

Masterarbeit gemäß § 10 der Studien- und Prüfungsordnung vom 17.08.2009  
im Masterstudiengang Artificial Intelligence and Data Analytics  
an der Hochschule für angewandte Wissenschaften Neu-Ulm

**From Bots to Coaches: Designing Human-Like AI Trainers to Increase  
Athlete Motivation**

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Thema erhalten: 28.05.2025

Arbeit abgeliefert: 26.11.2025

# Abstract

Motivation represents a key determinant of athletes' performance, persistence, and overall well-being. Yet, in many sports contexts, athletes lack access to continuous, personalized coaching that fosters long-term motivation and engagement. While recent advances in artificial intelligence (AI) have led to the emergence of digital sports systems, most existing solutions focus primarily on technical training support or performance tracking rather than addressing the psychological and relational aspects of coaching. Against this background, this thesis investigates how conversational human-like AI trainers can emulate the motivational and relational qualities of effective human coaches. The study focuses on the design of an AI-based trainer that integrates autonomy-supportive coaching behaviors and anthropomorphic social cues to strengthen the coach-athlete relationship and enhance athletes' motivation.

Building on Self-Determination Theory (SDT) and Social Presence Theory (SPT) as kernel theories, this research explores how AI-driven communication can satisfy athletes' basic psychological needs for autonomy, competence, and relatedness. SDT provides the theoretical foundation for understanding motivation through needs satisfaction, while SPT explains how human-like cues and perceived social presence can evoke authentic, empathic experiences in human-AI interaction. The central research question addresses which design principles are appropriate for creating conversational AI trainers that promote autonomy-supportive coaching and foster athlete motivation.

Following the Design Science Research methodology, this thesis develops and evaluates a set of meta-requirements and design principles that translate theoretical insights into actionable design knowledge. The resulting design artifact is instantiated as a text-based chatbot capable of natural and adaptive conversation. The AI trainer demonstrates autonomy-supportive behaviors by offering meaningful choices, providing constructive and non-controlling feedback, and expressing empathy and trust. To create a human-like and socially intelligent impression, the AI trainer employs verbal, mental, and identity cues such as personalized addressing, emotional expressions, contextual memory, and adaptive dialogue strategies.

The prototype is evaluated in a real-world sports context with adult amateur handball athletes through an empirical study employing a mixed-methods approach. The findings show that, while the AI trainer succeeds in creating socially engaging, empathetic, and human-like interactions, its impact on athletes' motivational orientation and relationship quality remains limited. No significant behavioral changes emerged among the athletes' over the study period, and motivational outcomes did not show substantial improvements. These nuanced patterns suggest that, although the current AI trainer does not yet achieve the desired motivational effects, it demonstrates promising potential as a complementary digital coaching tool. Improvements in contextual adaptation, memory capabilities, and sport-specific expertise may enhance its effectiveness in future iterations.

The study contributes to Information Systems and Sports Informatics research by integrating motivational psychology and social presence into AI-based coaching design. It advances theoretical understanding of how autonomy-supportive and human-like communication can enhance athletes' motivation and relational engagement, while offering practical guidance for designing AI systems that act as socially competent and motivationally effective digital coaches.

*Keywords: conversational agents, social presence, self-determination theory, coach-athlete relationship, design science research*

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# List of Abbreviations

AI	Artificial Intelligence
CAs	Conversational Agents
CART	Coach-Athlete Relationship
CASA	Computers Are Social Actors
DSR	Design Science Research
HCI	Human-Computer Interaction
IS	Information Systems
LLMs	Large Language Models
ML	Machine Learning
NLP	Natural Language Processing
SDT	Self-Determination Theory
SPT	Social Presence Theory

# 1 Introduction

Understanding and fostering motivation has long been a central concern in sport psychology and applied coaching research, as motivation determines both athletes' engagement and their sustained participation in physical activity (Weiss and Amorose 2008). Regular exercise contributes substantially to individuals' physical and psychological well-being (Teixeira et al. 2012). Nevertheless, many athletes struggle to initiate and sustain physical activity over time. A lack of motivation can be explained by low interest in exercise or the low perceived competence at physical activities (Ryan et al. 2009). Although behavioral change in sport could prevent or relieve various health conditions, maintaining such change over the long term has proven to be particularly difficult (Bouton 2014). In the sports context, motivation plays a crucial role in shaping athletes' development, persistence, and overall well-being. Research consistently emphasizes the pivotal role of the coach as a primary socializing agent, whose behavior, feedback, and leadership style significantly affect athletes' motivation, performance and satisfaction (Amorose and Anderson-Butcher 2007; Horn 1985; Mageau and Vallerand 2003; Smith et al. 2010; Smoll and Smith 1989). The way coaches structure practice, make decisions, provide feedback, and build relationships influences athletes' cognitive, emotional, and behavioral outcomes (Weiss and Amorose 2008). A successful team environment therefore requires coaches who can both foster high performance and maintain supportive interpersonal relationships (Jowett 2017). However, access to such effective coaching is often limited. Many athletes do not have a personal trainer who continuously monitors their training progress, analyzes the results, and provides motivated feedback, as professional coaching is very costly and not always available (Strunk et al. 2024).

