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Designing new digital tools to augment human creative thinking at work: An application in elite sports coaching

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Abstract

Creative thinking is desirable in many professions. This article reports new research that followed a design science approach to develop and investigate a co-creative tool called *Sport Sparks* in one profession – the coaching of professional football players. In response to a coach entering a text description of a coaching challenge (e.g., *struggling to maintain the fitness of an athlete*) into the tool, the tool automatically generated potentially novel ideas (e.g., *reducing game time* and *changing their nutrition*) that the coach could select and/or adapt and evolve into a simple action plan (e.g., *which links nutrition to increased game time*). This *Sport Sparks* tool was designed to be an example of human-centred artificial intelligence that aspires to empower humans, to deliver high levels of human control as well as automation, and empower people rather than emulate their expertise. It was engineered with rule-based reasoning to automate the generation of potential new ideas that coaches could select and refine during interactions which provide high user control over this automation. The potential of such a co-creative tool, and value of the guidelines, were demonstrated during the tool's evaluation by coaching practitioners at a Premier League football club. The practitioners used the tool to generate new ideas to coaching challenges, and reported evidence of different forms of creative thinking, although some also reported the need for more support for creative collaborations and solution planning. The paper ends by discussing future directions for both the *Sport Sparks* tool and other co-creative AI tools.

KEYWORDS

co-creative AI tools, creativity, design guidelines, elite coaching, human-centred AI, sports

1 | INTRODUCTION

Creativity is defined as the ability to produce work that is novel and original, as well as appropriate and useful (Sternberg, 1999). The need for more creative thinking and outcomes is well-documented, for example, to solve complex problems (e.g., Isaksen et al., 2011) and facilitate innovation (e.g., Design Council, 2011). Digital tools to support human creativity and more creative engagement has become one of the means to meet this need (e.g., Candy, 2007). People use these tools to, for example, discover new information, synthesize novel content from existing material, and direct their thinking to generate new ideas. Published examples include *combinFormation*, which supported people to search, browse, collect, mix and think creatively using digital information (Kerne et al., 2008), and *Crowdboard*, which allowed online crowds to provide real-time creative input during early-stage design activities (Andolina et al., 2017).

However, in spite of extensive research over the last 30 years, there has been little long-term uptake of these digital tools in professional work. A recent review of papers reporting these tools (Remy et al., 2020) revealed three limitations of the existing research. The first was the lack of longitudinal studies of tool use in-situ. Most of the reported evaluations of digital creativity support tools were short-term, and took place only in controlled settings (Remy et al., 2020). The second was the absence of expert participants. Most of the reported evaluations of the new tools involved novice rather than expert users, with obvious implications for the limited validity of the findings (Remy et al., 2020). And the third was an evaluation focus on the usability rather than the creative effectiveness of the tools (Remy et al., 2020). In this article, to overcome these three limitations, we report new design research that investigated the longer-term use of one tool by expert practitioners to produce more creative thinking and outcomes in one professional domain.

One of the possible reasons for the limited take-up of digital creativity support tools has been the challenge posed by machine intelligence. Recent publications have revealed that more of these tools are leveraging artificial intelligence algorithms. Examples of these tools include *Calliope*, a virtual reality system that enabled users to explore and manipulate generative design solutions in real time (Davis et al., 2021), and *Shelley*, a deep-learning horror writing engine deployed as a Twitter bot to crowd-source human inputs (Yanardag et al., 2021). These tools are often referred to as *co-creative AI tools* (e.g., Long et al., 2021). Many are framed as examples of 'humans-in-the-loop' around artificial intelligence systems (Shneiderman, 2020), in which the research focus is to design machine intelligence, rather than to augment human behaviour. For example, *Calliope* encourages data exploration and synthesis using a tight '*human-in-the-loop*' collaboration with underlying algorithms that generate design alternatives. Indeed, most reported computational creativity research seeks to construct programs to emulate human creative processes, rather than augment human capabilities to be more creative. We argue that this focus on automating, rather than augmenting, is one possible reason for the limited take-up of co-creative AI tools in work environments.

By contrast, human-centred artificial intelligence (HCAI) aspires to empower human rather than automate human work (Xu, 2019; Yang et al., 2020). Ben Shneiderman argues that HCAI needs to reframe AI to be 'in-the loop' around humans to support people's self-efficacy, creativity and social participation (Shneiderman, 2021). To direct the development of new digital tools with humans at their centre, he offered what he called three fresh ideas: (1) to deliver high levels of human control as well as automation, (2) to design to empower people with powerful tool-like appliances, rather than emulate human expertise and (3) to promote a governance structure that describes how to develop more reliable systems and maintain a safety culture. Modern smartphone cameras, thermostats, elevators and dishwashers are new tools with AI capabilities that implement these ideas (Shneiderman, 2020).

However, so far, there are no reports of Shneiderman's ideas being applied to design co-creative AI tools. Therefore, in this article, we report new design research that implemented the first 2 ideas – to deliver high levels of human control as well as automation, and to design to empower people with powerful tool-like appliances, rather than emulate human expertise – in one such tool.

The chosen professional domain was elite sports, and in particular the coaching of elite athletes. Coaching elite athletes often requires solving complex problems such as recurring injuries, unmotivated athletes, and sub-optimal performance at competition time (e.g., North et al., 2020). Many of these problems are wicked, ill-structured, and lack simple solutions. Furthermore, coaches are encouraged to operate at the edge of chaos in complex interpersonal systems (Bowes & Jones, 2006). Creative thinking that challenges existing norms was interpreted as one possible means of encouraging operating at this edge of chaos.

The authors followed a design science approach to develop and evaluate a new co-creative AI tool for use by coaching practitioners at a leading professional football club. The tool was designed so that a coaching practitioner would enter a text description of a current coaching challenge (e.g., *struggling to maintain the fitness of an athlete*). In response, the tool would use artificial intelligence algorithms to generate alternative possible ideas (e.g., *reducing game time, changing some social activities* or *adjusting their nutritional intake*) with which to overcome the challenge from different, less-common perspectives – perspectives such as the athlete's *motivation*, *coaching environment*, *home life*, *team relationships* and *competition status*. The practitioner could then select and/or adapt one or more of these possible ideas in the tool, and evolve them into a simple action plan. During this use, the tool was designed to deliver high levels of both human control (e.g., *the coaching practitioner was able both to change their entered text* and *to choose which of the tool's algorithms to use*) and automation (e.g., *the tool automatically parsed and made sense of the entered text description* and *generated large numbers of alternative possible ideas*) to solve coaching problems. What is more, the coaching knowledge was engineered to empower the coach's creative thinking, rather than simulate their current practices. The tool was then evaluated during a period of use by 10 coaching practitioners at the professional football club.

The next two sections report related previous work and the set of HCAI guidelines for designing co-creative AI tools developed. The paper then describes the application of these guidelines to design a new version of a co-creative AI tool for use by coaching practitioners at the professional football club, and the resulting new version, called *Sport Sparks*, as well as its first evaluation by 10 practitioners at the club. The paper ends with a discussion of the tool and its evaluation findings, then outlines future design science research to enable the take-up of co-creative AI tools.

2 | RELATED WORK

The development of *Sport Sparks* built on the related research reported in this section. This research investigated the challenges facing human-centred AI, common creative processes, digital creativity support and co-creative AI tools, and previous uses of creative thinking and technologies in elite sports.

2.1 | Human-centred AI challenges

There is a growing body of work that is seeking to understand HCAI. Multiple authors (e.g., Shneiderman, 2020) and institutions (e.g., Stanford, 2022) agree on the aims of HCAI to empower rather than replace humans, for example, using conversational agents that support communities (Wang et al., 2021). However, so far, there has been little progress to operationalize Shneiderman's (2020) three key ideas to deliver more effective HCAI. Instead, most reports have focused on the need to develop user-centred processes to design AI systems that learn and evolve. For example, Yang et al. (2020) investigated why systems that learn and evolve are more difficult than conventional ones to design by mapping different human-AI interaction design challenges onto user-centred design processes. Similarly, Xu (2019) proposed a HAI framework for developing more effective AI tools based on new challenges for usable and useful systems, which Olsson and Väänänen (2021) extended with their 4P model of AI design to describe the expected dynamics in UX design practices, as a baseline for new design processes.

Like most of this reported work, Xu's (Xu, 2019) framework assumed that AI tools use black-box machine learning systems with neural networks for pattern recognition in deep learning systems that require capabilities to explain reasons for outputs to users. Indeed, Yang et al. (2020) highlighted an absence of a common definition of AI from the research discourse around human-AI interaction. Their review revealed a range of poorly-defined terms such as machine learning, intelligent and AI-infused systems, which led them to propose an AI design complexity map defining four levels of AI system. According to this map, simple probabilistic systems at level-1 exploit self-contained datasets to produce a small, fixed set of outputs, whereas evolving adaptive systems at level-4 learn from new data even after deployment, to produce adaptive, open-ended outputs that resist abstraction. All four of these levels assumed the use of black-box machine learning algorithms that need to explain their outcomes to end-users – an approach that so far has met with only limited success (e.g., Dosilovic et al. 2018). By contrast, other types of AI system that can deliver explanations to users, for example, rule-based expert systems, continue to be effective and deliver valuable outcomes in domains such as medical billing (Abdullah et al., 2017) and e-government (Hossain et al., 2015). These types of AI systems could be considered within the remit of HCAI and co-creative AI tools, and enable the more human-centred approaches required for more explainable AI, as outlined in Ehsan et al. (2021).

2.2 | Established creative processes and types of outcomes

Numerous creative thinking processes and techniques now exist to guide individuals and groups to generate creative outcomes. Many can be traced back to the creative solving processes reported by Osborn (1953), Gordon (1960), de Bono (2007) and the TRIZ method for structured creative problem solving (Altshuller, 1999). These processes and methods have resulted in a large number of structured creative thinking techniques (e.g., Michalko, 2006) that have been applied successfully to solve problems by guiding humans to generate different levels of creative outcome.

Kaufman and Beghetto (2009) defined four different types of creative outcome that enable us to distinguish between different levels of creative outcome resulting from the use of structured creative thinking techniques. *Big-C* creativity is eminent, relatively rare contributions to society, and *Pro-C* creativity exhibits professional-level expertise that can be applied to earn a living, sometimes in non-creative fields, but does not produce *Big-C* outcomes. By contrast, *Mini-C* creativity outcomes are novel and personally meaningful interpretations of people's experiences, actions and events, and *Little-c* creativity is an everyday but novel outcome not often perceived to be creative in society.

We assert that, in elite sports coaching, the use of creative thinking techniques can result in not only *Pro-C* creativity outcomes using professional coaching expertise, but also *Mini-C* creativity outcomes, for example, in the form of professional learning by individual coaches, and *Little-c* creativity outcomes that change, for example, a training practice or athlete diet in ways that were new and valuable to an individual athlete. There is considerable potential for new uses of creative processes, techniques and tools.

