limits the extent to which task performance reflects the strategic and adaptive nature of real-game behaviour.

In addition to perceptual and decisional constraints, the representativeness of motor execution within the SB360 warrants careful consideration. Although kicking is a *football-specific* action, striking a *stationary* ball on each trial during assessments represents a highly constrained and context-specific movement pattern in football, most closely aligned with set-piece situations, such as kick-offs or quick restarts from free-kicks. This contrasts with the dynamic and continuously adjusted motor actions observed

during open play, where movement kinematics are shaped by ongoing interactions with opponents, teammates, and ball trajectory (see Section 2.3.1). Evidence from other domains supports the importance of preserving such informational constraints, with studies in cricket demonstrating that batting kinematics differ significantly when responding to a live bowler compared to a bowling machine, despite apparent task similarity (Peploe et al., 2014; Renshaw et al., 2007). These findings highlight that even subtle alterations in task constraints can lead to meaningful changes in movement organisation, raising questions about action fidelities that refer to which motor responses within the SB360 diagnostic-mode reflect real-world action processes.

At the same time, it is important to acknowledge that the SB360 training-mode may still offer value from a motor learning perspective. The system provides a high volume of repetitions of specific football *techniques* (e.g., passing, receiving, and turning), while allowing manipulation of task parameters (e.g., target speed, height, angle, and timing), alongside some degree of unpredictability in stimulus presentation. In this sense, the SB360 may align, to some extent, with the principle of *repetition without repetition* (Bernstein, 1967), whereby learners repeatedly solve a movement problem under varying conditions rather than reproducing identical movement patterns. However, this repetition primarily targets *technique*, understood as coordination patterns of kinematic movement (e.g., accurately striking the ball towards a target area), rather than *skill*, which involves the functional adaptation of these movement patterns to dynamic and context-specific demands, such as executing a through pass that penetrates a defensive line (Bennett & Fransen, 2023). Given the absence of representative perceptual information and decision-making constraints within the SB360 tasks, the system appears to promote the development of football-related *neuromuscular* coordination rather than fully integrated football-specific perceptual-cognitive-motor skills.

Building on this, although the SB360 training-mode provides a greater degree of perception–action coupling than the testing-mode, the current task structure may only partially reflect sport-specific perceptual–action processes. For example, football players rely on kinematic cues from other players and must continuously update decisions based on unfolding interactions (Abernethy & Zawi, 2007; Roca et al., 2013). Conversely, the SB360 task structure allows players to anticipate ball delivery through a self-pass-and-receive mechanism, effectively positioning them as both passer and receiver. This alters the informational constraints of the task and may reduce uncertainty compared to real-game scenarios, where intention and outcome are only partially predictable. Consequently, while the SB360 integrates elements of perception–action coupling, the nature of this coupling may differ from that observed in competitive environments.

Taken together, findings suggest that the SB360 may achieve surface-level *football-specificity* through the inclusion of sport-related response modalities. However, the current system exhibits limited functional representativeness in relation to the perceptual, decisional, and motor demands of football. This distinction challenges the tendency within the literature to define *football-specific* tasks primarily based on motor characteristics or visual appearance (Heilmann et al., 2021; Hicheur et al., 2017; Knöbel & Lautenbach, 2023; Musculus et al., 2022; Rodrigues et al., 2024). Instead, the present findings suggest that representativeness should be evaluated based on how well a task preserves the underlying informational constraints and action possibilities that define real-world performance.

Moreover, despite the absence of direct comparisons with football performance in this thesis, the current findings raise questions regarding the diagnostic value of domain-general cognitive tasks in elite football. Although the SB360 test battery employed validated EF paradigms, these measures demonstrated limited ability to distinguish

developmental stages across the academy, with sensitivity largely confined to specific RT-based metrics that appeared to reflect biological maturation under particular task constraints. Accordingly, caution is warranted when attributing the label of *football-specific* to emerging cognitive assessment and training tools, particularly in the absence of evidence demonstrating functional validity and transfer to performance contexts. To operationalise this perspective, Table 6.1 provides key components that may serve as a conceptual guideline for defining and designing *football-specific* decision-making tasks.

Table 6.1 Key components of football-specific decision-making practice.

Dimension	Core feature	Operational definition (football context)	Implications for assessment / training design
Visual stimuli	Multi-source, dynamic cue utilisation.	Continuous sampling of ball, teammates, opponents, and space, with context-dependent attentional allocation.	Use representative (e.g., player kinematics, ball trajectories), multi-agent, dynamic visual stimuli, not isolated cues.
Spatial constraints	Emergent affordance landscape and tactical context.	Decisions shaped by dynamic team structures, space occupation, and positional context.	Simulate realistic spatial proximity, density, and pitch location within an immersive 360° environment.
Temporal constraints	Constrained action windows and temporal coordination.	Decisions occur within short windows, requiring precise timing relative to dynamic environmental elements.	Replicate match-tempo constraints and require temporally coordinated actions.
Perception–action coupling	Functional coupling of perception and movement.	Decisions emerge through continuous perception–action interaction.	Require whole-body, representative motor responses.
Embodiment (action capabilities)	Individual constraint interaction.	Action possibilities depend on technical ability, body orientation, and movement capacity.	Account for player–environment interaction, not generic responses.
Risk–Reward Trade-offs	Contextual decision value.	Multiple viable options exist; decision value depends on tactical context (not binary correctness).	Evaluate decisional value and behavioural tendency beyond simple accuracy.
Contextual dynamics	Continuous environmental change.	Opponent behaviour, teammate availability, and game phases dynamically reshape decision-making context.	Include unpredictability and evolving scenarios, not static trials.

6.3.2 Fidelity in Football-Specific Cognitive Tasks

A recurring concern throughout this thesis relates to the fidelity of SB360 assessment tasks, particularly in relation to their perceptual, motor, and decision-making demands. As outlined in Chapter 2 (Section 2.7.2), *physical fidelity* refers to the sensory and structural features of a task environment resemble those of real-world performance, including visual information, spatial layout, and movement dynamics (Harris et al., 2020). Within the current SB360 system, key limitations in *physical fidelity* arise from the nature of the perceptual stimuli and task structure, which are largely domain-general and therefore limit players' exposure to representative football information. Consequently, the system only partially reproduces the informational constraints that underpin perception–action coupling in competitive football.

Beyond sensory and structural characteristics, findings further highlight concerns regarding *psychological fidelity*, defined as the extent to which a task elicits similar perceptual, cognitive, and decision-making processes to those required in real-world performance (Gray, 2019). In Chapter 4, SB360 assessment tasks were predominantly perceived as low in physical loads, contrasting with football-specific training contexts (e.g., SSG), where players typically report substantially higher PD (Díaz-García et al., 2021; Montini et al., 2025). This discrepancy is theoretically important, as the intensity of physical exertion has been shown to influence cognitive and decision-making processes. Research indicates that human decision-making differs significantly between resting and physically demanding states (Van de Walle et al., 2026), with acute physical exertion altering neural resource allocation and reducing the availability of prefrontal control processes (Dietrich, 2006). As a result, athletes may rely more heavily on automated and implicit decision-making systems under fatigue.

In sport contexts, such physiological and cognitive changes have been shown to influence speed of decision-making (Fontana et al., 2009), often leading to a prioritisation of response speed at the expense of accuracy under conditions of increased load (Thomson et al., 2009). This speed–accuracy trade-off can negatively affect tactical performance when compared to rested conditions (Royal et al., 2006). From this perspective, the relatively low PD of SB360 tasks suggests that the system may not sufficiently replicate the broader cognitive demands experienced during match play, where decision-making is tightly coupled with physical exertion. Consequently, *psychological fidelity* of the SB360 assessment may be inherently constrained by its low-intensity physical workload profile, despite the presence of football-related motor response modalities.

These findings reflect a broader paradox in the design of technology-based cognitive training systems in sport. Such systems aim to isolate specific performance components to increase repetition, control task conditions, and target particular cognitive processes (Richlan et al., 2023). However, this reductionist approach may limit the extent to which tasks capture the integrated and context-dependent nature of real-world performance (Pinder et al., 2011). As reviewed in Chapter 2, most cognitive training paradigms do not incorporate concurrent physical exertion, despite its central role in shaping decision-making in competitive sports. While this simplification is functionally justified in terms of experimental control and training focus, it raises important questions regarding the extent to which such tasks can transfer to performance contexts.

An additional consideration relates to the degree to which the SB360 environment can *immerse* performers within representative football situations. Although *immersion* is a foundational concept within virtual and extended reality research, its definition remains debated, with some authors conceptualising it as an objective property of the technological system (Slater & Wilbur, 1997), whereas others emphasise the user's

subjective psychological experience of presence and involvement within the virtual environment (Witmer & Singer, 1998). Regardless of perspective, the current SB360 projection system is unlikely to provide the level of *immersion* associated with representative football performance. Visual information is presented via two-dimensional wall projections within a fixed indoor environment, meaning that performers remain continuously aware of the surrounding room rather than experiencing the spatial relationships, depth information, and environmental geometry characteristic of real match situations. Therefore, even a football-specific stimulus library would not necessarily produce fully representative perceptual-cognitive processing if the underlying projection environment cannot sufficiently recreate the spatial and immersive characteristics of football performance (e.g., Dicks et al., 2010).

At present, there is limited empirical evidence to define the optimal balance between task simplification and representativeness required to facilitate transfer in elite sport settings. The dynamic, multifaceted nature of football further complicates the identification of a sweet spot at which cognitive training tasks can effectively replicate the perceptual, cognitive, and motor demands of competition. The present discussion further suggests that achieving high *psychological fidelity* extends beyond incorporating football-specific stimuli or response modalities and depends on recreating the perceptual conditions under which decisions are naturally made. Accordingly, football-specific cognitive technologies, including the SB360, continue to face inherent challenges in balancing experimental control with representative task design. Nevertheless, the integration of football-specific motor actions alongside dynamic perceptual-cognitive stimuli may offer a platform for the systematic training and evaluation of football decision-making capacities. The implications of this approach will be considered further in the following sections.

6.3.3 Motor Action, Affordances, and the Perception–Action Cycle in Football

To understand the potential implications of integrating motor action components within football-specific cognitive tools, it is necessary to consider the perception–action cycle that underpins decision-making in football. At a fundamental level, technical skill execution is grounded in physical capacity, as the ability to perform football actions depends on how effectively the neuromuscular system coordinates body segments to meet task demands. Although physical, technical, and tactical components are often conceptually separated in football, technical skill can be understood as the functional expression of physical capabilities within task-specific contexts.

Within this framework, the concept of *affordances* provides a key link between action capabilities and decision-making. Originally proposed by Gibson (1966, 1977, 1986), *affordances* refer to the opportunities for action that the environment offers to the performer. In sport, perception–action coupling describes how athletes detect and utilise such information to guide behaviour in real time. However, while much of the literature has emphasised how perception informs action, comparatively less attention has been given to how action capabilities constrain perception (Fajen et al., 2009). From an ecological perspective, *affordances* are relational, emerging from the interaction between environmental properties and the performer’s effectivities, that is, their available movement repertoire and functional capacities (Witt, 2011). Consequently, the range of action possibilities perceived by a player is inherently shaped by their physical and technical capabilities (Jadzack et al., 2019; Paillard & Noé, 2005).

From a cognitive perspective, this relationship may be explained through attentional resource limitations. The human cognitive system has finite attentional capacity, and when executing unrefined or non-automated motor actions, athletes must allocate substantial resources to conscious motor control. This can result in dual-task interference,

limiting the ability to perceive and process relevant environmental information (Beilock et al., 2002; Leavitt, 1979). In contrast, the automation of domain-specific technical movements can reduce this neural effort (Guan et al., 2025; Guo et al., 2017; Kim et al., 2014; Naito & Hirose, 2014; Zhang et al., 2019), potentially allowing greater allocation of attentional resources to higher-order perceptual-cognitive processes. This notion also aligns with the affordance competition hypothesis (Cisek, 2007), whereby repeated exposure and practice strengthen neural representations of specific actions, increasing their likelihood of dominating competitive selection processes. In parallel, improvements in physical and technical competency expand an athlete's action capabilities, thereby broadening the range of *affordances* that can be perceived and utilised during performance (Fajen et al., 2009; Renshaw et al., 2019). For example, a right-foot dominant player with limited left-foot proficiency may be less likely to perceive left-foot passing or shooting options as viable affordances, thereby constraining both perception and action. As such, motor competence not only influences how actions are performed, but shapes what actions are perceived as possible in the first place (Fajen et al., 2009).

From this perspective, the integration of domain-specific motor components within systems, such as the SB360, may provide a platform for systematically developing selected action capabilities that underpin football decision-making. Although the current perceptual stimuli within the SB360 remain largely domain-general, the dynamic and unpredictable nature of target presentation requires players to continuously adapt their body position and movement patterns in response to changing task demands. Each interaction with the system involves the coordination of football-specific techniques, influenced by factors such as ball rebound trajectory, spatial orientation, and individual technical capabilities. Accordingly, players are not merely selecting a pre-planned movement pathway to abstract stimuli but actively solving spontaneous movement problems in a way that integrates perception and action.

Importantly, the implications of this distinction may differ for assessment and training applications. As discussed in Section 6.3.2, the limited perceptual immersion afforded by the current SB360 projection system is likely to constrain its ability to assess football decision-making (i.e., perceptual-cognitive processing) as it occurs in representative competitive environments. However, this limitation may be less restrictive from a broader long-term training perspective. Rather than attempting to replicate the full perceptual complexity of match play, the SB360 may provide a controlled environment in which football-specific action capabilities can be systematically developed through repeated trials. In particular, repeated practice of football-specific movement patterns may strengthen the functional relationship between action capabilities (effectivities) and the affordances perceived during task performance, thereby targeting one component of the broader decision-making process.

As discussed earlier, the variability in task constraints and the requirement for spontaneous motor responses align with the principle of *repetition without repetition*, a key component of motor learning (Bernstein, 1967). In this sense, improvements in domain-specific *neuromuscular* function, including increased action capabilities (affordances) and movement efficiency, may partially facilitate decision-making processes in football by expanding the range of perceivable and executable action possibilities. However, the transferability of these adaptations is necessarily constrained by the range of football actions that can be performed within the system. Current task designs primarily involve movement patterns associated with limited ball reception and release techniques, whereas many football actions, such as crossing, shooting, and aerial duels, may not be meaningfully represented within the available task constraints. Consequently, any improvements in movement efficiency or affordance perception are likely to be specific to the action repertoire trained within the system rather than reflecting a general enhancement of football decision-making (see Section 6.4.2 for further details).

6.3.4 Familiarisation and Individualisation in Cognitive Research and Training

The findings of this thesis highlight the importance of *familiarisation* and *individualisation* in the design and interpretation of cognitive assessment and training protocols. As discussed in Section 2.7.5, repeated exposure to cognitive tasks can lead to systematic improvements in performance that are independent of true cognitive adaptation, reflecting practice effects rather than underlying changes in ability (Friebe et al., 2023; Soveri et al., 2018). This issue was evident in the intervention findings (Chapter 5), where improvements in performance were observed across both intervention and control groups, suggesting that repeated task exposure and learning effects may have contributed substantially to observed changes over time. Importantly, cognitive intervention research in football frequently relies on pre–post testing designs to evaluate training effects (e.g., Heilmann, Formenti, et al., 2023; Schumacher et al., 2020; Theofilou et al., 2022), often without incorporating sufficient familiarisation or additional baseline assessments. Furthermore, given that the assessment of cognitive skills in football has emerged recently compared to conventional fitness testing, many players are unlikely to be familiar with such paradigms, increasing the likelihood that early performance reflects task novelty rather than underlying ability. Collectively, these findings reinforce the need to account for *familiarisation* when interpreting longitudinal changes in cognitive performance, particularly in applied sport settings where repeated testing is common (Asimakidis et al., 2024).

Beyond familiarisation, findings emphasise the importance of *individual variability* in cognitive performance and training responsiveness. LMM demonstrated that inter-individual differences accounted for a substantial proportion of variance across all performance metrics, exceeding the effects of time or group-level intervention. This supports previous work highlighting that group-level analyses may obscure meaningful

variation in how individuals respond to cognitive tasks and training interventions (Parasuraman & Jiang, 2012).

From a theoretical perspective, these findings challenge the continued reliance on standardised protocols and average effects in cognitive research. While standardisation enhances experimental control, it may limit the alignment between task demands and individual capabilities, thereby reducing both sensitivity and effectiveness. In contrast, approaches that incorporate *individualisation*, such as adaptive task difficulty, personalised progression, and individual-level analysis, may provide a more accurate representation of cognitive performance and learning processes (see Section 6.4 for further details). This is particularly relevant in elite sport contexts, where performance development is inherently individualised and small differences in performance can have meaningful practical implications (Dowling et al., 2018; Layton et al., 2023; Turner et al., 2015).

Accordingly, cognitive research examining longitudinal performance changes should integrate and report sufficient familiarisation procedures alongside analytical approaches that capture individual trajectories rather than relying solely on group averages. Such approaches align with contemporary perspectives in both cognitive science and skill acquisition, which emphasise variability, adaptability, and context-dependency as central features of human performance (Hodges & Lohse, 2022; Pennington et al., 2025). In this context, cognitive-motor training systems, such as the SB360, may benefit from shifting towards more individualised and adaptive frameworks, in which task demands are continuously aligned with the performer's capabilities to optimise learning and performance outcomes.

6.4 Implications for Practice

6.4.1 Application of SoccerBot360 in Assessment and Player Monitoring

6.4.1.1 Age-Specific Benchmarking

Performance differences within the SB360 were most evident when comparing boundary age groups (e.g., U13 vs. U21; FP vs. PDP), whereas differentiation within narrow age bands was limited. Therefore, benchmarking players within closely matched age groups may lack sensitivity and should be interpreted with caution in applied settings. Moreover, when the number of players analysed within a dataset is small, variability in standard deviation increases and the reliability of group-derived thresholds, such as the smallest worthwhile change, is reduced (Turner et al., 2015). In professional youth academy environments, where squad sizes within each age group are inherently limited, there is a risk of treating group-based thresholds as absolute benchmarking criteria without sufficient data volume. Accordingly, such benchmarks should be interpreted cautiously unless supported by sufficiently large and accumulated longitudinal datasets (e.g., Altmann et al., 2024).

6.4.1.2 Individualised Monitoring

Given the limited sensitivity of between-player comparisons within homogeneous cohorts, the SB360 appears more suitable for intra-individual monitoring rather than group-based evaluation. Tracking changes relative to a player's own baseline over time is likely to provide more meaningful insight into development than cross-sectional comparisons within narrow age bands. Collectively, these considerations highlight the importance of establishing robust and standardised data collection processes in applied settings, enabling both large-scale developmental benchmarking across age groups and reliable longitudinal monitoring at the individual level.

6.4.1.3 Applied Testing Protocols

From an implementation perspective, SB360 testing appears robust to variations in protocol design. The absence of task order effects across CF and WM tasks suggests that these paradigms are not systematically influenced by sequencing within a testing session. Furthermore, the lack of meaningful influence of pre-test physical state on performance indicates that testing may be flexibly integrated within academy schedules. This enhances the practical feasibility of SB360 implementation, as strict control of task order or pre-testing conditions may not be necessary to obtain reliable performance data. However, testing protocols should incorporate sufficient familiarisation procedures, as findings from Chapter 5 indicated that a single familiarisation session may be insufficient to stabilise performance in SB360 EF tasks. Accordingly, inadequate familiarisation may lead to misinterpretation of performance outcomes, particularly when early improvements reflect task-specific learning rather than underlying cognitive adaptation.

6.4.1.4 SoccerBot360 Performance Metrics

Findings indicate that different SB360 metrics may serve distinct applied purposes. Accuracy-based measures, particularly those reflecting binary decision correctness, appear more suitable for longitudinal within-player monitoring due to their sensitivity to cognitive workload and lack of developmental effects. In contrast, RT measures, especially in tasks requiring overt motor responses, appear more closely linked to neuromuscular development and may therefore be more informative for cross-sectional comparisons in skilled youth football players. A further consideration is the potential presence of ceiling effects in accuracy-based measures, which may limit their sensitivity in high-performing populations. This highlights the need for improved task scaling and the inclusion of more sensitive performance indicators, such as execution precision or increased decision complexity, to enhance the diagnostic utility of the SB360.

6.4.1.5 Football-Specific Technique Assessment

Findings raise important questions regarding the applied value of domain-general cognitive tasks in football, particularly given their limited ability to distinguish players across developmental stages. This thesis therefore highlights the importance of incorporating football-specific technique assessments that capture overt motor execution, unless the objective is to assess general psychological constructs. Tasks that more closely reflect the dynamic nature of football perception–action demands, such as anticipation paradigms or training-mode games, may offer greater sensitivity to football-related techniques. However, the use of such approaches within the SB360 is currently constrained by methodological limitations, including low trial numbers (e.g., anticipation tasks with limited repetitions), which may reduce reliability (Musculus et al., 2022). Accordingly, future work should prioritise the development and validation of domain-specific tasks that more directly reflect football-relevant performance demands (Kalén et al., 2021), alongside the inclusion of more sensitive performance metrics, particularly those capturing movement accuracy and execution quality. In this context, integrating standardised training-mode tasks that combine spontaneous motor responses and football-specific visual information may better leverage the system’s immersive and motor-integrated features to provide more informative data within football-specific contexts.