2.3 | Digital creativity support and co-creative AI tools

Digital creativity support tools have been the subject of research and development for 30 years, and been applied in different forms to diverse artistic, scientific and professional domains. Most of the tools have supported the generation of *Pro-C* and *Little-c* creative outcomes, were interactive, and used different forms of interaction (e.g., visualizations) to help people be more creative. One early system was *Dynamic HomeFinder*, a prototype for real-estate agents that used dynamic queries that allow users to adjust the cost, number of bedrooms, and locations (Williamson & Shneiderman, 1992). *CombinFormation* was a mixed-initiative system that integrated searching, browsing and exploring information, to support creative thinking (Kerne et al., 2008). *TweetBubble* was a browser extension to Twitter that enabled the expansion of social media associations in usernames and hash-tags in-context, and supported exploratory browsing on top of metadata type system with new presentation semantics (Jain et al., 2015). Other tools were developed to support creative thinking in science and engineering, for example, new tabletop visualizations to support biological discoveries (Wu et al., 2011) and social media to support collaborative creativity in education (Aragon et al., 2009). Researchers have also investigated how existing technologies such as social media platforms afforded collaborative creativity in creative domains (e.g., Díez et al., 2014; Lee et al., 2014).

The number of digital creativity support tools for use by professionals in work domains has been growing, and some have been implemented in creative industries. Examples include *StoryCrate*, a collaborative editing tool developed to drive users' creative workflows within a location-based television production environment (Bartindale et al., 2013), *Trigger Shift*, which appropriated information technologies into performance art in theatre (Honauer & Hornecker, 2015) and *Crowdboard*, which allowed online crowds to provide real-time creative input during early-stage design activities such as brainstorming and concept mapping (Andolina et al., 2017). Other tools supported collaborative creative tasks during early design activities, as reported in (Chan et al., 2017; Huang & Quinn, 2017; Schnädelbach et al., 2016).

By contrast, developments for the non-creative industries have been rarer. For example, studies had investigated the effectiveness of the *Risk Hunting app*, which supported creative thinking to resolve health-and-safety risks in manufacturing (Maiden et al., 2017), and *Carer*, a smartphone app that supported professional care workers to think creatively about how to manage the challenging behaviours of older people with dementia (Zachos et al., 2013). However, long-term evaluations of these tools with experts in professional workplaces remain scarce, consistent with the limitations reported in Remy et al. (2020).

While earlier generations of digital creativity support tools relied primarily on interactive techniques to encourage human creativity, more recent co-creative AI tools deploy different forms of machine reasoning. As reported earlier, for example, *Calliope* deployed generative design algorithms to search large possible design spaces (Davis et al., 2021), and *Shelley* implemented deep-learning algorithms to generate horror stories (Yanardag et al., 2021). Elsewhere, Karimi et al. (2019) reported a co-creative design system that used a computational model of conceptual shift based on clustering of deep features from a database of sketches, and the *JECT.AI* tool implemented creative search algorithms to retrieve news content that journalists could use to discover new angles on stories (Maiden, Zachos, Brown, et al., 2020). Long et al. (2021) reported different interactive museum exhibits to support creative thinking when learning about different forms of AI technologies. So far, however, advances in co-creative AI tools are limited, as demonstrated by the recent set of principles with which to design explainable computational creativity tools (Llano et al., 2020). Furthermore, there has been no application of digital creativity support or co-creative AI tools in professional sports.

2.4 | Reports of creative thinking in elite sports

The need for creativity in elite athlete performance is established. For example, developing more creative players was central to a vision for the future of English football (Football Association, 2013), and increased team creativity was associated with goal scoring and progressing to later rounds of elite football tournaments (Kempf & Memmert, 2018). Some research has sought to foster the creative capabilities in athletes in different sports. For example, Memmert (2007) proposed method principles for tactical creativity approaches for team sports – principles such as deliberate practice, memory and diversification. He argued for the use of these method principles to train divergent thinking abilities, tactical creativity and creative thinking to children and young people who were engaged in sports (Memmert, 2015). Evidence of the effectiveness of the use of these principles in studies revealed that, for example, training in attention-broadening techniques over 6 months facilitated greater improvements in creative performance in complex team sports tasks than in simple tasks (Memmert, 2007). In a similar vein, Rasmussen et al. (2019) conceptualized creativity as a developmental resource in sport training activities. Creativity was framed as the exploratory and playful processes of discovering, exploiting and originating unusual action possibilities, which led to stimulation of creative actions during training. A common characteristic of most of this reported research was its focus on increasing the creative capabilities of athletes, rather than their coaches.

By contrast, reports of creative thinking during professional coaching have been scarce. There have been no reports of digital tools that support the usage scenarios outlined in the introduction of this paper. UK Sport did adopt creative thinking methods based on rapid trial-and-error of ideas to search for novel ideas to have a positive impact on medals for the Great Britain and Northern Ireland team at the 2012 Olympic/Paralympic Games (Hunter, 2010). However, the use of these methods conflicted with the established values of evidence-based science from clinical practices that underpinned elite sports coaching. The CPS creative thinking process (Isaksen et al., 2011) was also used by 45 strength-and-conditioning coaches at the English Institute of Sport after the Rio 2016 Olympic Games to resolve everyday coaching challenges (Wolf, 2017). However, few other reports exist, and this absence revealed an opportunity – one that was explored by the design research reported in this article.

2.5 | Data-centric technologies in the sports sciences

Research in the sport sciences has developed new analytic capabilities based on AI algorithms that analyse large datasets in sports such as professional football (e.g., Herberger & Litke, 2021) and swimming (e.g., Costa et al., 2021). Technologies used in elite athlete coaching included force-time curve analysis of athletic movements such as countermovement jumps, isometric joint position holds and sidestep changes of direction (Millett et al., 2018), and GPS tracking of athletes in training and competition to profile running intensities, accelerations and decelerations. Although numerous algorithms to support sense making from this data have been developed (e.g., De Silva et al., 2018), few of them support explicit creative thinking. One exception is self-tracking data as art to offer an alternative view on the concept of the quantified self (O'Neill, 2019), and builds on a four-stage model of artistic creativity (Mace & Ward, 2019) that was demonstrated using artworks constructed from self-data during cycling.

2.6 | An opportunity: Engineering a new co-creative AI tool in elite sports coaching

This review confirmed the limitations of digital creativity support research identified in Remy et al. (2020). There are relatively few reports of the long-term use of digital creativity support tools by expert practitioners in professional domains. Moreover, there were no reports of design guidelines for co-creative AI tools that operationalize Shneiderman's fresh ideas for HCAI. Elite sports and athlete coaching is one professional domain that requires creative thinking, but little progress has been reported, and elite sports organizations have been seeking new solutions to encourage creative thinking by professional coaches about elite athletes.

Therefore, new design science research was undertaken to design, implement and evaluate a new co-creative AI tool to support the coaches of elite athletes to undertake the usage scenarios by coaching practitioners reported in the introduction to this paper. To inform this design science approach, the team drew on an existing set of HCAI guidelines that had evolved to provide a more principled approach to designing co-creative AI tools. This set of guidelines is summarized in the next section.

3 | HCAI GUIDELINES FOR DESIGNING CO-CREATIVE AI TOOLS

The HCAI guidelines described features of co-creative AI tools with the potential to deliver high levels of automation and high levels of human control, and to empower people in their work during creative processes. In previous research the guidelines had been structured according to the Warr and O'Neill (2005) synopsis of the four stages of most creative processes – stages that generalize across domains: (1) *analysis of the problem*, which included preparing, fact-finding and collecting relevant information; (2) *generating ideas*, which included incubation, illumination, idea finding and generating responses; (3) *evaluating* ideas that are generated and; (4) *donating* or sharing the generated ideas for others to use and build on. Earlier versions of the guidelines had been extracted from analyses of existing digital creativity support tools, then refined through experimentation by the authors during experimentation with their own tools (e.g., Maiden, Zachos, Brown, et al., 2020; Maiden, Zachos, & Lockerbie, 2020). The guidelines had been developed by a core team of three researchers over a 3-year period.

TABLE 1 The seven HCAI guidelines to support the creative process stage: *Analysis of the problem*

Purpose	Name	Capability	Citations of examples
High levels of automation	Sensemaking	Automated sense-making from natural language and other descriptions of a problem	Bevilacqua et al. (2021)
High levels of automation	Extracting	Automated extraction of challenges and topics and their relative importance from natural language and other descriptions of a problem	Maiden, Zachos, and Lockerbie (2020)
High levels of automation	Discovering	Automated discovery of information content related to a problem from the internet and other digital repositories	Maiden, Zachos, Brown, et al. (2020)
High levels of human control	Marking-up	Capabilities to allow a user to input, select and/or markup all discovered information content	Kerne et al. (2008)
High levels of human control	Choosing	Capabilities to allow a user to choose between automatically discovered challenges and topics	Remy et al. (2021)
High levels of human control	Directing	Capabilities to allow a user to direct different automated processes using strategies expressed in user rather than machine terms	Williamson and Shneiderman (1992)
High levels of human control	Pivoting	Capabilities to allow a user to revise their problem in terms of ideas generated for this topic	Hery and Drew (2019) Kerne et al. (2008)

A total of 21 guidelines were available to design the *Sport Sparks* tool. Most were applied to the design of the first two creative stages – (1) *analysis of the problem*, and; (2) *generating ideas*. Table 1 summarizes seven guidelines that supported the *analysis of the problem* stage. The guidelines were *Sensemaking*, *Extracting*, *Discovering*, *Marking-up*, *Choosing*, *Directing* and *Pivoting*. For example, *Sensemaking* and *Extracting* had been implemented previously in the *Risk Hunting App* (Maiden, Zachos, & Lockerbie, 2020) to extract semantic concepts automatically from risk descriptions entered by production line workers, and *Pivoting* had been implemented in the *CombinFormation* tool to allow its users to select discovered information to redirect automated information searches in real-time (Kerne et al., 2008).

Table 2 summarizes five guidelines that supported the *generating ideas* stage. The guidelines were *Generating*, *Prompting*, *Focusing*, *Creating* and *Filtering*. For example, *Creating* had been implemented in the *CrowdBoard* tool by providing a white canvas where users could draw and erase digital post-it notes freely using IR-pens and barcode-based erasers (Andolina et al., 2017).

The equivalent guidelines to support the evaluating ideas and the idea sharing stages are summarized in Table form in Appendix A.

The next section describes how five of the guidelines – *Choosing*, *Discovering*, *Directing*, *Generating* and *Focusing* – were applied to co-design the new co-creative AI tool. These guidelines were perceived to be more impactful because each could be applied to design the essential features required to analyse the problem – the athlete challenge – and to generate new ideas with which to solve the problem.