6.4.1.6 Contextual Factors

Biological maturation should be considered when interpreting SB360 performance, particularly during early adolescence. In the present study, maturity status explained meaningful variance during the U13–U14 period, especially in tasks characterised by lower cognitive and higher motor demands. In contrast, pre-test readiness measures, such as RPE, demonstrated limited explanatory value for performance outcomes. Accordingly, age- and maturation-related characteristics may provide a more interpretable proxy for physical state in youth populations. While readiness measures may still contribute to

broader monitoring frameworks (e.g., motivation profiling), they should not be relied upon as primary covariates when evaluating SB360 performance or longitudinal change.

6.4.2 Application of SoccerBot360 in Training and Player Development

6.4.2.1 Transferable Skill Components

A central consideration for the applied use of the SB360 is identifying which aspects of performance are realistically transferable to on-pitch behaviour. Based on thesis findings, the system appears to primarily target domain-specific neuromuscular and technical coordination patterns rather than fully integrated perceptual-cognitive-motor skills. At a broader level, SB360 training may contribute to general neuromuscular function, including movement efficiency and coordination under time constraints. More specifically, it may support the development of football-related techniques, such as short-range passing, receiving, turning with the ball, and basic ball control. However, the extent to which these improvements transfer to complex, context-dependent match situations remain unclear. Accordingly, practitioners should explicitly define what is being trained within the SB360 and design complementary activities outside the system to target the perceptual and tactical components required for skill transfer, such as video analysis and representative on-pitch training (see Section 6.6 for further details).

6.4.2.2 Integration Within Individual Development Plan (IDP)

Once the specific training outcomes of the SB360 are clearly defined, the next step is to determine which players may benefit from its inclusion within their Individual Development Plans (IDPs). Given the variability in player needs and developmental trajectories, the SB360 should not be applied uniformly across squads but instead utilised selectively to address individual training needs. For example, players requiring improvements in technical consistency or coordination under time pressure may derive greater benefit from SB360 training than those already demonstrating high levels of

proficiency in these areas. This individualised approach aligns with the broader objective of academy environments, which prioritise long-term player development over standardised training interventions.

6.4.2.3 Training Dosage and Programme Design

Another practical consideration concerns training dosage. Chapter 5 findings indicated limited evidence for intervention effects, which may be explained by the relatively low training exposure implemented. As discussed in Chapter 2, evidence regarding dose–response relationships in cognitive training within skilled athletes remains limited, with no empirically established guidelines for session duration, frequency, or intervention length in athletic populations (Walton et al., 2018; Harris et al., 2018). Nevertheless, current thesis findings, alongside broader literature, indicate that core training principles, including volume, frequency, duration, and the provision of appropriate challenge points, are central to effective cognitive intervention design. Collectively, future research may consider interventions comprising approximately 20–30 min per session, delivered two to three times per week, over periods of 6–12 weeks, as an initial reference point for examining group-level adaptations. However, it is important to acknowledge that such recommendations are primarily derived from non-athletic populations, including older adults and clinical groups (e.g., Shao et al., 2022; Walton et al., 2018), and may not directly translate to football contexts. Accordingly, while these reference points may guide intervention designs, further research is required to systematically examine dosage effects in football-specific cognitive training and to establish pragmatic, evidence-based frameworks that demonstrate meaningful transfer to on-pitch performance.

6.4.2.4 Applied Implementation in Elite Environments

From a practical standpoint, the implementation of the SB360 within applied contexts is constrained by logistical and programme design considerations. The use of standardised

SB360 training protocols can constrain individual playing time and limit fully individualised training prescriptions (Chapter 5). This is particularly relevant in academy settings, where training time is shared across squads and individual developmental needs vary substantially. Given that the SB360 is best positioned as a supplementary training tool rather than a replacement for football practice, practitioners must carefully consider how it is integrated within the broader training programme. This includes ensuring sufficient training volume and frequency while maintaining alignment with player IDPs. For real-world examples of how the SB360 can be implemented within elite player development programmes, including its integration within player IDPs and broader training structures, see Section 6.6 Contribution to Applied Practice.

6.4.3 Broader Implications for Cognitive Practice in Football

6.4.3.1 Interpreting Domain-General Cognitive Tasks in Football

Despite ongoing questions regarding the validity of domain-general cognitive tasks in sport, it is important to acknowledge that conventional cognitive paradigms (e.g., number-letter, *n*-back) have consistently demonstrated their capability to assess core executive processes within cognitive and neuroscience research. In applied football contexts, where the direct link between such tasks and domain-specific performance remains unclear, a more appropriate interpretation may be to consider these measures as indicators of minimal cognitive *prerequisites* for the level of football performance already demonstrated by the player rather than direct markers of football-specific ability. For example, lower scores may reflect the approximate minimum level of domain-general cognitive performance required to operate at a given performance level, whereas higher scores do not necessarily imply greater football-specific potential. Accordingly, in the absence of validated links to match performance (i.e., cause-effect relationship), domain-general cognitive assessments should be interpreted cautiously and positioned as

complementary indicators rather than definitive measures of football skills or potential for successful progression through a talent development pathway.

6.4.3.2 Towards a Football-Specific Rationale for Cognitive Training

A further implication concerns the lack of clearly defined football-specific frameworks that articulate *why* particular cognitive skills should be trained. While limitations in the current evidence base regarding perceptual-cognitive mechanisms in football partially explain this gap, the absence of explicit theoretical links between cognitive constructs and football actions remains a key issue. In contrast to physical training, where exercise selection is often grounded in well-established performance and injury-prevention rationales, cognitive training in football is frequently justified in general terms without clear alignment to positional demands, playing style, or specific match behaviours. Importantly, recent evidence indicates that this gap is reflected in applied environments. For example, professional youth academy coaches in the UK demonstrate broad agreement in their definitions of perceptual-cognitive skills and their importance for player development, yet show considerable variation in familiarity, confidence, and frequency of identifying and assessing these skills in practice (Triggs et al., 2026). This discrepancy suggests that, although cognitive constructs are conceptually valued, their translation into applied practice remains inconsistent, likely due to the absence of clear frameworks linking these constructs to football-specific contexts. Therefore, developing frameworks that explicitly link cognitive constructs to football contexts (e.g., anticipation for successful interceptions or working memory for effective scanning and awareness) may enhance both the precision of applied practice and the design of research examining transfer to performance. In this context, understanding not only *what* is transferable from a given training modality, but also *why* it should be trained from a football-specific perspective, represents a critical step towards more targeted and effective cognitive training approaches.

6.4.3.2 The Neurocognitive–Neuromuscular Continuum

The present findings highlight the need to consider how cognitive training tools are integrated within broader practice environments. Although the SB360 provides a greater degree of perception–action coupling than other football-specific technologies (e.g., Helix, Footbonaut), the current results indicate that its assessment tasks do not consistently elicit fully representative perception–action-coupled processes, with performance metrics reflecting differential sensitivity to cognitive and motor components. More broadly, this limitation applies to most existing cognitive training tools, which tend to emphasise either perceptual-cognitive or motor elements while underrepresenting the other.

Accordingly, the use of such technologies should be complemented by additional activities that address these gaps, whether through enhancing response modalities (e.g., technical drills) or embedding perceptual-cognitive demands within representative training environments (e.g., video analysis, opposed drills). Importantly, programme design should ensure that motor action components are aligned with cognitive objectives at least at one stage. To support this process, the present thesis proposes the neurocognitive–neuromuscular continuum as a conceptual framework for positioning training tools across two related dimensions (Figure 6.1). The first dimension (domain-general) reflects the extent to which a task primarily elicits perceptual-cognitive (neurocognitive), or motor-execution (neuromuscular) demands, regardless of task specificity. The second dimension (football-specific) situates these tools based on their observable football-specific task characteristics, while acknowledging that such positioning does not inherently reflect task validity or transferability to match performance. Within this framework, the most effective training approaches are likely to occupy intermediate positions across both dimensions, combining perceptual-cognitive engagement with corresponding motor execution. Understanding where a given tool lies

across these dimensions can help practitioners make more informed decisions regarding its role within a broader training programme and how it should be combined with other methods. Therefore, rather than seeking a single optimal cognitive training solution, practitioners may benefit from strategically integrating multiple approaches that collectively address the multidimensional nature of football performance.

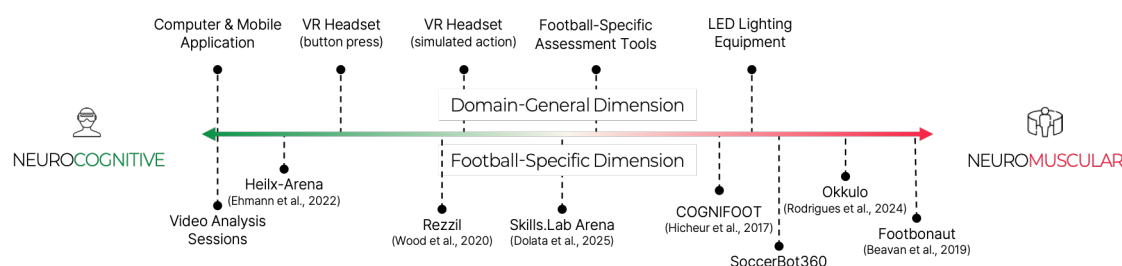


Figure 6.1 Conceptual framework illustrating the neurocognitive–neuromuscular continuum across domain-general and football-specific dimensions. The technologies displayed are illustrative examples only. Their positioning on the continuum does not inherently reflect task validity or transferability to match performance. The domain-general dimension represents the extent to which a task elicits perceptual-cognitive (neurocognitive) versus motor-execution (neuromuscular) demands, regardless of task specificity. The football-specific dimension reflects observable task characteristics but does not imply functional representativeness. Importantly, different tasks within the same technology may occupy different positions on the continuum depending on their design and demands. For example, the SoccerBot360 *n*-back task may align more closely with the neurocognitive end, whereas its training-mode games may occupy more central or neuromuscular positions.

6.5 Limitations and Recommendations for Future Research

Several methodological and conceptual limitations should be considered when interpreting the findings of this thesis. First, a key limitation across all empirical chapters relates to study design and sampling. The cross-sectional approach employed in Chapter 3 limits causal inference and restricts the ability to disentangle the independent contributions of age and biological maturity to SB360 performance. Although secondary analyses attempted to address this through subsample modelling, these were based on reduced sample sizes and should be interpreted cautiously (Button et al., 2013). Similarly, the uneven distribution of players across age groups and academy phases (Chapters 3 and

4), along with the aggregation of multiple age groups within the intervention study (Chapter 5), may have reduced statistical power and increased the likelihood of Type II error in detecting subtle developmental effects (Cohen, 1988; Maxwell et al., 2008).

In addition, the single-club sample used in this thesis introduces potential selection bias and limits the generalisability of findings to broader academy populations (Kalén et al., 2021). However, this context allows the identification of transferable methodological insights, including the importance of longitudinal data collection in applied settings, where experimental control is inherently constrained. Notably, although this thesis captured data across almost the entire academy pathway (U12–U21), aggregating players into broader age-group categories still reduced analytical sensitivity, highlighting a limitation of applied research in balancing ecological validity with statistical power. Collectively, these limitations highlight the need for future research employing longitudinal designs with larger, age-stratified, and multi-club samples to more robustly examine developmental trajectories and intervention effects in cognitive-motor performance.

Second, limitations related to measurement and construct validity are evident across the studies. As highlighted in Chapter 3, SB360 performance metrics reflect an interaction between cognitive processing and large motor execution, meaning that observed effects cannot be attributed solely to cognitive function, a limitation common to perception–action tasks in sport (Dicks et al., 2010; van Maarseveen et al., 2018). This issue is further reinforced by concerns surrounding the use of behavioural EF paradigms, such as inhibition tasks derived from Stroop or flanker paradigms, where motor response components may confound the interpretation of cognitive constructs in applied sport contexts (Cremen & Carson, 2017). In Chapter 4, the exclusive use of subjective measures of perceived readiness and workload (e.g., RPE, motivation, NASA-TLX) without

concurrent physiological or biomechanical data limited the ability to triangulate perceptual and objective task demands (Dixon et al., 2026). Moreover, workload was assessed retrospectively following task completion, introducing potential bias due to recency effects and outcome-dependent perceptions. Together, these findings indicate a need for future research to adopt multimodal measurement approaches, integrating behavioural, physiological, and biomechanical indicators to improve the validity and interpretability of cognitive-motor performance metrics.

Third, several limitations relate to experimental control and ecological constraints inherent in applied research environments. Across studies, structural constraints such as academy scheduling, player availability, and integration within ongoing training programmes limited the degree of experimental control and precluded causal inference (Fullagar et al., 2019). In Chapter 5, the use of regular football academy activities as control conditions meant that perceptual-cognitive engagement was not standardised, complicating interpretation of intervention effects. Additionally, all SB360 testing and training sessions were conducted following school attendance, which may have influenced cognitive performance through accumulated mental and physical fatigue (Dong et al., 2022; Smith et al., 2017). These constraints reflect the practical challenges of conducting research within elite development environments but also emphasise the importance of designing studies that balance ecological validity with experimental rigour.

Finally, an important conceptual limitation concerns the absence of direct links to football performance. Although the SB360 is positioned as a football-specific cognitive-motor system, this thesis did not examine the relationship between SB360 performance and in-game behaviour or match performance outcomes. Accordingly, the extent to which SB360-derived metrics reflect meaningful football-specific skills or predict performance remains unclear. This limitation is particularly relevant given that domain-general

cognitive tasks demonstrated limited sensitivity in distinguishing developmental stages across the academy, raising questions regarding their diagnostic value in elite football contexts. Therefore, future research should prioritise the integration of representative performance measures, such as match event data or *in-situ* behavioural assessments, to evaluate the transferability and ecological validity of cognitive assessment tools.

6.6 Contribution to Applied Practice

Key strength of this thesis lies in its applied nature, with the researcher (WC) embedded within a professional youth academy throughout the project. Within sport science, research is ultimately intended to inform practice and support improvements in athlete performance when effectively translated into applied environments (Coutts, 2017), yet persistent research–practice gaps remain (McLean et al., 2021). In this context, the present thesis aimed not only to generate empirical findings but integrate these insights directly into the academy environment. More broadly, a central aim of sport science PhD programmes is to develop research that has impact beyond academia through embedded, industry-relevant practice (Mujika & Abbiss, 2025). The following sections outline the main areas in which this thesis contributed to applied practice, particularly in relation to curriculum development, player development processes, and the integration of SB360 within existing training structures.

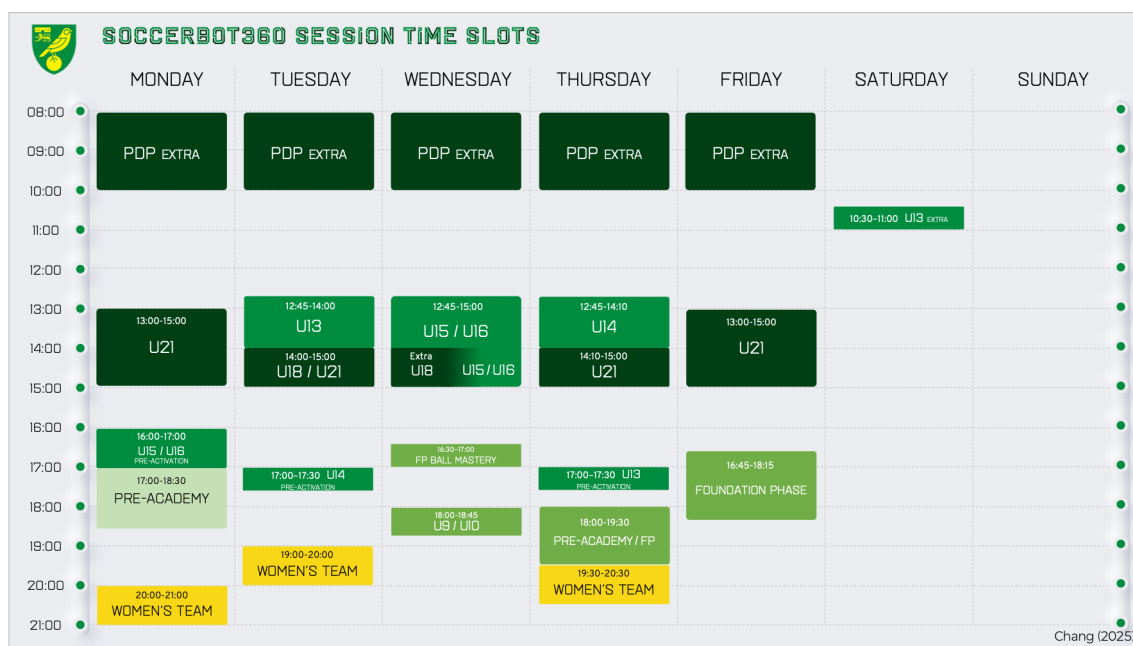
6.6.1 Establishing the Academy SoccerBot360 Curriculum

A primary applied contribution of this thesis was the design, implementation, and iterative refinement of a structured SB360 curriculum within the academy. At the outset of the project, the football club’s objective for the SB360 installation was clearly defined:

“To produce players with fast and effective decision-making on the pitch.”

Accordingly, the integration of the SB360 into the player development curriculum was positioned as an initial step towards achieving this broader aim, with a key operational target being to provide all academy players with regular exposure to the system. To support this objective, an initial standardised SB360 curriculum was developed in collaboration with academy staff. Players in the Foundation Phase (FP) and Youth Development Phase (YDP) followed a consistent selection of tasks with progressive difficulty, supported by predefined weekly session allocations (Figure 6.2). This structure enabled systematic access across age groups and provided a controlled framework for data collection, forming the basis of the intervention study in Chapter 5.

However, findings from Chapter 5 highlighted limitations of this standardised format, particularly reduced individual playing time and limited scope for individualised training. In response, the curriculum was redesigned towards a more flexible and individualised model (Figure 6.3). A key priority was increasing accessibility by creating sufficient session opportunities for all players. This was achieved by removing strict time allocations and promoting a more open and accessible system, reducing the perception of the SB360 as a restricted or specialised resource and rather encouraging more frequent, player-driven engagement. This shift in curriculum design resulted in a substantial increase in SB360 usage across all academy levels (Figure 6.4). This increase reflects not only improved logistical integration but also a cultural shift in how the technology was perceived and utilised within the academy environment. Overall, this process demonstrates that effective implementation of training technologies requires alignment with organisational demands and ongoing adaptation of delivery structures.



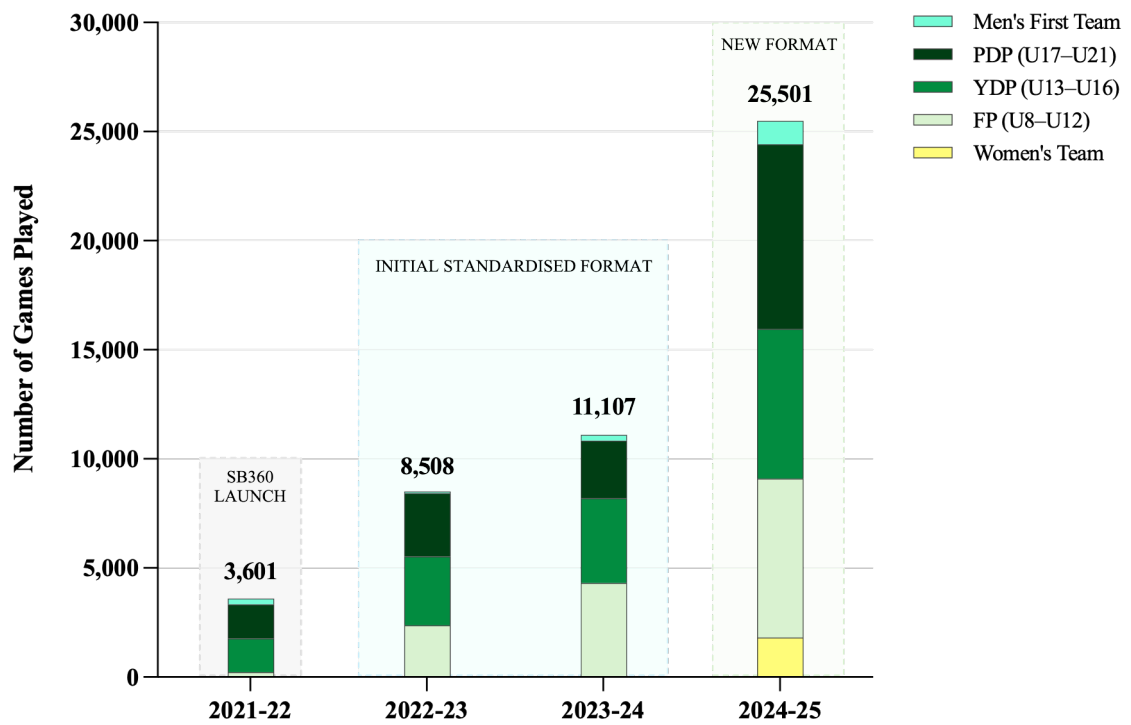


Figure 6.4 Club-level SoccerBot360 usage (number of games played) since installation at the training ground in the 2021-22 season.