4 | DESIGNING A CO-CREATIVE AI TOOL FOR ELITE ATHLETE COACHING

Therefore, new research was undertaken to design a new co-creative AI tool that would support coaching practitioners to enter text describing athlete challenges, explore new ideas to overcome these challenges generated by the tool, then manipulate these ideas to form an action plan for athletes. The research followed a design science approach – one that sought to design and investigate artefacts that interact in and with a problem context, to improve something in that context (Wieringa, 2014). The authors researched and co-designed a new version of an artefact to interact with – the *Sport Sparks* co-creative AI tool – that they analysed in the context of use at an English Premier League football club, to investigate whether it had the potential to improve the creative thinking of some of the coaching staff. The tool was developed by interleaving the co-design of interactive features with the engineering of knowledge manipulated by the tool's machine reasoning mechanisms.

4.1 | Co-designing a powerful application for coaches

Previously the authors had developed and collected coach feedback on a first proof-of-concept of the *Sport Sparks* tool. This simple digital prototype presented a web-page that enabled a coach to enter a text description of an athlete challenge. When the coach requested it to, the protoype automatically extracted topics of interest from the entered text, and used these topics as the focus for new ideas to overcome the challenge. For example, if the challenge description made reference to topics such as *fitness* and *diet*, the protoype automatically generated and presented ideas about *fitness* and *diet* such as *making the fitness more transparent* and *combining the diet with something else* (Maiden et al., 2021). The coach could then print these ideas, but the prototype did not provide either user accounts or persistence beyond a single transaction. Although the prototype's machine reasoning manipulated first versions of codified knowledge elicited from experienced coaches, there was no application of the principles or guidelines presented in the previous section. However, first feedback from more than half of the 22 professional coaches from six sports who used the prototype revealed that it changed their perspectives and influenced their decision-making about their entered challenge. Therefore, this proof-of-concept provided the foundation for engineering a new version of the *Sport Sparks* tool.

First, the author team undertook a collaborative co-design process with key stakeholders – namely the head and selected coaches at the football club's academy. Requirements collated from interviews with stakeholders led to the development of three design scenarios that described

TABLE 2 The five HCAI guidelines to support the creative process stage: *Generating ideas*

Purpose	Name	Capability	Citations of examples
High levels of automation	Generating	Automated generation of partial and/or complete ideas or content with which generate ideas	Maiden, Zachos, and Lockerbie (2020)
High levels of automation	Prompting	Automatic re-expression of incomplete ideas in forms that can encourage the user to develop and complete ideas	Lockerbie and Maiden (2016)
High levels of human control	Focusing	Capabilities to allow a user to select and apply alternative processes for the automated generation of ideas	Maiden, Zachos, and Lockerbie (2020)
High levels of human control	Creating	Capabilities to allow a user to generate and document new ideas more quickly than could be done manually	Andolina et al. (2017)
High levels of human control	Filtering	Capabilities to allow a user to edit and reject existing ideas quickly	Jenkin et al. (2011)

how these coaches wanted to use *Sport Sparks* and maximize high levels of both automation and human control. The first described how an individual coach should use *Sport Sparks* to explore one player's challenge, while the second and third described how groups of coaches should use it to explore individual and recurring challenges. The first scenario described how a coach should be able to enter the text description of the athlete challenge, explore and collect automatically generated ideas in an ideas space, and select one of these ideas as the starting point to explore the challenge again. The other scenarios extended this first one by describing how the coach could select fellow coaches to share both challenges and other ideas with, and visualize their ideas as a simple mindmaps. Interactive mock-ups of a tool design that implemented the first scenario received regular feedback from the head of the academy.

The mock-ups incorporated features described in different guidelines. For example, the high automation *Discovering* guideline led to a feature that used the text that was entered to describe the athlete challenge to retrieve research papers automatically from sports science journals, and the high human control *Directing* guideline led to the design of interactive tabs that gave the coach control over which types of machine-generated ideas to explore at any moment (e.g., ideas with which to solve the challenge or to reimagine it). The types of machine-generated ideas included ideas related to the entered challenge, solutions that might solve the challenge, and constraints to either remove and/or reimagine to open up new conceptual spaces of potential ideas.

The mock-up then evolved into an increasing sophisticated interactive prototype. During this process, other guidelines were applied. For example., the high human control *Choosing* guideline led to a feature that gave coaches control over which ideas to select to include in a solution. Likewise, the high automation *Prompting* guideline led to a feature that transformed automatically-generated potential ideas, expressed as questions, into incomplete how-to statements that coaches could instantiate and complete more effectively.

4.2 | The machine reasoning approach

In parallel, the *Sport Sparks* tool was engineered to deliver high levels of automation needed to extend the coaches' current creative abilities. Different machine reasoning approaches were explored. Data-centric approaches using machine learning were rejected because the football club lacked extensive quantitative data about athlete challenges and resolutions. The club also lacked the documented challenges needed to implement a case-based reasoning approach (e.g., Kolodner, 1993).

Instead, the *Sport Sparks* tool was engineered to combine different forms of rule-based reasoning to deliver the planned high automation. Rule-based expert systems continue to be applied to solve real-world problems, for example, to detect events during data pre-processing (Ramírez et al., 2021), personalize medical education (Quinn et al., 2017), and detect inconsistencies in domain engineering processes (Elfaki, 2016), as well as to deliver benefits in domains such as medical billing (Abdullah et al., 2017) and e-government (Hossain et al., 2015). A rule-based reasoning technique was selected to implement the *Generating* guideline and automate the generation of partial and/or complete coaching ideas. This technique also had the advantage of providing coaches with a comprehensible, predictable and controllable set of rules capable of boosting their cognitive creative thinking (Shneiderman, 2020).

Three different rulesets were engineered, to generate different ideas types corresponding to different tabs resulting from the co-design process: (1) rules to generate ideas about the player's problem challenge, (2) rules to generate ideas about possible solutions to the challenge and (3) rules to generate constraints to either remove and/or reimagine, to open up new conceptual spaces of potential ideas. Each ruleset was designed to be accessible to the coaches via the interactive tabs that implemented the *Directing* guideline and offered high human control over the machine reasoning.

4.3 | Engineering the conceptual spaces of potential ideas

To inform the design of the three rulesets, two facilitators from the Sport Sparks design team ran a 90-minute workshop with two senior coaches, each with more than a decade of elite coaching experience, to surface known good practices for resolving athlete challenges. To surface this knowledge systematically, the team applied the *SCAMPER* creative thinking technique (e.g., Michalko, 2006). The technique guided the coaches to report practices that substituted, combined, adapted, modified, purposed, eliminated and reversed challenges that the coaches experienced regularly in their coaching work, as well as the cause(s) of challenge resolved by each practice. The coaches recalled these regular challenges themselves during the workshop. Examples of the raw data generated in the workshop are depicted in Figure 1. Each practice and cause was documented on a separate post-it note. A total of 85 unique best practices linked to 11 different challenge causes were surfaced. Common challenges recalled by the coaches included *determining the total training load*, *the type of fitness required*, and *deciding the balance of short-term* versus *long-term gains*. Surfaced good practices included *using only one exercise*, *continuous training all day without breaks*, and *having the athlete write their own training plan*.

Each good practice was then categorized by the challenge cause(s). The causes that were identified were then grouped according to their association to one of four more coarse-grained types of problem challenge – *people*, *process*, *competition* and *environment*. These causes and types

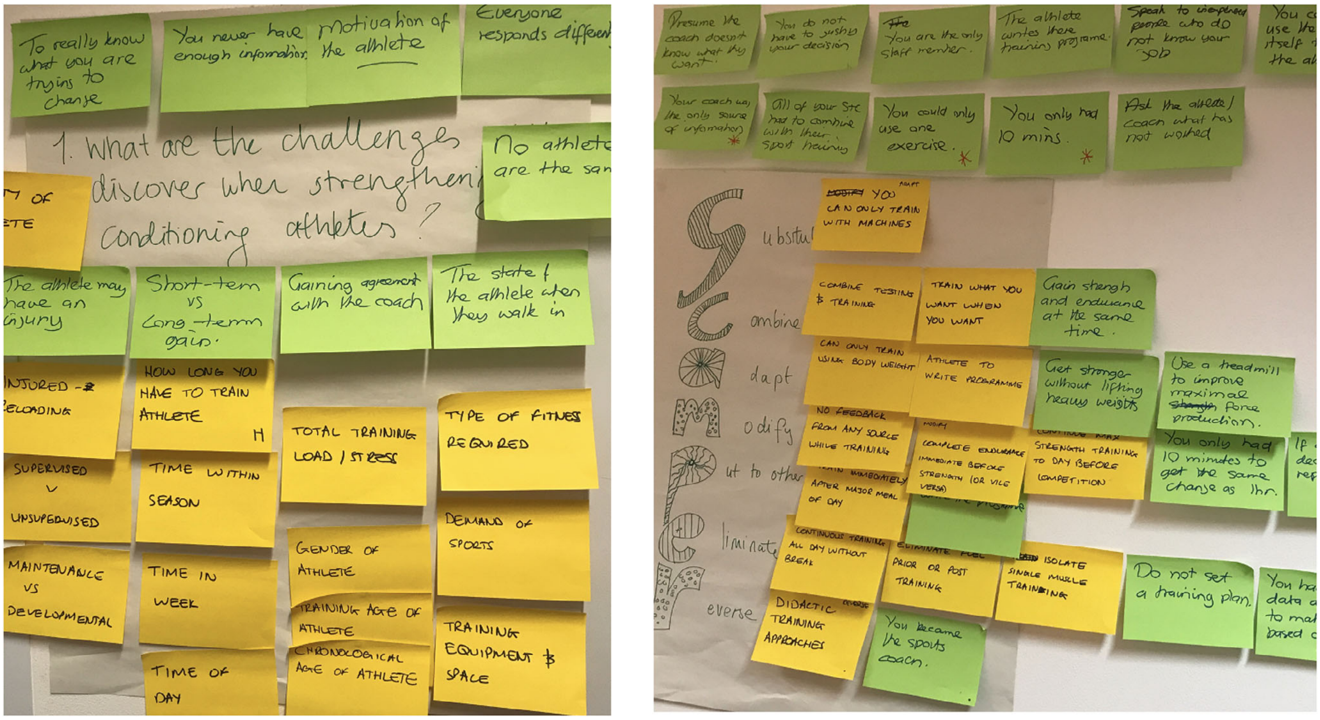

FIGURE 1 Examples of types of challenge surfaced during a 90-min workshop with two senior coaches

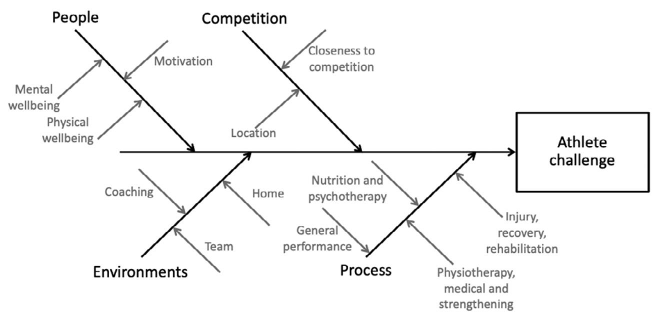

FIGURE 2 The Ishikawa diagram generated for the types of challenge, based on the 4Ps (Isaksen et al., 2011), and their causes, reported to be encountered by elite athletes in our research

were then mapped by one member of the design team onto an *Ishikawa* diagram. *Ishikawa* diagrams were developed originally to show the causes of events, often used in manufacturing and product development to demonstrate where issues might arise (Ishikawa, 1976). The authors used this type of diagram to structure the elicited coaching knowledge by challenge cause and develop the rulesets to implement the *Generating* guideline.

The diagram, shown in Figure 2, revealed that many of the contributing types of cause for non-optimal performance in training and competitions were not directly sports-related. Other causes related to the personal motivations of the athlete (e.g., *income to provide for family over competition success*), the coaching environment (e.g., *personality differences with the coach or other team members*), home life (e.g., *life styles* and *priorities*) and locations of competitions (e.g., *preferred climates*, and *cultures* and *distances to travel*). Each of the types of cause (e.g., *mental wellbeing*, *competition location*, *team environment* and *nutrition and physiotherapy*) was interpreted as a different conceptual space of potential ideas (Boden, 1990) with which to resolve challenges. Furthermore, following on from anecdotal reports of successful uses of the CPS method's 4Ps (Isaksen et al., 2011) by experienced coaches to investigate athlete's *person*, *process*, *product* and *press*, each of the 11 cause types was categorized using four coarse-grained types of problem challenge specialized to sports coaching – *people*, *process*, *competition* and *environment*, as also shown in Figure 2. This diversity of types of cause was consistent with the increasing recognition for the need to coach more holistically as a complex social process and involve a myriad of interacting variables (Jones & Turner, 2006). Although our machine reasoning approach did not support problem-based learning per se, it was developed to direct coaches to explore athlete challenges from diverse perspectives.

4.4 | Engineering the rules to generate potential ideas about challenge problems

Next, to implement the *Generating* guideline in the *Sport Sparks* tool, the team engineered a set of rules to generate possible ideas about challenge causes based on the structure shown in Figure 2. These rules were designed to generate ideas automatically about both more general problem causes (e.g., the *competition*) and more specific ones (e.g., the *competition location*). The intention was to generate ideas that might encourage exploratory creativity, that is, explore a defined conceptual space more efficiently than without the rules (Boden, 1990). A total of 58 rules were specified. Each rule was composed of a unique ID that was accessible to the coaches, parameters to instantiate with content from the entered athlete challenges, a natural language expression, and the precondition conceptual space(s) for which the rule was instantiated. A small subset of these rules are listed in Table 3. An example of one generated potential idea presented by *Sport Sparks* presented to coaches for the extracted topic *U17 player* was '*How might we utilize the emotional state of the U17 player?*'

4.5 | Engineering the rules to generate potential ideas about challenge solutions

An equivalent set of *Generating* rules was developed to encourage coach's exploratory creative thinking about different possible conceptual spaces of possible of ideas to solve challenges. Each surfaced best practice was engineered as a discrete rule to be processed by *Sport Sparks* algorithms. A total of 36 rules were specified. Each of these rules was simpler than the previous ruleset, and specified a unique ID visible to the coaches and a natural language expression. Another small subset of these rules is listed in Table 4. An example of one generated potential idea presented to coaches by *Sport Sparks* for the extracted topic *U17 player* was '*How might we change the fitness of the U17 player by imagining other types of sport?*

Furthermore, some of the interviewed coaches reported using non-sports creative thinking apps to help to generate ideas. In response, the coaches were asked to explore the potential of informal heuristics for creative thinking from the *TRIZ* method (Altshuller, 1999) to think creatively about coaching challenges. Examples of these heuristics included '*Think about how to make it do more or less,*' and '*Think about how to make it do different things.*' Each heuristic was presented on a separate physical card, and the coaches were asked to select cards that had the potential to stimulate creative ideas for athlete coaching. The coaches agreed a set of 63 heuristics with potential, and from these a further 26 *Generating* rules were engineered based on these heuristics. Again each rule specified a unique ID and a natural language expression. A small subset of these rules is listed in Table 5. An example of one generated potential idea presented to coaches by *Sport Sparks* was '*How might we improve the fitness of the player by being more transparent?*'

The full sets of the codified rules engineered for use in the *Sport Sparks* tool are listed in Appendix B.

4.6 | Engineering the ideation generation rules

Before implementation in the *Sport Sparks* tool, each engineered *Generating* ruleset was prototyped using interactive Excel sheet macros to experiment with and elicit feedback on different forms of rule output. Each output was presented as a natural language sentence, which coaches had

TABLE 3 Five codified rules that operationalized the *generating* guideline in the *sport Sparks* tool, to generate potential ideas about challenge problems automatically

ID	Rules generating ideas about challenge causes	Conceptual space(s)
Person-A	The location of the (extracted athlete)	People
Person1	The physical state of the (extracted athlete)	People
Person3	The emotional state of the (extracted athlete)	People
Person19	The personal ambitions of the (extracted athlete)	People
Person25	The self-awareness of the weaknesses of (extracted athlete)	People

TABLE 4 Five codified rules that operationalized the *generating* guideline in the *sport Sparks* tool, to generate potential ideas about challenge solutions automatically

ID	Rules generating ideas about coaching best practices
Spark40	By combining strength and endurance training
Spark46	By making the trainer the only source of information
Spark51	By achieving the same result in less time
Spark56	By following our intuition
Spark63	By imagining other types of sport

reported was easier to understand than graphical representations of ideas. A design decision to present potential ideas as instructions (e.g., '*Think about how to…*') was changed in light of coach feedback to present them as idea questions (e.g., '*How might we…*'). Furthermore, the set of different question verbs (e.g., '*change*,' '*improve*' and '*utilize*') was reduced, and the structure was modified to improve readability. The modified *Generating* rulesets were implemented in the first working version of the *Sport Sparks* tool described in the next section.

5 | THE SPORT SPARKS TOOL

The new version of the *Sport Sparks* tool was implemented as a responsive web application with a three-tier architecture: (1) the web application that enabled *Sport Sparks* to be used on different devices; (2) a data layer of codified *Generating* rulesets and (3) an application layer of software algorithms to generate candidate ideas and constraints using the rules in these rulesets. The tool was designed to support a coach to describe an athlete's challenge, explore new ideas about it, then refine these ideas to generate and document possible solutions to the challenge. The tool was implemented with user accounts and report generation features. It was then usability-tested and made available to coaches. The next sections describe how coaches were intended to interact with features that implemented the guidelines introduced earlier.

5.1 | The coach describes the athlete's challenge

The *Sport Sparks* tool allowed a coach to describe one or more athlete challenges using natural language phrases and one or more selected challenge types. The challenge types to select (e.g., *nutrition and psychotherapy*, and *coaching environment*) were derived from the Ishikawa diagram shown in Figure 2. Each type defined a different conceptual space of potential ideas to explore.

The *Sport Sparks* page for describing the athlete's challenge is depicted in Figure 3 – in this example the coach has entered the challenge *the U23 player struggles to maintain fitness throughout the match, and has to be substituted in most matches*, and tagged it with the challenge type *General performance issue*. To maximize automation, the tool implemented shallow natural language parsing algorithms to extract noun and verb terms

TABLE 5 Five codified rules that operationalized the *generating* guideline in the *sport Sparks* tool to generate potential ideas automatically about challenge solutions based on TRIZ heuristics

ID	Rules generating ideas about challenge solutions
Spark1	How to make it do more or less
Spark5	Make it do different things
Spark22	Make it more transparent
Spark34	Combine it with something else
Spark26	Make it smoother

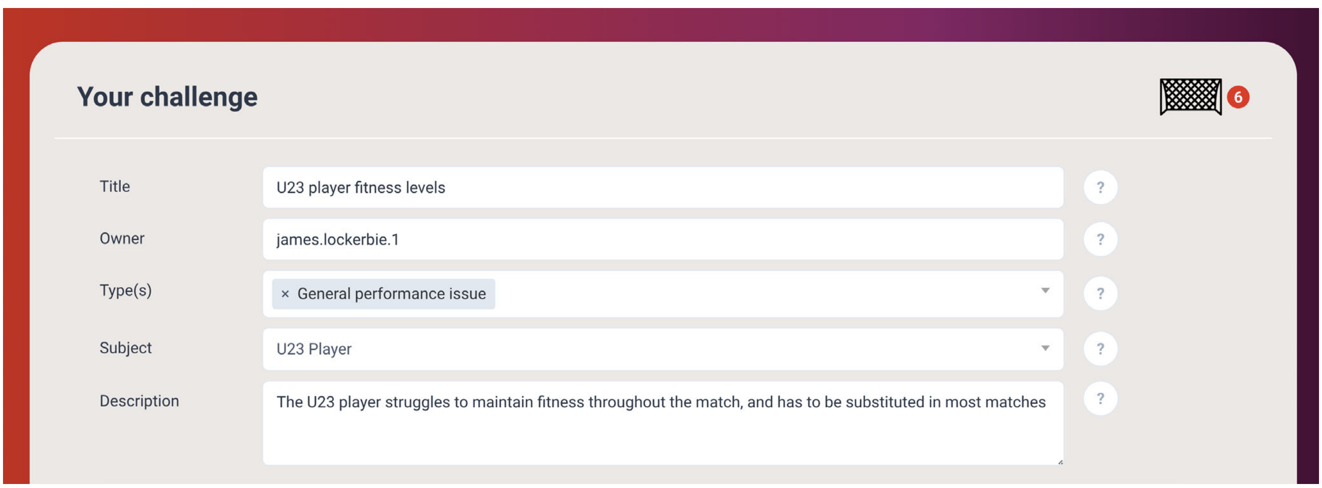

FIGURE 3 The *sport Sparks* page that a coach used to describe a new challenge

from the challenge description (the *Extracting* guideline), then disambiguated each term by discovering its correct sense (the *Sensemaking* guideline) according to the online lexicon at WordNet using context knowledge from other terms in the description (McCarthy et al., 2004; Stevenson & Wilks, 2001). For example, the term *match* was inferred to mean a *formal contest in which two or more persons or teams compete* rather than *a burning piece of wood or cardboard*. Therefore, the tool delivered high automation by returning an unordered set of stemmed noun and verb terms in the challenge descriptions without any coach involvement.

5.2 | Exploring ideas to solve the challenge

With the extracted nouns and verbs and the entered challenge type as inputs, *Sport Sparks* algorithms implementing the *Generating* guideline generated potential creative ideas automatically. Based on coach feedback, each algorithm was set to generate a batch of five candidate ideas at a time. One batch was composed of different constraints on the challenge, using the rules that engineered different conceptual spaces of potential ideas. A second was composed of potential ideas about the challenge solution, using the rules to generate ideas about challenge solutions. And a third was composed of potential ideas about the challenge problem, using the rules to generate ideas about challenge problems reported. Moreover, the algorithms generated different balances of constraints and ideas in each batch, for example, the batch of ideas about the challenge problem combined 3 more general ideas with 2 more concrete ones.