6.6.2 Enhancing Player Development Programme Using the SoccerBot360

Following the increase in SB360 usage across the academy, the next step was to optimise how this additional exposure contributed to player development. In elite environments, increasing training time without clear effectiveness can be counterproductive. Hence, a key focus was to ensure that SB360 usage was aligned with specific developmental objectives rather than simply increasing volume. As outlined in Section 6.4.2.1, an essential step in this process was understanding what the technology functionally offers. Findings from this thesis indicated limited evidence supporting the role of SB360 in developing domain-general cognitive functions in highly skilled youth football players but highlighted its potential value for supporting neuromuscular functions, including football-specific technical execution. Accordingly, SB360 sessions were reframed to target specific technical actions.

To operationalise this, training opportunities were analysed within the broader weekly programme. For example, comparisons were made between players’ involvement in team training and additional SB360 or on-pitch individual sessions to quantify exposure to key actions (Figure 6.5). This allowed practitioners to identify gaps in training volume for specific technical behaviours and use SB360 sessions to supplement these areas within player IDPs. In parallel, a set of practical guidelines was developed to support coaches in designing SB360 sessions that align with football-specific objectives and integrate with other training activities (Figure 6.6). These guidelines emphasise linking the SB360 with on-pitch practices, considering factors related to skill acquisition and transfer. This approach enabled SB360 to be used more purposefully within the player development programme, ensuring that its application complemented, rather than duplicated, existing training content.



Figure 6.5 Comparisons of number of passes completed during team training, individual SoccerBot360, and unit-based technical-tactical sessions in two U18 central midfielders.

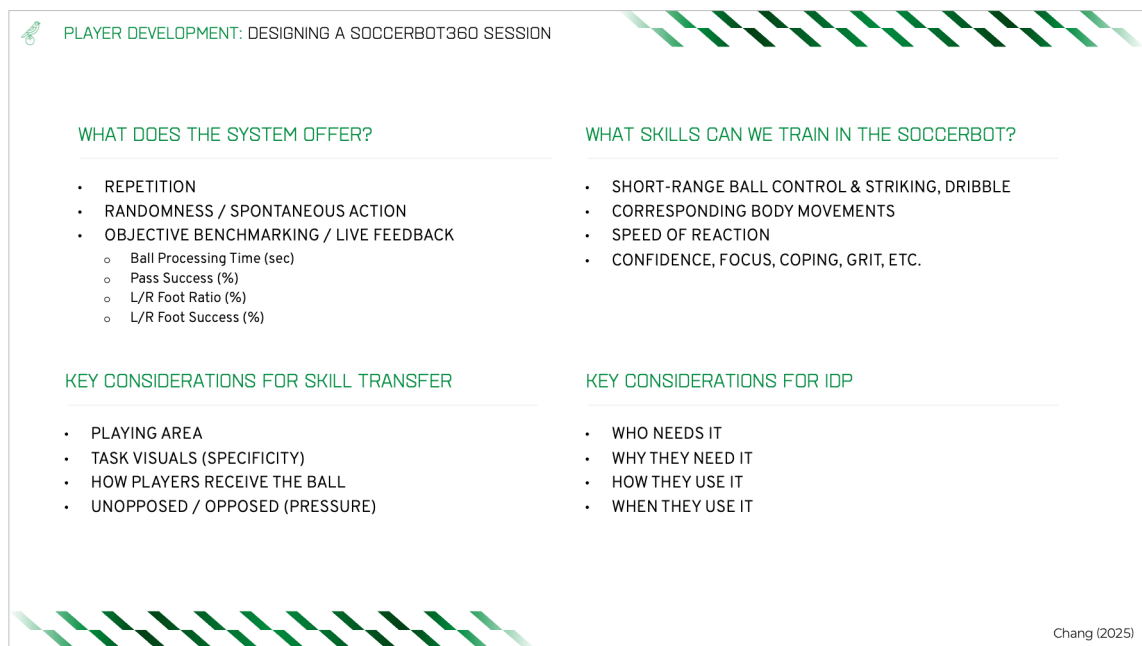


Figure 6.6 Key considerations when designing SoccerBot360 sessions.

6.6.3 Integration of SoccerBot360 within Individual Development Plan (IDP)

This section presents a case example illustrating how the SB360 was integrated within an IDP through a combined approach involving football coaching, video analysis, and SB360 training. The player was transitioning from the U16 to U18 programme, while changing position from a full-back to central midfielder roles. As part of this transition, the coaching staff, performance analyst, and researcher (WC) identified key IDP focuses centred on ball reception under pressure in 360° contexts. This reflected the increased perceptual and spatial demands of central midfield play, combined with the higher match tempo at older age groups, particularly the need for effective scanning, body orientation, and first-touch actions under multidirectional pressure.

To support this development, one SB360 training-mode was selected that provided visual stimuli and target-based tasks capable of inducing the kinematic behaviours associated with the player's IDP (Figure 6.7a–6.7c). These sessions were integrated within a broader training cycle linking three key components. First, *video analysis* sessions were conducted to review match performance, identify areas for improvement, and provide the

player with a clear understanding of the technical and perceptual demands of his new role. Second, *SB360 training* was used to develop movement coordination and efficiency through repeated exposure to relevant actions, supporting the automation of scanning, receiving, and turning behaviours under time constraints. Third, *on-pitch training* sessions were designed to embed these behaviours within football-specific contexts, requiring the player to execute the same technical actions under positional, tactical, and opposition-related constraints (Figure 6.7d–6.7f). This integrated approach allowed the SB360 to function as a bridge between isolated technical repetition and fully representative game scenarios. While the SB360 facilitated high-frequency controlled rehearsal of specific movement patterns, on-pitch sessions with bespoke coaching instructions ensured that these behaviours were transferred into context-dependent performance.



Figure 6.7 (a) In the SoccerBot360 task, a red dot (i.e., pre-orientation) indicates the location of the upcoming target panel. (b) The red dot prompts the player to scan and anticipate the next action. (c) After scanning, the player adjusts body orientation and first-touch to receive and pass quickly and efficiently towards the target. (d) In the on-pitch session, teammates (red circles) replace the red dot as sources of pre-orientation information. (e) Within team and unit sessions, individualised (yellow circle) and group-based (grey circle) coaching are delivered simultaneously. (f) Directional, position-specific practice. The player highlighted in the yellow circle represents the IDP target player.

6.7.4 Developing Scalable SoccerBot360 Monitoring Processes

The final stage of implementation focused on establishing scalable monitoring processes to support the sustained and effective use of SB360 within the academy. As overall usage increased and guidelines for SB360 integration within player IDP were established, it became essential to develop systems that allow key stakeholders to track, evaluate, and refine player engagement in a consistent and objective manner. To address this, a series of interactive dashboards were developed for both staff and players. These included monitoring systems at club, team, and individual levels, capturing key indicators such as SB360 training volume, session frequency, and performance outputs (Figures 6.8 and 6.9). These tools enabled practitioners to move beyond simple usage tracking and instead evaluate the effectiveness of SB360 engagement in relation to player development outcomes. For example, coaches could identify cases where high SB360 exposure did not translate to observable on-pitch improvements, or conversely, where limited usage was associated with positive performance changes, allowing for more informed decision-making processes around training prescription.

In parallel, a player-facing SB360-IDP dashboard was developed to facilitate more individualised and autonomous use of the system (Figure 6.10). This platform provides recommended training modes, levels, and challenge points aligned with each player's IDP, alongside structured weekly session plans based on match-day cycles (e.g., MD-3). Importantly, this allowed players to engage with SB360 training with clear purpose and direction, even in the absence of direct staff supervision, supporting a more player-driven approach to development. Collectively, these monitoring processes enabled the SB360 to be embedded not only as a training tool, but as part of a broader data-informed player development system. This approach highlights the importance of scalable infrastructure in applied environments, ensuring that increased access and usage are accompanied by meaningful evaluation and targeted application.

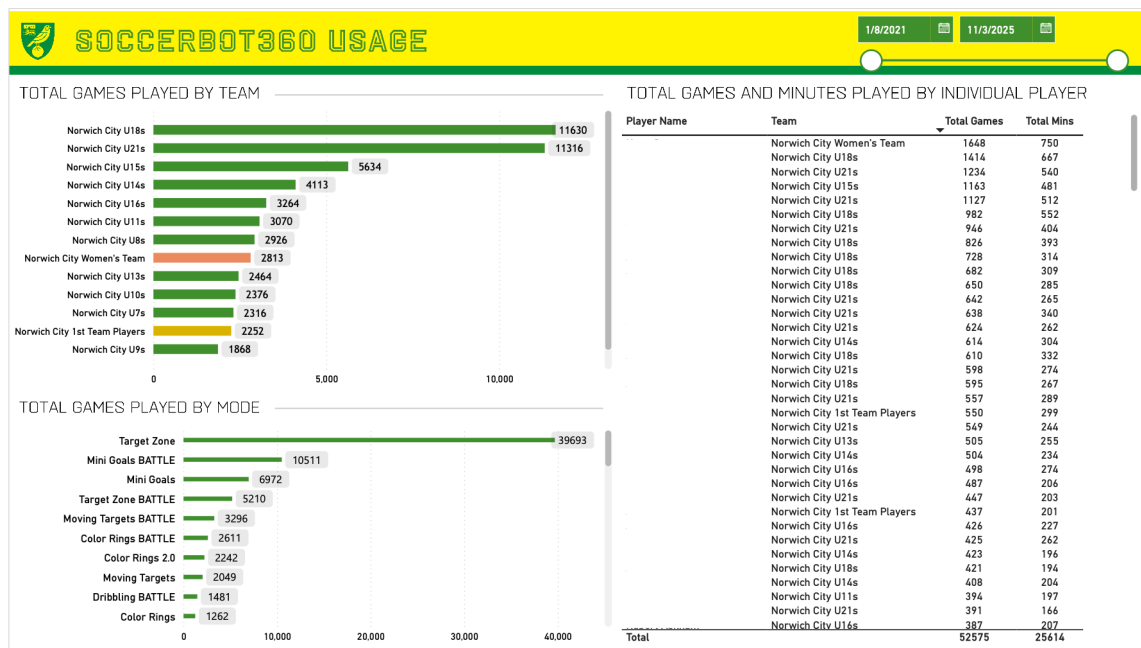


Figure 6.8 Club-level SoccerBot360 usage dashboard.