Each sentence was framed as a question (e.g., *How can we …?*) rather than an instruction (e.g., *Think about how to …*), again based on feedback from coaches. Each was structured to encourage the coach to think about the described actors (e.g., *the U23 player*), objects (e.g., *the match*) and activities (e.g., *substituting*) differently. For example, ideas related to the example player's fitness challenge included *How can we change the immediate activities of the U23 player?* and *How might we change the different coaching styles offered to the U23 player?* Example ideas about possible solutions included *How could we focus on the fitness of the U23 player by making other uses of nutrition?* and *How might we utilize the match of the U23 player by speeding things up?* By contrast, the generated constraints were designed to increase the size of the conceptual space of possible ideas, for example, *Imagine working around the limitations of the match. Visualize this alternative scenario. What alternative ideas can you realize?*

At any time during a session, coaches were able to use interactive tabs to switch between potential constraints to challenge, ideas about the challenge problem and ideas about the challenge solution (i.e., the *Directing* guideline). These interactive tabs are shown in Figure 4. Each switch generated new content for the current tab (e.g., a new batch of potential ideas about the challenge problem), to implement the *Choosing* guideline, but left content on other tabs (e.g., potential ideas about the challenge solution) unchanged, for coaches to return to later. Furthermore at any time, coaches could click each potential idea and constraint to add the idea automatically to an ideas basket (the *Creating* guideline).

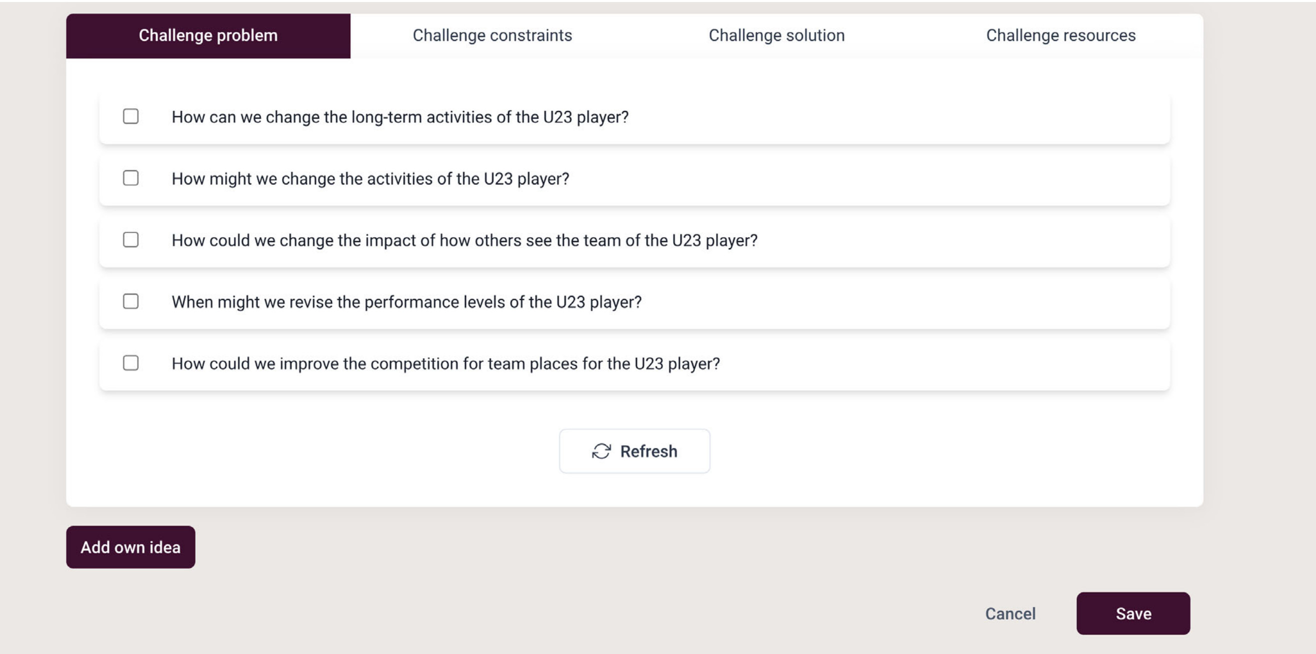

FIGURE 4 Different interactive tabs in the *sport Sparks* tool, to provide coaches with a degree of control over creative thinking about an entered challenge. The selected tab shows five machine-generated potential ideas about the challenge problem

5.3 | Exploring published research papers

A fourth interactive tab presented information about published research papers related to the coach's challenge, to implement the *Discovering* guideline. The stemmed noun and verb terms extracted from the challenge description were also input automatically to a Google Scholar API that retrieved the titles and source URLs for up to five close-matching research papers. These machine-generated Google Scholar queries offered a high automation solution to existing uses of the Google Scholar website by coaches. The tab listed each paper as a hyperlink that coaches could click on to access that paper at its publication source. As with the constraints and ideas, coaches could add each paper to the ideas basket for further use by clicking on the box next to the title (the *Creating* guideline).

5.4 | The ideas basket

The *Sport Sparks* tool collected all user-selected constraints, potential ideas, research papers and user-added ideas in one digital area, called the ideas basket. An example of how a coach interacted with the basket is shown in Figure 5. The basket enabled coaches to evaluate content prior to generating possible resolutions to challenges, consistent with the *Managing* guideline. All basketed ideas were automatically transformed from questions into incomplete idea statements for coaches to complete, consistent with the *Prompting* guideline. For example, the potential idea was transformed from the question '*How can we revise the performance levels of the U23 player?*' to the statement '*We can revise the performance levels of the U23 player by …*' The basket also enabled coaches to drag the constraints, ideas and paper sources into a prioritized list, to provide more focus for problem-solving. Coaches could also add new ideas of their own using freeform textboxes, and edit and delete ideas using one click (the *Filtering* guideline).

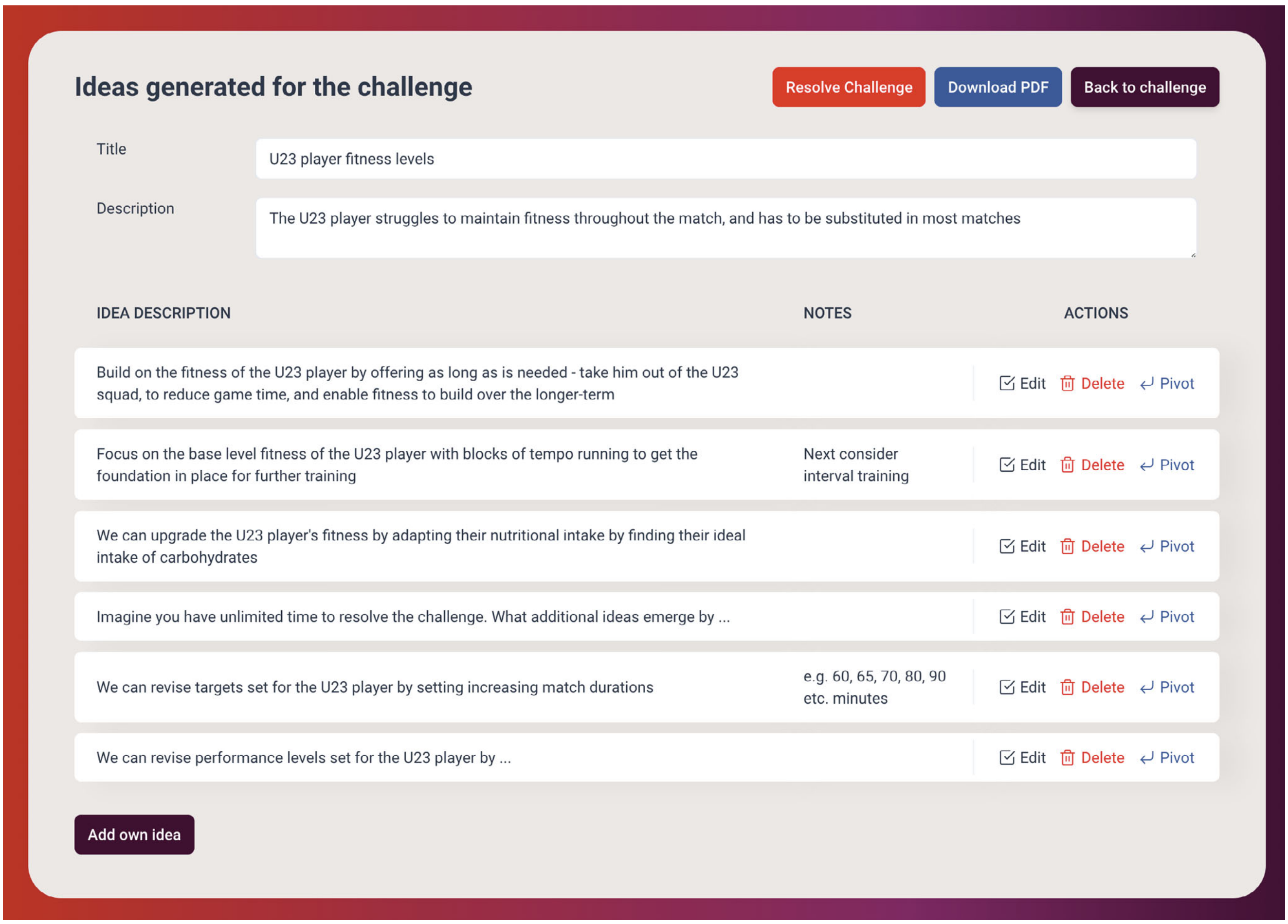

FIGURE 5 The ideas basket in the *sport Sparks* tool

Furthermore, interactive guidelines enabled coaches to refine ideas into more concrete plans of action, and supplement the refined idea with notes, as shown in Figure 6.

6 | EVALUATING THE *SPORT SPARKS* TOOL IN CONTEXT

The next stage of the design science approach was to investigate how the artefact – the new version of *Sport Sparks*– interacted with the problem context, for example, a professional football club and improved something in it, which was creative thinking by elite coaches. The *Sport Sparks* tool was made available to 10 professional coaching practitioners working with footballers at an English Premier League football club. These practitioners, all males, fulfilled different roles in the club. Seven were coaches, two were physiotherapists, and the tenth was head of the club's academy. All but one was educated to degree level in subjects related to their roles, such as sports science and physiotherapy. One of the practitioners also had a PhD and a second was studying for a research degree. All of the practitioners had a minimum of 3 years of professional coaching experience. The most experienced had 20 years of coaching experience in different professional football clubs.

6.1 | Evaluation method

At the start of the evaluation the 10 practitioners took part in one face-to-face workshop that lasted 2 h during which a facilitator – an experienced sports coach – presented a process for creative thinking that guided the practitioners, working in pairs, to undertake a number of paper-based exercises to resolve coaching challenges. This process followed the creative thinking process steps supported by the *Sport Sparks* tool, and the exercises used physical cards with simplified versions of implemented *Sport Sparks* rules (e.g., *How can we build on the personal ambitions of the person?*). The practitioners were then asked to evolve the ideas generated during these steps into an action plan to resolve the challenge. The tool recorded all challenge, idea and action plan information added to it, as well as the date and time that additions occurred. Afterwards, all of the practitioners were given access to the *Sport Sparks* tool via their own user accounts, and the facilitator walked throughout the equivalent interactive features at each step of the process.

After the workshops, the practitioners were provided with access to the *Sport Sparks* tool for 10 weeks across the first 3 months of the English football season, from August to October 2021. Again, the tool recorded all added challenge, idea and action plan information and the date and time that additions occurred. Each coach was asked use the tool on a minimum of six different occasions over the period of 7–8 weeks. During this period, each practitioner was able to contact one of the researchers to request guidance and report issues. The practitioners were also requested to participate in two short telephone interviews with one researcher, the first 3 weeks after the workshop and the second a further 2 or 3 weeks after that, to describe their uses of the tool and any impact of this use on their coaching. Interview topics included the frequency of tool use, where and how the tool was used, any challenges entered, any standout ideas that were generated, and how the tool informed or impeded practitioner thinking about coaching work.

At the end of the period, the researcher conducted one longer, semi-structured exit interview with each practitioner. Interview themes included practitioner experiences with the tool, the extent to which this use changed their coach thinking, examples of these changes, and barriers

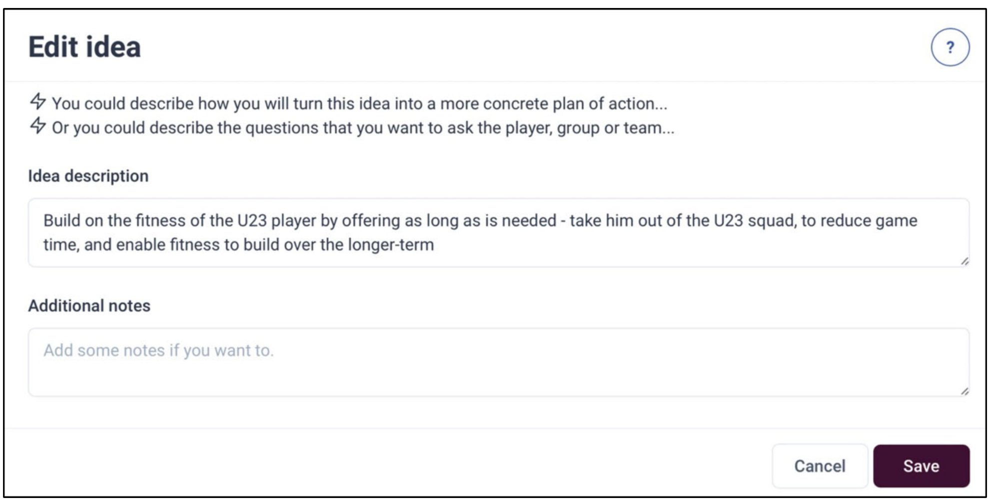

FIGURE 6 Guidance for editing and evolving ideas provided by the *sport Sparks* tool

to tool use. Interview topics included if and how tool use had informed the practitioners' understanding of coaching challenges, supported them to develop different views and change their decision-making, and what the practitioners learned from *Sport Sparks*. All interviews were undertaken remotely using Zoom, then recorded and transcribed to enable analysis. Because of the structured use of the same questions asked to all practitioners, responses were analysed thematically by question response.

Data collected during this evaluation process was analysed in order to answer three open-ended research questions that investigated the impact of tool's implementation of selected high automation and user control guidelines in the selected problem context – the football club:

RQ1: To what degree did the machine-computed sparks that implemented the high automation *Generating* guideline encourage practitioner creative thinking?

RQ2: To what degree did the machine-retrieved research papers that implemented the high automation *Discovering* guideline encourage practitioner creative thinking?

RQ3: To what extent did the interactive tabs linked to the tool's implementation of the high human control *Choosing*, *Directing* and *Focusing* guidelines encourage practitioner creative thinking?

6.2 | Evaluation results

During the evaluation period, all 10 practitioners used the *Sport Sparks* tool to investigate coaching challenges. Some used the tool more than others, and the exit interviews revealed some reasons for this. For example, one practitioner was new to his role in the club and still learning new practices, whilst another reported that *Sport Sparks* was too time-consuming to use during his daily work.

Nonetheless, a total of 18 different challenges were documented, and all 10 practitioners described challenges and documented ideas based on the machine-computed potential ideas. Two examples of these challenge descriptions were '*How to improve the Under 15 group of players' intent and execution of physical development tasks during training sessions*,' and '*An U18 Player asking for strategies to reduce tiredness from week-to-week. No reporting of lack of sleep, nutrition and diet is balanced, player undergoes recovery processes post-exercise to promote healing and reduce fatigue, however the problem still presents itself*.' The challenges were between 16 and 88 words in length. A content analysis of their descriptions revealed that: all 18 described the type of player that was the focus of the challenge (e.g., U18 player); 14 described a challenge faced by the player, and 13 described a desired outcome. By contrast, only two challenges described possible ways to achieve the outcome, only one was phrased as an open question, and another eight also described some related contextual information.

New ideas were documented in *Sport Sparks* for all but three of the challenges. The median number of ideas generated per challenge was 5, and the highest was 14. Most documented ideas were still incomplete, and in their auto-generated form, for example, '*We can evolve the sleep of the U18 player by asking what other experts might recommend by …*', and '*We can evolve the U18 Player reporting of the U18 player by making some elements of it more adjustable by…*' Moreover, the tool recorded few concrete resolutions to the 18 entered challenges. The practitioners appeared to create new ideas to resolve challenges with the tool, but did not document their resolutions to these challenges with it. Indeed, most challenges and ideas were generated and documented in the tool over relatively short periods. Fourteen of the 18 challenges and ideas to resolve it were generated in less than 20 min, and another three were generated in 27, 31 and 35 min. Only one challenge was extended with new ideas much later – almost 24 h after its generation.

Unsurprisingly, the pressures of work in a Premier League football club led to practitioners not attending all of the scheduled interviews. Table 6 shows both workshop and interview attendance and use of key features by each coach, labelled A-J. Of the 10 practitioners, 3 did not attend any of the interviews, but all 10 entered at least 1 challenge and generated at least 1 idea using the *Sport Sparks* tool. More importantly, 6 of the 10 practitioners participated in the semi-structured exit interviews. These interviews lasted between 14 and 24 min each. Although the documented ideas were incomplete and the periods that the tool was used to generate ideas digitally, some of the practitioners recognized the value of the digital support for resolving challenges. For example, A reported that the tool '*helped to focus on the challenge – normal approach is to write things done on lots of bits of paper and then gather them together. This makes it difficult for others to understand where thinking and ideas have come from*.' E also reported other benefits arising from automation '*It has impacted my decision making because I've used and gone about problems in a certain way that I previously wouldn't have should I not use the tool. I guess I might have done with more time, but it definitely accelerated that process*.'

Feedback from the practitioners could be associated with the guidelines applied to design the related *Sport Sparks* features. Four of the six practitioners talked about defining the player challenges, using the tool's implementation of the *Sensemaking* and *Extracting* guidelines. For example, C reported '*Inputting of the info is quite a good feature. Keeping your problem quite concise can be a problem. I like that you can input in sentences what it is, and the AI will draw out the key words and phrases that will help you with an answer to the question*.' B added '*…this is the main focus and this where we should think around more than anything*.' Some practitioners reported the need to practice to maximize the tool's benefits. E stated '*The key is getting the description right in the first bit. It's a skill in itself for me anyway. To be able to get as much meaningful information out of the tool*,' and F said '*Initially it is constructing a better question and thinking about the words – take more time to formulate this for better answers*.' These comments revealed the importance of defining challenges with sufficient precision for the *Sport Sparks* tool to generate potential ideas perceived to be relevant.

TABLE 6 Practitioner participation in the different data collection activities, and their use of core *sport Sparks* tool features

Prac.	Workshop	Interview-1	Interview-2	Exit interview	Entered challenge(s)	Generated ideas
A	Yes	No	No	No	Yes	Yes
B	Yes	Yes	Yes	Yes	Yes	Yes
C	Yes	Yes	No	Yes	Yes	Yes
D	Yes	Yes	No	Yes	Yes	Yes
E	Yes	No	No	No	Yes	Yes
F	Yes	No	No	No	Yes	Yes
G	Yes	Yes	No	Yes	Yes	Yes
H	Yes	No	No	No	Yes	Yes
I	Yes	Yes	Yes	Yes	Yes	Yes
J	Yes	Yes	No	Yes	Yes	Yes

Three of the practitioners reported detailed feedback about the machine-computed potential ideas that implemented the *Generating* guideline. E was positive, and claimed that the sparks '*challenged my thinking to think a little bit wider with some things. I had narrowed it down in my head and put the blinkers on and I said its sort of this sort of problem as opposed to thinking about others ways I could approach the issue. It just probed my thinking a little bit and helped me to explore my thoughts before I hone in on those sorts of discussions and approach the actual issue itself. So, it was very helpful.*' He added '*At that point I usually try and take a breather. I review the number of sparks and refine the sparks a bit then I take a break from it and re-visit it a day later, or later that day in order to flesh out the sparks and start to look into it. Because I feel I like to take time away and reflect and think about those sorts of things before I dive straight into.*' B reported other advantages '*I think it gave some more clarity on stuff. Like this is the main focus and this where we should think around more than anything. I don't think it perhaps generated new ideas. It perhaps was 'I thought this was a direction we should be going in.*' However, F reported that the machine-computed ideas repeated after several refreshes '*I've found the ideas under the sections are repetitive. Some is the same thing that comes around or some it's the same just a different ordering,*' indicating possible limitations to the current rulesets. The same practitioner also struggled with the machine-computed constraints: '*I personally struggle with 'imagine you haven't got this problem…' for example, if working with under 12 s and it says imagine you are not working with under 12 s then I do struggle with that.*'

Two of the practitioners also reported value from the machine-retrieved research papers that implemented the *Discovering* guideline. C said '*In problem solving would normally looking for literature – with the app providing those resources for you is very helpful. That would be an immediate source to go online and find some journals or articles that have explored those issues. Not quite surrounding the problem you are after but could expand your thinking around your problem.*' Likewise, F claimed '*It's a bit of a rabbit hole, but the resources that come up are really good.*' No practitioner reported negative comments about the machine-retrieved research papers.