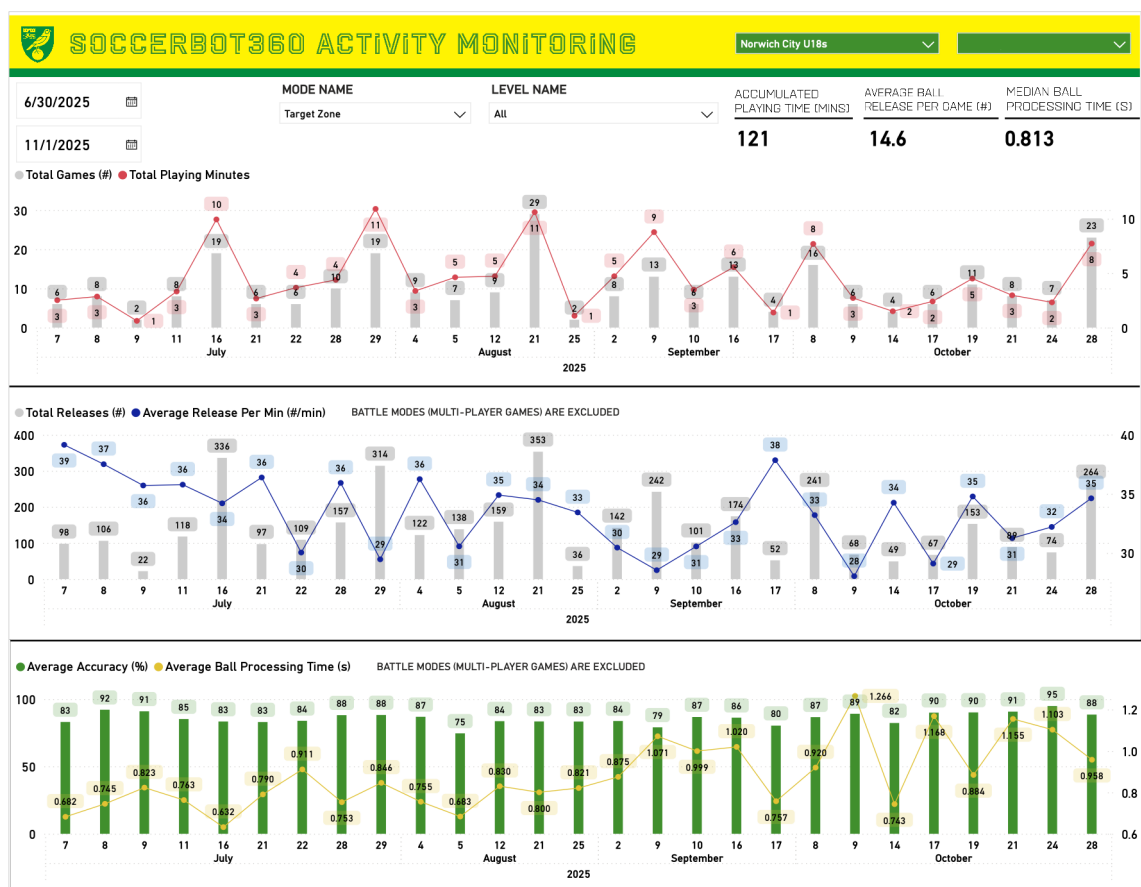


Figure 6.9 SoccerBot360 activity monitoring dashboard.



Figure 6.10 Player-facing SoccerBot360 individual development plan (IDP) dashboard.

6.7 Conclusion

This thesis aimed to evaluate the methodological and applied utility of the SoccerBot360 as a football-specific cognitive-motor assessment and training system within an English professional youth academy context. Across three empirical studies, findings demonstrated that SB360 performance reflects a complex interaction between cognitive demands, motor-execution characteristics, and developmental factors. While certain performance metrics, particularly response time, exhibited sensitivity to age and biological maturation, other outcomes, such as RT cost, accuracy, and error-based measures, were more strongly influenced by contextual factors, including perceived workload. In contrast, the intervention study provided limited evidence that the six-week SB360 training programme produced measurable group-level cognitive adaptations beyond expected learning or developmental effects, highlighting the importance of training dosage, task specificity, measurement sensitivity, and individualisation when designing cognitive-motor interventions.

From a theoretical perspective, these findings challenge simplified interpretations of *football-specific* cognitive training based solely on response modality or surface-level task design. Instead, they emphasise the importance of functional representativeness, particularly the preservation of perception–action coupling and context-dependent decision-making processes. From an applied perspective, the results suggest that the SB360 may be most appropriately positioned as a supplementary tool for supporting specific components of player development, particularly *neuromuscular coordination* and structured cognitive-motor engagement, rather than as a standalone solution for enhancing football-specific decision-making performance.

It is important to acknowledge that this thesis evaluated the integration of the SB360 within a single English professional academy context. As such, findings may not be

directly generalisable to other environments, particularly given that the SB360 is not yet widely adopted across football settings. However, this work represents one of the first attempts to systematically embed and evaluate an integrated cognitive-motor assessment and training system within a real-world youth academy programme. In this sense, the thesis provides a valuable applied and methodological foundation for future research and practice.

Accordingly, the contribution of this thesis may be better understood in terms of *transferability* rather than *generalisability*. While the specific outcomes are context-dependent, the underlying insights relating to measurement interpretation, task design, training integration, and the balance between cognitive and motor demands, offer meaningful guidance for both researchers and practitioners in football and other performance domains. Collectively, the findings contribute to a more nuanced understanding of cognitive training in sport and provide a platform for the continued development of evidence-based, contextually grounded approaches to enhancing decision-making in football.

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Appendix

Appendix 1: Ethics Approval and Gatekeeper Consent Form.

Chang, Woohyuk Thursday, April 24, 2025 at 10:29:48 British Summer Time Subject: UREC Minimal risk registration number - 23/SPS/003 Date: Wednesday 11 January 2023 at 11:55:15 Greenwich Mean Time From: UREC Minimal Risk Registration <MinimalRiskUREC@ljmu.ac.uk> To: UREC Minimal Risk Registration <MinimalRiskUREC@ljmu.ac.uk>, Chang, Woohyuk <W.Chang@2022.ljmu.ac.uk> CC: McRobert, Alistair <A.P.McRobert@ljmu.ac.uk> Attachments: Chang Woohyuk minimal risk registration form v2.0 June20(25).docx Dear Woohyuk Woohyuk Chang, PGR - Developing tactical knowledge and performance using 360-degree immersive technology (Alistair McRobert) Ref: 23/SPS/003 Approval is given on the understanding that: • The study is conducted in accordance with the Minimal Ethical Risk Guiding Principles • Any adverse reactions/events which take place during the course of the project are reported to the Committee immediately by emailing researchethics@ljmu.ac.uk; • Any unforeseen ethical issues arising during the course of the project will be reported to the Committee immediately emailing researchethics@ljmu.ac.uk; • The LJMU logo is used for all documentation relating to participant recruitment and participation e.g. poster, information sheets, consent forms, questionnaires. The study consent forms, data, information etc. will be accessible on request to a student's supervisory team and/or to responsible members of Liverpool John Moores University for	monitoring, auditing and data authenticity purposes. • Where any substantive amendments are proposed to the protocol or study procedures that change the associated risk from minimal to low risk (use the decision tool to establish the associated risk), the investigators must complete an ethics application form describing all aspects of the study and submit for ethical review and approval as required. • Where relevant appropriate gatekeeper / management permission must be obtained prior to the study commencing at the study site concerned. Please note that approval is given for a period of five years from the date granted and therefore the expiry date for this project will be 5 years from the approval date. An application for extension of approval must be submitted if the project continues after this date. Best wishes UREC
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1 of 2

2 of 2

 LIVERPOOL JOHN MOORES UNIVERSITY GATEKEEPER INFORMATION SHEET Developing tactical knowledge and performance using 360-degree immersive technology Woohyuk Chang and School of Sport and Exercise Science (Football Exchange) 1. What is the reason for this letter? This letter seeks formal permission to use anonymised player performance and training data collected within Norwich City Football Club as part of a PhD research project jointly conducted by Liverpool John Moores University and Norwich City Football Club as well as publication to academic journals. 2. What is the purpose of the study/rationale for the project? The project aims to develop a greater understanding of how a 360-degree immersive technology (SoccerBot360) can be used to assess and improve perceptual-cognitive and tactical performance in football. 3. What are we asking you to do? We request permission from Norwich City Football Club (as gatekeeper) to: • Grant access to existing anonymised performance and testing datasets collected by the club (e.g., GPS, PlayerMaker, physical test, match event, and SoccerBot360 data). • Allow publication to publicly available academic journals using the anonymised data. The gatekeeper's role is to confirm that data access and collection are aligned with club policies and welfare procedures. 4. How will we use the information/questionnaire? • Used solely for academic research purposes related to the PhD. • Analysed in aggregated and anonymised form to ensure confidentiality. • Stored securely on LJMU's encrypted research server and within the football club's approved systems. Results may appear in academic theses, journal articles or presentations. 5. What will taking part involve? What should I do now? Participation involves confirming access to existing datasets and allowing data use within the defined research aims. The gatekeeper (e.g., Academy Director or Head of Performance) is asked to sign the approval form or provide written confirmation via email. No further action is required beyond this approval unless additional data collection or facility access is requested later, in which case separate approval will be sought. Should you have any comments or questions regarding this research, you may contact the researchers. This study has received ethical approval from LJMU's Research Ethics Committee (Ref: 23/SPS/003) Lead Researcher: Woohyuk Chang (W.Chang@2022.ljmu.ac.uk) Lead Supervisor: Alistair McRobert (A.P.McRobert@ljmu.ac.uk) If you have any concerns regarding your involvement in this research, please discuss these with the researcher in the first instance. If you wish to make a complaint, please contact researchethics@ljmu.ac.uk and your communication will be re-directed to an independent person as appropriate.	 LIVERPOOL JOHN MOORES UNIVERSITY GATEKEEPER CONSENT FORM Title of Project: Developing tactical knowledge and performance using 360-degree immersive technology Name of Researchers: Woohyuk Chang Please tick to confirm your understanding of the study and that you are happy for your organisation to take part and your facilities to be used to host parts of the project. 1. I confirm that I have read and understand the information provided for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily. ☒ 2. I understand that any personal information collected during the study will be anonymised and remain confidential. ☒ 3. I agree for our organisation to provide relevant anonymised data to the above study for the purposes of the PhD research project and any future academic publications arising from it. ☒ <i>By signing this form, the gatekeeper agrees to the use of existing anonymised player performance datasets collected by Norwich City Football Club within its Academy and First Team squads for the purposes of the PhD project "Developing tactical knowledge and performance using 360-degree immersive technology".</i> <i>(Please note: the project title may be amended at the final submission of the PhD thesis.)</i> <i>This agreement includes permission for the researchers to analyse and report findings based on these datasets within the PhD thesis and in any subsequent academic journal publications or conference presentations, ensuring that no individual player or staff member will be identifiable in any outputs without their explicit consent.</i> Name of Gatekeeper: <u>A.P. McRobert</u> Date: <u>24/10/2025</u> Signature:  Name of Researcher: <u>Woohyuk Chang</u> Date: <u>24/10/2025</u> Signature: 
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Appendix 2 (Chapter 3): Participant-level exclusion and trial-level response time filtering procedures for data preparation of the SoccerBot360 number-letter (cognitive flexibility) task, adapted from Musculus et al. (2022). The secondary analysis dataset followed identical procedures and is presented only as the final dataset.

Stage	Description	Data excluded	Data retained
Initial dataset ^{Primary}	97 participants (4,480 recorded trials)	-	-
Participant exclusion	Low average accuracy ($\leq 60\%$)	$n = 5$	$n = 92$
Participant exclusion	Long average RT (≥ 3000 ms)	$n = 12$	$n = 80$
RT eligibility	Incorrect trials removed prior to RT analysis	406 (9.1%)	4,074
RT plausibility	RTs < 400 ms or > 3000 ms excluded	315 (7.7%)	3,759
RT variability	RTs outside ± 3 SD of individual mean excluded	23 (0.6%)	3,736
Final dataset ^{Primary}	80 participants (3,736 RT trials)	-	-
Final dataset ^{Secondary}	48 participants (2,279 RT trials)	-	-

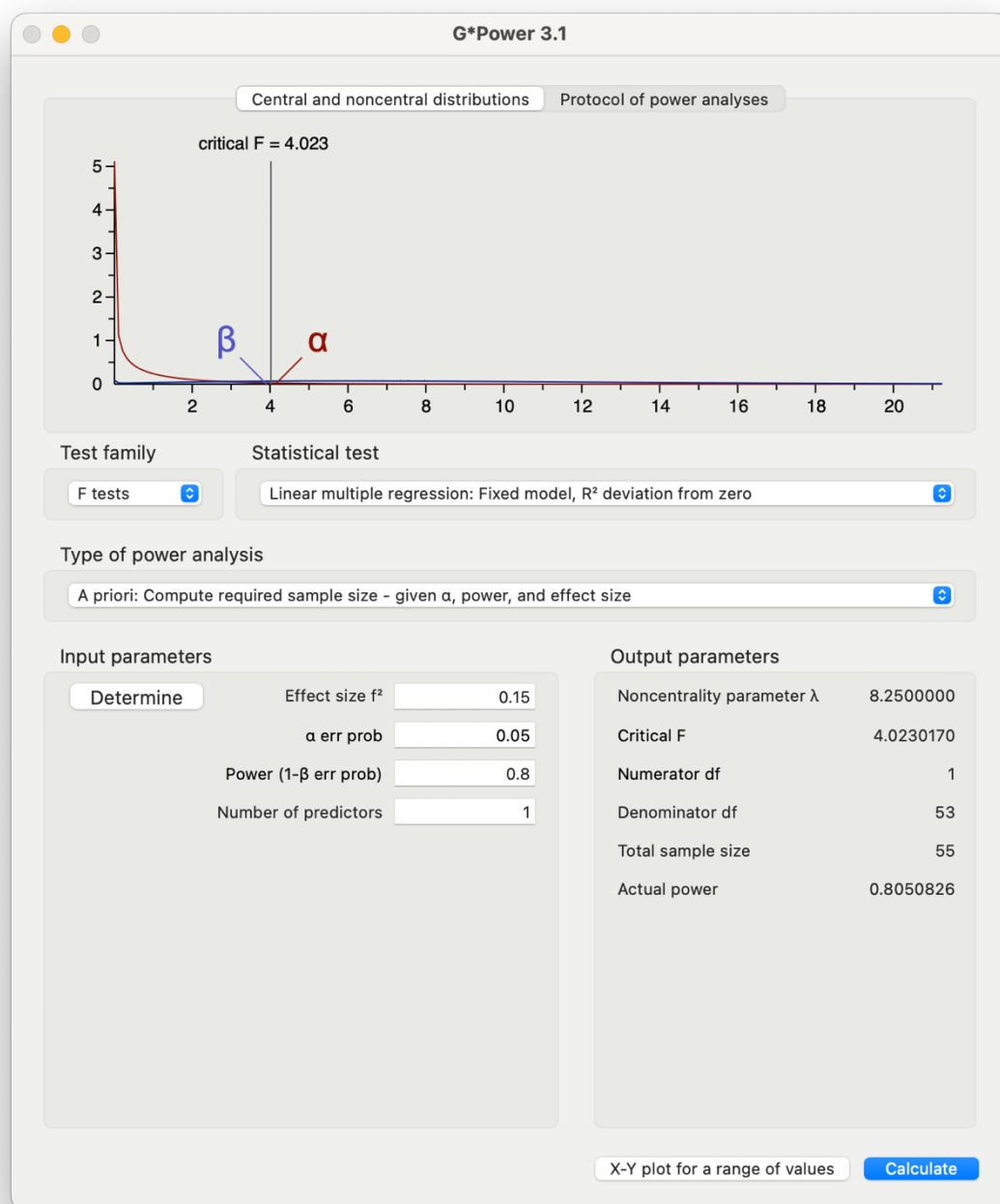
Nb. ^{Primary} indicates samples used for the exploratory and primary analyses. ^{Secondary} indicates samples used for the secondary analysis.

Appendix 3 (Chapter 3): Participant-level exclusion and trial-level response time filtering procedures for data preparation of the SoccerBot360 3-back (working memory) task, adapted from Knöbel and Lautenbach (2023). The secondary analysis dataset followed identical procedures and is presented only as the final dataset.

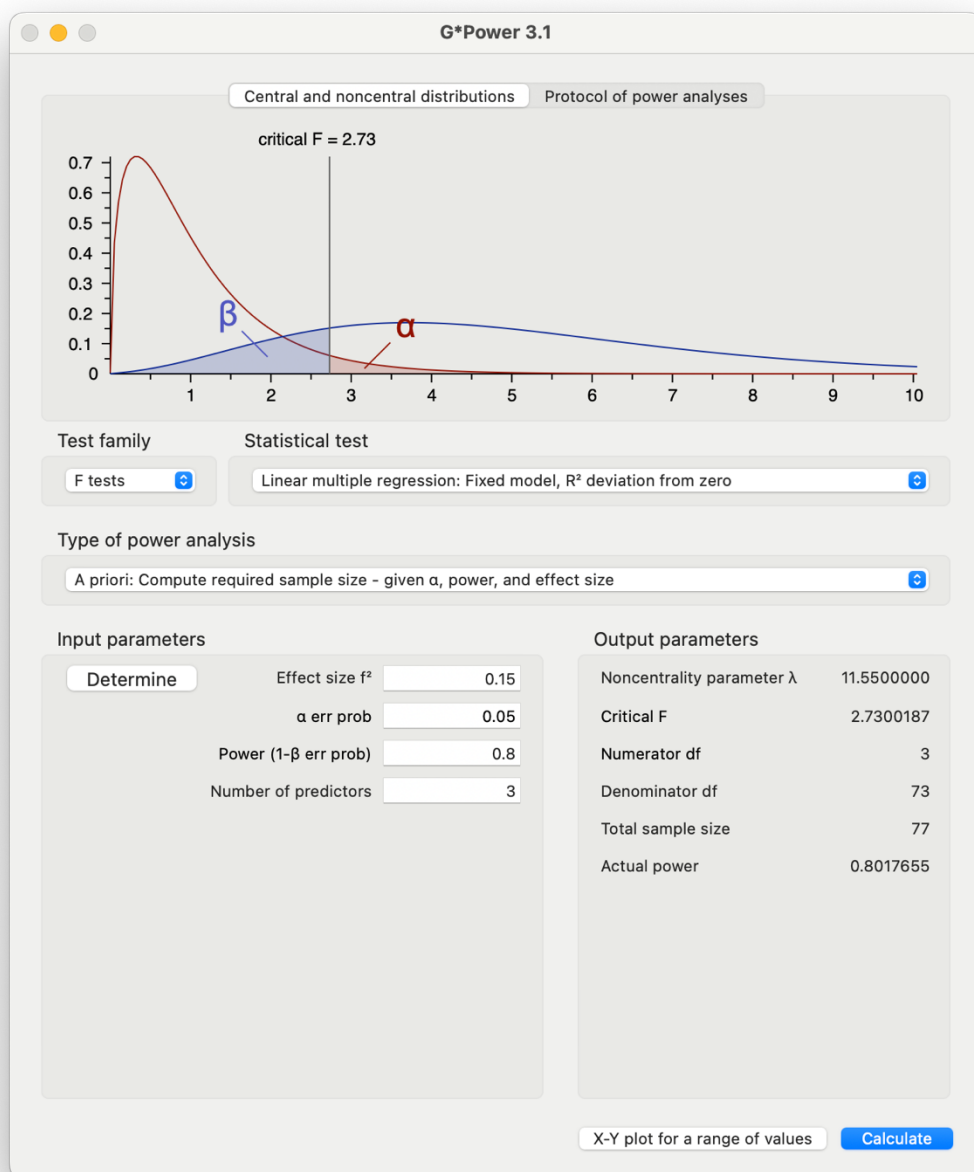
Stage	Description	Data excluded	Data retained
Initial dataset ^{Primary}	130 participants (6,500 recorded trials)	-	-
Participant exclusion	Incomplete testing data	$n = 1$	$n = 129$
RT trial classification	Non-target trials identified	-	4,550
RT trial classification	Target trials identified	-	1,950
RT eligibility	Correctly responded target trials	703 (36%)	1,247
RT plausibility	RTs < 400 ms or > 3000 ms excluded	4 (0.3%)	1,243
RT variability	RTs outside ± 3 SD of individual mean excluded	0 (0%)	1,243
Final dataset ^{Primary}	129 participants (1,243 RT trials)	-	-
Final dataset ^{Secondary}	47 participants (445 RT trials)	-	-

Nb. ^{Primary} indicates samples used for the exploratory and primary analyses. ^{Secondary} indicates samples used for the secondary analysis.