The importance of the interactive tabs, linked to the tool's implementation of the *Choosing*, *Directing* and *Focusing* guidelines was also reported. E said '*I liked the way it split up the sparks into those four sections. It's not always been relevant in all of those four sections but the majority of the time it is useful in at least three of those so it gives you more of a 360-degree view of a problem. Even if it's not entirely relevant, a spark isn't entirely relevant, it sort of probes your thinking.*'

Furthermore, tool features that implemented the *Filtering* and *Managing* guidelines received positive feedback. For example, B reported '*It's hard isn't it to get it into be more direct or specific to what you put in… I did like that filter or funnel. Really good idea,*' and E stated '*I ended up with lots of sparks as I was ticking, ticking, ticking, as I was 'oh that's relevant' and then I sort of tried to hone it in more as it would be overwhelming to go through 15 sparks. So, I tried to hone it down, prioritise into the top 5 or 3 most pertinent to me and then edit those and build on those thoughts.*'

However, the interviews also revealed two key capabilities missing from the *Sport Sparks* tool – support for solution planning and for collaborative problem solving. The need to support solution planning was highlighted by E, who said '*Challenge is still open as there will be other cases that require that so I wanted to try those action points that I've put into place following the tool to see of they worked.*' Most of the practitioners also expressed a desire for more collaboration when problem solving. E asked '*is there some way if someone has the same sort of issue or problem and they're coming at it form a different approach is there a way or mapping that or linking that especially if you are in the same organisation?*' and B referred to the earlier collaborative training workshop, stating '*I think that team working together, that team bouncing ideas off each other is probably where the best ideas come from. You haven't thought about that yourself then someone else comes from another point of view. By yourself you think one way and someone comes from a different, thinks differently from me. It generates those new ideas.*' C also referred back to the workshop '*I like to collaborate and ask questions to other people and form a discussion around the problems. The more minds you can involve the better. You can come up with a greater understanding or someone will input ideas you hadn't thought of. Going back to the workshop it was helpful to work with a partner as we did for those problems.*' D stressed that resolving challenges was a social process '*I like to see stuff and chat to other people about it – the back and forth. I sometimes don't find the right solutions because I don't spend the time to really sit there and deeply think about the problem and to write it down. So that's also a benefit that I'd make time for myself and actually use the app in that sort of way.*' The feedback revealed the need to support different forms of collaborative creative thinking by the practitioners about player challenges.

A more general issue that impacted on *Sport Sparks* use was the lack of time available in coaching environments. For example, A reported '*Needs to be in office and on laptop to do so. Time is a challenge for using it as not often behind computer and prefers to be working with clients and doing actions*,' and D stated '*In an elite sports environment, its hectic and to get the time and sit down. It's a bit time consuming to input your problem and then to make it more specific to really nail it down and get the benefit of the app it really takes time to sit and do that*.' These reports were consistent with the relatively short periods of active use of the tool to document challenges and ideas. Other practitioners reported requests to implement *Sport Sparks* for mobile devices. For example, B requested '*Whether you could get that into an app as an option for an iPad or phone. Something easy to do. Something you could do while on the move on the bus or train or something*.' That said, some practitioners also reported that using mobile devices during training sessions with players was frowned upon.

Finally, some of the more experienced practitioners were less prepared to use digital technologies. A reported '*I'm a bit of a technophobe I'm a bit of a dinosaur*,' and '*I don't like or want emails. I like having conversations with people I like to go and talk to the players, talk to the staff, try get a feel for them*.' He said '*Our [team] is quite mixed, so have a couple old guys in there, they're not really big on computers then we got couple of young guys that are quite big on the computer stuff*.' With regard to coaching issues '*we try and raise them in the meetings… we have a daily meeting so we have a pre training meeting where we will go through who's available for training any injuries, any issues. Instruct anyone who's coming back to training, what they're doing in the session*.' He concluded with '*Voice based note taking, that might be the best way for me*,' indicating possible extensions to an alternative mobile version of *Sport Sparks*.

6.3 | The research questions revisited

This first evaluation revealed that 10 professional coaching practitioners at a Premier League football club used the new version of the *Sport Sparks* tool. All documented challenges in the tool and used machine-computed potential ideas to think about how to resolve these challenges. However, *Sport Sparks* was used periodically rather than regularly, over relatively short periods to document challenges and ideas to resolve them, and it was not used to document concrete the resolutions to the challenges, perhaps because of the limited support for solution planning reported in the exit interviews. Nonetheless, the exit interviews provided clear evidence that *Sport Sparks* use influenced the thinking of at least some of the practitioners when resolving challenges. These results enabled us to offer preliminary answers to the three research questions:

RQ1: The exit interviews revealed that the machine-computed potential ideas that implemented the *Generating* guideline encouraged creative thinking by at least some of the club's professional coaching practitioners;

RQ2: The exit interviews revealed that the machine-retrieved research papers that implemented the *Discovering* guideline also encouraged creative thinking by some of the club's professional coaching practitioners;

RQ3: And the exit interviews revealed that the interactive tabs linked to the tool's implementation of the *Choosing*, *Directing* and *Focusing* guidelines also guided creative thinking by some of the club's professional coaching practitioners.

The failure to encourage creative thinking by all of the practitioners was associated with different barriers to *Sport Sparks* use that the practitioners identified. These barriers included lack of time to use the tool during workdays, a lack of digital technologies in the workplace with which to access the tool, and a more general unwillingness to use digital tools for coaching work. Furthermore, some of the machine-computed guidance to think creatively might not have been as effective as planned without more explicit creativity training and/or support for collaborative creative thinking as practiced in the training workshop.

Of course, these results were subject to different threats to their validity (Wohlin et al., 2000). For example, internal validity threats were the influences that affected independent variables related to causality (Wohlin et al., 2000). Two possible influences that could have biased feedback about *Sport Sparks* positively were pressure from the head of academy to use the tool and responses from the practitioners designed to placate the researcher during the exit interviews. However, the evaluation provided no evidence of either influence. A third possible influence was the education levels of the practitioners. All but one was educated to degree level, and we argue that this academic education might have resulted in the practitioners being more familiar than practitioners without such an education with research papers retrieved using research-based support implemented in *Sport Sparks*. Likewise, threats to the validity of conclusions (Wohlin et al., 2000) drawn about the relations between *Sport Sparks'* introduction and the creative thinking reported by some of the practitioner included other creative thinking practices taking place in the football club. Again, however, no such practices were reported, and the reported creative thinking occurred in spite of the time pressures of professional coaching and the limited time available to adopt a new tool and/or train in the creative thinking techniques supported by it.

Threats to the evaluation's external and construct validity (Wohlin et al., 2000) limited the ability to generalize results from the evaluation of one tool that took place in one club over 10 weeks to think creatively about only 18 documented challenges. The results were limited to professional football coaching practitioners at one leading club, so care needs to be taken extrapolating the results to coaching in other sports, to amateur football coaching, to female coaching, and to the coaching of children. We claim only that the evaluation provided preliminary evidence to encourage other researchers to experiment with HCAI guidelines to design co-creative AI tools. Likewise, the evidence for the guidelines that implemented Shneiderman's first two ideas is preliminary and limited to decisions to design a single tool. That said, the empirical results do reveal one possible architecture of co-creative AI tools that can be used in professional work contexts.

7 | DISCUSSION AND NEXT STEPS

This paper reports recent design research to explore the limited take-up of digital creativity support tools in professional work contexts, and related challenge posed by machine intelligence. This design research was informed by Shneiderman's three ideas (2020) to develop new digital tools with humans at their centre: (1) deliver high levels of human control as well as automation, (2) design to empower people with powerful tool-like appliances, rather than emulate human expertise, and (3) promote a governance structure that describes how to develop more reliable systems and maintain a safety culture. The first two of these ideas were refined to guide the design of co-creative AI tools using a synopsis of creative problem-solving processes (Warr & O'Neill, 2005) that revealed four stages shared by most. The resulting *Sport Sparks* tool built on an earlier proof-of-concept, and was designed and implementing using guidelines for the first two of these stages – *analysing the problem* and *generating ideas*. The result was a tool that sought to situate machine reasoning in-the-loop around, in this case, coaching practitioners, rather than continue the human-in-the-loop collaborations reported for co-creative AI tools such as *Calliope* (Davis et al., 2021) and *Shelley* (Yanardag et al., 2021).

The decisions made by a Premier League football club to deploy *Sport Sparks*, and by at least some of its professional coaches to use the tool and report creative thinking associated with this use can be interpreted early evidence that Shneiderman's ideas and the design guidelines have at least the potential to enable take-up of co-creative AI tools in professional work environments. The design science approach – one that sought to design and investigate artefacts that interact in and with a problem context, to improve something in that context (Wieringa, 2014) – was effective for revealing this evidence. However, *Sport Sparks* was only implemented to support the *analysing the problem* and *generating ideas* stages of creative problem solving, so evidence to support the other two stages – *evaluating ideas* and *sharing ideas* – is still missing.

During the design process, the application of the high automation *Generating* and *Discovering* guidelines, based on fresh ideas reported by Shneiderman (2020) influenced the architecture of the tool. *Sport Sparks* was designed to implement different machine-reasoning approaches – different forms of rule-based reasoning and the creative search of information artefacts – in this case published sports science research papers. The resulting choices that *Sport Sparks* offered to the coaches implemented the *Directing* guideline, and we believe increased both the tool's robustness and reliability, and enabled individual coaches to adapt tool use to their preferred creative thinking styles. The potential of rule-based reasoning to augment human creative thinking extends the set of recent success stories in other domains such as personalized medical education (Quinn et al., 2017), medical billing (Abdullah et al., 2017) and e-government (Hossain et al., 2015). Furthermore, the hybrid machine-reasoning architecture can be extended with other forms, For example, case-based reasoning and data-centric approaches using machine learning as more information and data becomes available.

The first evaluation sought to rebalance the limited long-term uptake of digital creativity support tools in work contexts reported by Remy et al. (2020). It revealed some evidence that deployment of the *Sport Sparks* tool alone was insufficient to encourage regular creative thinking by all of the coaches and other practitioners. The two-hour face-to-face workshop was revealed to be important in demonstrating the creative thinking process. Furthermore, the exit interviews revealed that some of the coaches experienced difficulties understanding techniques that required more human reasoning. One obvious conclusion is that more explicit training will be needed for creative thinking techniques (e.g., Michalko, 2006) that need more human cognitive effort to use. More evaluations of how such training supports effective tool uses in different work contexts will also be needed. Another point of discussion was whether the *Sport Sparks* tool was a more effective collaboration partner than other human coaching practitioners. The evaluation did not generate any hard evidence related directly to this. However, several of the exit interviews revealed that the practitioners met and collaborated regularly to resolve athlete challenges. Amabile and Pratt (2016) assume three major components necessary for creativity in any domain: expertise, intrinsic task motivation, and creative thinking skill. We observed that most practitioners had work expertise and intrinsic motivation to coach players. But most lacked the creative thinking skills needed for creativity. Sport Sparks was designed to introduce these skills.

One frustration from the first evaluation was the lack of documented coach outcomes from *Sport Sparks* use, perhaps due to the tool's lack of support for solution planning, which impeded any evaluation of the degree and levels of the creativity of these outcomes. Kaufman and Beghetto (2009) distinguished between *Pro-C* creativity outcomes that exhibit professional-level expertise that can be applied to earn a living, *Mini-C* creativity outcomes that are novel and personally meaningful interpretations, and *Little-c* creativity outcomes not often perceived to be creative in society. Informal insights gathered from the exit interviews provide tentative evidence that coaching outcomes were primarily *Mini-C* and *Little-C*. Again, however, more tool evaluations to fill the gap reported by Remy et al. (2020) will be needed.