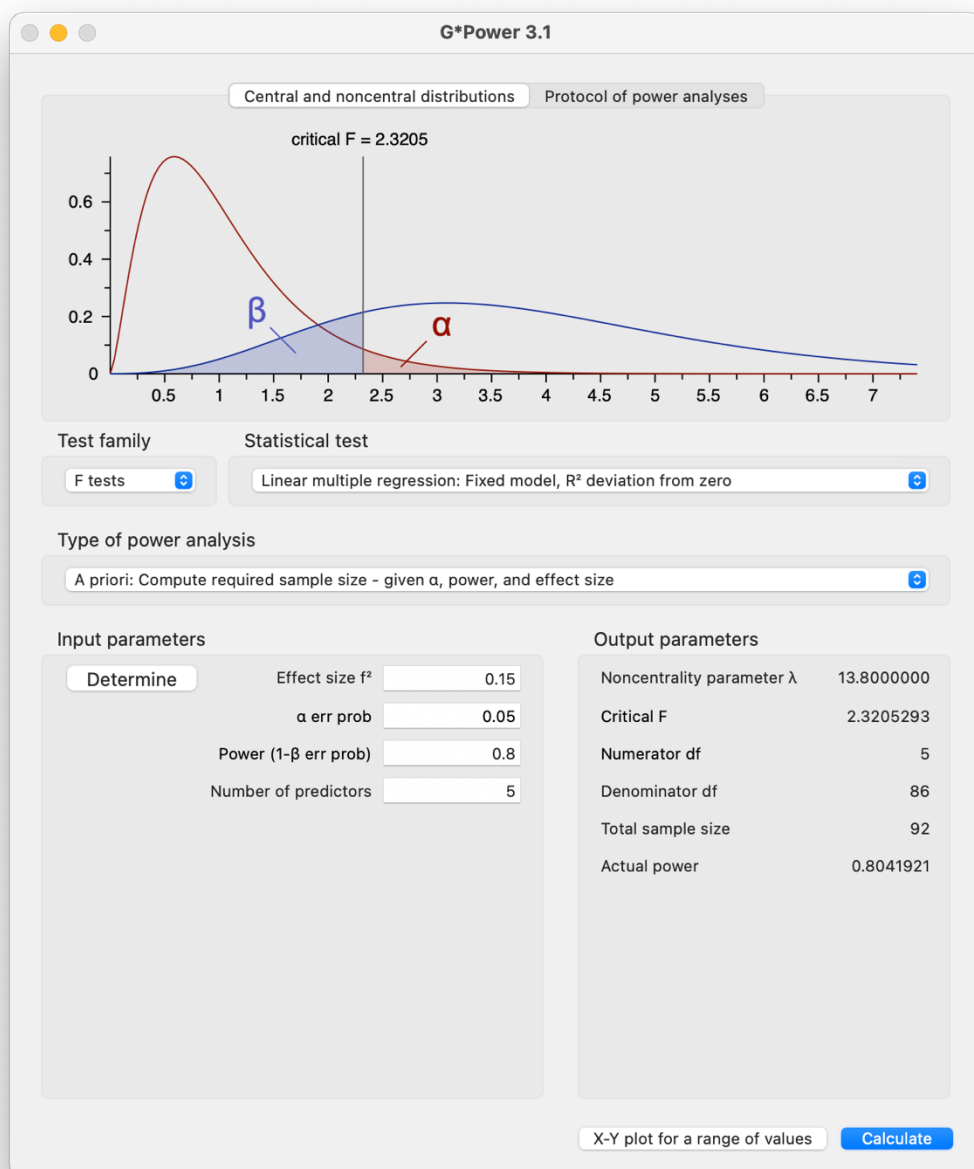
Appendix 4 (Chapter 3): G*Power output for sample calculation.



Appendix 5 (Chapter 4): G*Power output for sample calculation for pre-test perceived readiness analyses.



Appendix 6 (Chapter 4): G*Power output for sample calculation for post-battery perceived workload analyses.



Appendix 7 (Chapter 5): Mini Goals (MG) game difficulty was adjusted by varying the number of open goals, the switching time of open goals, and the size and distance between goals. In the easiest level, termed *10 Goals*, the goals measured 154 cm wide by 52 cm high and were spaced 141 cm apart. Three out of ten goals were open simultaneously, switching every 2.5 s or upon scoring a goal. The intermediate level, *8 Goals*, featured goals measuring 121 cm wide by 41 cm high, spaced 275 cm apart. Similarly, three goals opened at a time, switching every 2.2 s or upon scoring. The most difficult level, *5 Goals*, comprised larger goals measuring 154 cm wide by 53 cm high, spaced 487 cm apart, with two goals open simultaneously, switching every 1.7 s or upon scoring a goal.

Mini Goals difficulty levels.

Level	Duration	Displayed goals	Open goals at a time	Open goals switching time	Cognitive training focus
10 Goals	30 s	10	3	2.5 s or scoring	INH & CRT
8 Goals	30 s	8	3	2.2 s or scoring	INH & CRT
5 Goals	30 s	5	2	1.7 s or scoring	INH & CRT

Nb. INH = inhibition; RT = response time.

Appendix 8 (Chapter 5): The easiest difficulty level of Moving Targets (MT), *Pre-O Level 3*, required participants to achieve 25 points, with moving objects displayed at low heights, varying speeds, and different sizes. Bonus points were assigned to smaller and faster targets (1 point per target). The intermediate level, *Pre-O Level 4*, also required 25 points, featuring moving objects displayed at both low and high heights, varying speeds, and different sizes. Bonus points in this level were assigned to smaller (1 point), faster (1 point), and higher (3 points) targets. The most advanced level, *Level 3*, required participants to achieve 35 points and featured moving objects in traffic-light colours (green, yellow, and red) at low and high heights, varying speeds, and different sizes. Bonus points for this level were assigned to faster targets (1 point), higher targets (3 points), and colour-based targets (green = 2 points; yellow = 1 point; red = 0 point). All small and large targets had diameters of 65 cm and 90 cm, respectively. The slow and fast target speeds were set at 0.25–0.5 m/s and 1.1–1.5 m/s, respectively, while the low and high target heights were displayed between 0.0–0.1 m and 1.4–1.7 m, respectively.

Moving Targets difficulty levels.

Level	Duration	Height of targets	Number of target shapes / colours	Bonus points	Cognitive training focus
Pre-O Level 3	25 points	Low	3 / 3	Smaller targets: 1 Faster targets: 1	ANT, CF, & WM
Pre-O Level 4	25 points	Low & high	3 / 3	Smaller targets: 1 Faster targets: 1 Higher targets: 3	ANT, CF, & WM
Level 3	35 points	Low & high	3 / 3	Faster targets: 1 Higher targets: 3 Green colour: 2 Yellow colour: 1 Red colour: 0	ANT & CF

Nb. Pre-O = pre-orientation, when the game shows which target (shape, colour, etc.) has to be hit and which target follows next; ANT = anticipation; CF = cognitive flexibility; WM = working memory.

Appendix 9 (Chapter 5): Data Preparation and Exclusion Criteria.

Trial-level filtering (response time analyses): All incorrect trials (i.e., false responses) were excluded from the response time analyses, accounting for 9.0% of trials in CF, 1.9% in ANT, 3.2% in INH, and 3.4% in CRT. Predefined RT ranges were then applied to filter out extreme data points, except for the ANT task, which inherently recorded RT within the trial time bound of less than 3,200 ms. For the CF task, RT below 400 ms or above 3,000 ms were considered extreme values and excluded (8.1%) (Musculus et al., 2022). For the INH and CRT tasks, RT below 400 ms or above 2,000 ms were excluded (0.1% for both INH and CRT tasks). Additionally, $RT \pm 3$ SD from the individual mean were excluded for all tasks except the ANT task, resulting in the removal of 0.9% of CF, 0.8% of INH, and 0.2% of CRT data.

Participant exclusion: Four participants were excluded from the CF analysis due to either low overall accuracy ($\leq 60\%$; $n = 2$) or slow overall RT ($\geq 3,000$ ms; $n = 2$). Previous studies employing the number-letter task have used a higher accuracy threshold ($\geq 70\%$) but typically involved a computerised version without large motor responses (Adrover-Roig et al., 2012) or required participants to complete a computerised version before performing the SB360 number-letter task (Musculus et al., 2022). Based on the first author's observations, participants achieving over 60% correct trials demonstrated a clear understanding of the testing rules and exerted effort to perform optimally, thus warranting inclusion in the analysis. Additionally, two participants were excluded from the analysis of the INH task due to low overall accuracy ($\leq 60\%$; $n = 1$) or slow overall RT ($\geq 2,000$ ms; $n = 1$).

Participant details included in the analysis of SB360 Tasks (Chapter 5).

Demographic, football-specific information	Total	Experimental Groups	
		Group A	Group B
Cognitive Flexibility (CF)			
<i>n</i>	27	12	15
Age (years)	13.6 ± 0.9	13.7 ± 0.9	13.6 ± 0.9
Height (cm)	167.0 ± 12.8	169.9 ± 14.1	164.0 ± 11.2
Body mass (kg)	53.5 ± 10.0	54.6 ± 11.4	52.4 ± 8.9
Training age (years)	7.7 ± 1.1	8.1 ± 1.0	7.4 ± 1.2
Weekly football practice time (hours)	5.9 ± 0.4	5.9 ± 0.4	5.8 ± 0.4
Inhibition (INH)			
<i>n</i>	29	14	15
Age (years)	13.7 ± 0.9	13.7 ± 0.9	13.7 ± 1.0
Height (cm)	167.8 ± 12.4	170.8 ± 13.8	164.7 ± 11.1
Body mass (kg)	54.4 ± 10.3	55.1 ± 11.6	53.7 ± 9.0
Training age (years)	7.7 ± 1.2	8.0 ± 1.0	7.5 ± 1.3
Weekly football practice time (hours)	5.9 ± 0.5	5.9 ± 0.4	5.9 ± 0.5
Anticipation (ANT)			
<i>n</i>	31	15	16
Age (years)	13.7 ± 0.9	13.8 ± 0.9	13.7 ± 1.0
Height (cm)	168.0 ± 12.2	171.6 ± 13.6	164.4 ± 10.8
Body mass (kg)	54.4 ± 10.2	55.7 ± 11.4	53.1 ± 9.0
Training age (years)	7.8 ± 1.2	8.0 ± 1.0	7.6 ± 1.3
Weekly football practice time (hours)	5.9 ± 0.5	6.0 ± 0.4	5.9 ± 0.5
Choice Response Time (CRT)			
<i>n</i>	31	15	16
Age (years)	13.7 ± 0.9	13.8 ± 0.9	13.7 ± 1.0
Height (cm)	168.0 ± 12.2	171.6 ± 13.6	164.4 ± 10.8
Body mass (kg)	54.4 ± 10.2	55.7 ± 11.4	53.1 ± 9.0
Training age (years)	7.8 ± 1.2	8.0 ± 1.0	7.6 ± 1.3
Weekly football practice time (hours)	5.9 ± 0.5	6.0 ± 0.4	5.9 ± 0.5

Nb. Training age represents cumulative years of structured football training undertaken within professional and non-professional youth football teams. Weekly football practice includes academy football training and fixture.

우혁, 아빠, 우정이랑 셋이 축구하러 간다며 나섰는데,

우혁이 차림이 정말 멋지다.

그 짧은 사이 축구복, 축구양말, 축구화, 골키퍼 장갑까지 끼고

축구공 딱 들고 기다린다.

"사진 한 장 찍어 줄까?"

"아~ 아~ 됐어. 나 사진 싫어해."

그 말을 하는 동안도 표정은 함박웃음이다.

댓글을 작성해보세요.



확인

 싸이월드