The *Sport Sparks* design process and results from its evaluation revealed directions for further tool development. The content of the rulesets needs to be refined to ensure its usability and effectiveness to support coaches to generate valuable ideas quickly. Subsequently, the rulesets have been extended with noun terms describing common topics (e.g., *understanding* and *wellbeing*), to machine-generate more diverse ideas beyond what is described in the athlete challenge, and reduce idea repetition. More significantly, the rulesets were extended with rules designed to machine-generate potential ideas about athlete wellbeing. This topic was beyond the scope of the original scope of *Sport Spark's* design, but the importance of athlete wellbeing has grown (e.g., Biggin et al., 2017). Therefore, relevant literatures were reviewed (e.g., Purcell et al., 2019), and a further 200 rules to machine-generate wellbeing ideas were added. Themes covered by these rules include *depression*, *social support*, *emotional wellbeing* and *life circumstances*. Moreover, Thompson et al. (2015) revealed the importance of micro-politics for success in coaching teams, so future versions of the ruleset will also incorporate rules to direct creative thinking to both manage and utilize micro-politics when managing athlete challenges. Finally, to enable coaches to use *Sport Sparks* more immediately before, during and after coaching, the user experience is being redesigned to optimize for smartphone use.

Longer term, to implement a requested case-based reasoning (e.g., Kolodner, 1993) approach in the *Sport Sparks* hybrid architecture, a crowd-sourcing process with experienced coaches in different sports was initiated to collect challenge-solution case descriptions to be added to *Sport Sparks* in conjunction with creative search algorithms to retrieve case descriptions with similarities to a current challenge. This extension will implement the high-automation *Generating* and high user control *Directing* guidelines in an additional form, thereby offering more human control over the machine reasoning.

Finally, the guidelines and *Sport Sparks* tool architecture are informing the development of new co-creative AI tools for use in other professional contexts such as design and business consultancy. One of these tools is called *BOB* – the *Business Opportunity Builder* – and uses machine-generated ideas on top of published business model research (e.g., Aversa et al., 2017) to encourage senior staff in small- and medium-sized enterprises to think more creatively about their business models and strategies.

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DATA AVAILABILITY STATEMENT

The data from the evaluation cases and interviews will not be available publicly. The research protocol agreed as part of the research ethics process did not allow for publication of the data in any form, so the data is not available.

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APPENDIX A: HCAI GUIDELINES TO SUPPORT THE EVALUATING IDEAS AND SHARING IDEAS CREATIVE STAGES

Purpose	Name	Capability	Citations of examples
High levels of automation	Rating	Automated generation of ratings of the novelty and/or value of generated ideas	Maher et al. (2013)
High levels of automation	Explaining	Automated generation of user-understandable explanations of the novelty and/or value of generated	Goebe et al. (2018)
High levels of automation	Replaying	Automatic reframing of ideas in new forms and contexts to enable human evaluation (e.g., different modes, voice)	van Dijk et al. (2013)
High levels of automation	Sharing	Automatic distribution of generated ideas to targeted experts and other stakeholders in a community, to provide idea feedback	Zachos et al. (2013)
High levels of human control	Managing	Capabilities to allow a user to rank, prioritize and structure generated ideas	

The five HCAI guidelines to support the creative process stage: *evaluating ideas*.

Purpose	Name	Capability	Citations of examples
High levels of automation	Filing	Automatic recording all generated ideas, both complete and incomplete, to be available to distribute to other users	Andolina et al. (2017)
High levels of automation	Communicating	Automated redirecting of filed ideas to all identified users, to support them to overcome similar problems	
High levels of human control	Annotating	Capabilities to allow a user to annotate ideas to facilitate their sharing and use by other users	Knearem et al. (2019)
High levels of human control	Structuring	Capabilities to allow a user to sort, order and prioritize ideas, to facilitate their sharing and use by other users	

The four HCAI guidelines to support the creative stage: *sharing ideas*.

APPENDIX B: CODIFIED SETS OF RULES TO GENERATE POSSIBLE IDEAS

This appendix defines the complete sets of codified rules implemented in the Sport Sparks tool to generate possible ideas.

The rules to generate potential ideas about challenge problems.

The rules were composed of a unique ID that was accessible to the coaches, parameters to instantiate with content from the entered athlete challenges, a natural language expression, and the precondition conceptual space(s) for which the rule was instantiated.

ID	Rules generating ideas about challenge causes	Conceptual space
Person-A	The location of the (extracted athlete)	People
Person-B	The motivation of the (extracted athlete)	People
Person-C	The attitudes or beliefs of the (extracted athlete)	People
Person-D	The activities of the (extracted athlete)	People
Process-A	The everyday activities of the (extracted athlete)	Process
Process-B	The immediate activities of the (extracted athlete)	Process
Process-C	The long-term activities of the (extracted athlete)	Process
Process-D	How the trainee undertakes some activities?	Process
Product-A	The targets set for the (extracted athlete)	Product

ID	Rules generating ideas about challenge causes	Conceptual space
Product-B	The performance levels of the (extracted athlete)	Product
Product-C	The tools used by the (extracted athlete)	Product
Product-D	The tools used by the (extracted athlete)	Product
Environ-A	The current location of the (extracted athlete)	Environment
Environ-B	The team environment of the (extracted athlete)	Environment
Environ-C	The communication with the (extracted athlete)	Environment
Environ-D	The coaching offered to the (extracted athlete)	Environment
Person1	The physical state of the (extracted athlete)	People
Person3	The emotional state of the (extracted athlete)	People
Person5	The cognitive functioning of the (extracted athlete)	People
Person7	The moods of the (extracted athlete)	People
Person9	The domestic relationships of the (extracted athlete)	People
Person11	The family relationships of the [extracted athlete]	People
Person13	The background of the (extracted athlete)	People
Person15	The pressure on the (extracted athlete)	People
Person17	The anxiety of the (extracted athlete)	People
Person19	The personal ambitions of the (extracted athlete)	People
Person21	the approach to risk of the (extracted athlete)	People
Person23	the popularity of the (extracted athlete)	People
Person25	The self-awareness of the weaknesses of the (extracted athlete)	People
Person27	the fears or phobias of the (extracted athlete)	People
Person29	the values of the (extracted athlete)	People
Person31	the personal dreams of the (extracted athlete)	People
Person33	the existing knowledge of the (extracted athlete)	People
Process1	The processes that might help the (extracted athlete)	Process
Process3	The processes that might have impacted on rehabilitation of the (extracted athlete)	Process
Process5	The nutrition and food intake of the (extracted athlete)	Process
Process7	The processes that impacted the recovery of the (extracted athlete)	Process
Process9	The processes that impacted the psychotherapy of the (extracted athlete)	Process
Process11	The processes that impacted the physiotherapy of the (extracted athlete)	Process
Process13	The processes that impacted on the strengthen conditioning of the (extracted athlete)	Process
Process15	The quality of communications with the (extracted athlete)	Process
Process18	The different coaching styles offered to the (extracted athlete)	Process
Process20	The use of go-to people to talk with the (extracted athlete)	Process
Process22	The processes that monitor the (extracted athlete)	Process
Product1	The targets set for the (extracted athlete)	Product
Product3	The games played by the (extracted athlete)	Product
Product5	The locations of games played by the (extracted athlete)	Product
Environ1	The relationship with coach(es) of the (extracted athlete)	Environment
Environ3	The state of the career of the (extracted athlete)	Environment
Environ5	Relationships with team members of the (extracted athlete)	Environment
Environ7	The effect of the team's recent record on the (extracted athlete)	Environment
Environ9	The impact of how others see the team of the (extracted athlete)	Environment
Environ11	The impact of different groups in the team of the (extracted athlete)	Environment
Environ13	The relationships with others at the training ground of the (extracted athlete)	Environment
Environ15	The impact of different groups at the training ground of the (extracted athlete)	Environment
Environ17	The living conditions and lifestyle of the (extracted athlete)	Environment
Environ19	The competition for team places for the (extracted athlete)	Environment
Environ21	The pressure to perform on the (extracted athlete)	Environment

B.1. | The rules to generate potential ideas about challenge solutions

Two different types of rules were implemented to generate potential ideas about challenge solutions. The rules in each set were composed of a unique ID visible to the coaches and a natural language expression.

ID	Rules generating ideas about coaching best practices
Spark7	By removing a step from an activity
Spark27	By asking what external sources say
Spark28	By modifying strength training the day before a game
Spark29	By timing mealtimes differently
Spark30	By training without breaks
Spark31	By removing it from training
Spark32	By revising didactic training
Spark33	By planning age-related activities
Spark36	By repeating activities
Spark37	By only training with machines
Spark38	By combining training with testing
Spark39	By considering the impact of training at different times
Spark40	By combining strength and endurance training
Spark41	By training only with body weights
Spark42	By adapted the training programme
Spark43	By strengthening without heavy weights
Spark44	By using a treadmill to improve maximal force production
Spark45	By using just one exercise repeatedly
Spark46	By making the trainer the only source of information
Spark47	By seeking to achieve a goal in just 10 min
Spark48	By deciding quickly, based on instinct
Spark49	By increasing levels of feedback
Spark50	By increasing endurance training
Spark51	By achieving the same results in less time
Spark52	By choosing the number of repetitions to do
Spark53	By offering training plan choices
Spark54	By making other uses of nutrition
Spark55	By isolating one or more muscles
Spark56	By following our intuition
Spark57	By proceeding as others coaches would
Spark58	By imagining there is no challenge
Spark59	By offering unlimited resources
Spark60	By offering unlimited space/equipment
Spark61	By continuing for as long as possible
Spark62	By offering as long as is needed
Spark63	By imagining other types of sport
ID	**Rules generating ideas about challenge solutions**
Spark1	By making it do more or less
Spark2	By making it ready when it is needed
Spark3	By making it move and adjust more
Spark4	By making its parts move and adjust more
Spark5	By making it do different things
Spark6	By introducing feedback into it

ID	Rules generating ideas about coaching best practices
Spark8	By making it more flexible
Spark9	By speeding things up
Spark10	By returning to a previous approach
Spark11	By avoiding stressing it
Spark12	By balancing it with something else
Spark13	By dividing or splitting it
Spark15	By removing something from it
Spark16	By providing some kind of cover for it
Spark17	By making the environment richer
Spark18	By stopping it some of the time
Spark19	By changing its form
Spark20	By creating a copy of it
Spark21	By enabling it to adapt
Spark22	By being more transparent
Spark23	By recreating it
Spark24	With self-sustaining capabilities
Spark25	By planning for emergencies
Spark26	By making it smoother
Spark34	By combining it with something else
Spark35	By doing the opposite of what is expected