At the same time, the increasing digitalization of everyday life has also transformed the sports domain (ACSM 2024). A wide range of fitness applications, wearable devices, and digital training platforms now aim to provide accessible and data-driven support for athletes (Xiao et al. 2017). While these technologies democratize access to training support, they often focus primarily on performance data rather than the motivational and relational aspects of coaching (Helmefalk et al. 2020). As digital transformation continues to advance, the trend of integrating artificial intelligence (AI) into the sport domain could further redefine how athletes train, learn, and interact with technology (Hammes et al. 2022; Silacci et al. 2021). AI has become a defining technology of the digital era, revolutionizing how people live, work, and interact with intelligent systems (Gregory et al. 2021). Advances in AI capabilities, particularly in machine learning (ML) and natural language processing (NLP) have enabled the development of increasingly adaptive and human-like systems (Li and Suh 2022; Schöbel et al. 2024). Their capacity to perceive and adapt to human behavior has reshaped our perception of what technology can accomplish (Kim and Im 2023). Today, generative AI such as OpenAI's ChatGPT (OpenAI 2025a) mark a paradigm shift toward general conversational systems capable of supporting a wide range of complex tasks and offering personalized, human-like communication (Maedche et al. 2019).

One recent rapidly growing field of these advancements in research and practice is the rise of conversational agents (CAs), computer-based systems designed to communicate with humans through natural language (Schöbel et al. 2024). Initially, CAs were employed mainly for task automation and simple customer interaction; however, their potential has since expanded to context-sensitive and adaptive personalized dialogues with users, where they can act as non-human teammates, facilitators, or digital experts (Seeger et al. 2018). Today, CAs have been implemented in diverse application areas, including customer service (Adam et al. 2021; Gnewuch et al. 2017), marketing (Araujo 2018; Qiu and Benbasat 2009), healthcare (Beinema et al. 2021; Falala-Séchet et al. 2019), and education (Elshan and Ebel 2020; Hobert 2019; Lembcke et al. 2020; Smutný and Schreiberova 2020).

Increasingly, CAs are being explored not only for task efficiency but also for their potential to generate social value by enhancing autonomy, competence, and relatedness in users (Følstad et al. 2018). These new opportunities for user-centered interactions also raise new challenges in the field of human-computer interaction (HCI) concerning trust, user acceptance, and the social impact of such CAs. Therefore, research should intensively engage in the design and impact of such intelligent systems on users (Schöbel et al. 2024).

A particular area of growing interest within HCI research that addresses these emerging design challenges is the concept of anthropomorphism (Kim and Im 2023), which refers to the attribution of human-like characteristics to non-human entities (Epley et al. 2007). The anthropomorphic design of CAs, through the use of natural language and social cues, can enhance the feeling of human contact in technology-enabled communication and facilitate more engaging interactions (Feine et al. 2019). By embedding such human-like qualities, CAs can evoke the feeling of interacting with a social partner rather than a machine, thereby increasing trust, emotional connection, and motivation (Nass and Moon 2000). However, despite the growing interest in anthropomorphic design, researchers and practitioners still lack clear, theory-driven guidance on how to effectively integrate these human-like features into conversational systems (Konya-Baumbach et al. 2023; Li and Suh 2022). Empirical evidence on the effects of such anthropomorphic CAs remains fragmented and inconclusive (Seeger et al. 2018), resulting in a lack of design knowledge necessary to create successful CAs from a social point of view (Araujo 2018; McTear 2017).

Despite the widespread adoption of AI capabilities and conversational systems in business and more recently in education, the sports domain remains nearly unexplored within information systems (IS) research (Hammes et al. 2022; Rapp and Tirabeni 2018). Yet sports present unique computational and social challenges for AI, as for example effective coaching involves not only data analysis and performance optimization but also empathy, personalized communication, and interpersonal motivation (Beal et al. 2019). To date, most existing studies on AI in sports have approached the topic from a technical or performance-oriented perspective (Bunker and Thabtah 2019; Claudino et al. 2019; Silacci et al. 2021; Wang et al. 2019), rather than from a socio-behavioral one (Birnstiel et al. 2024; Strunk et al. 2024). Within this context, CAs offer new opportunities to move beyond purely analytical applications toward interactive and socially intelligent coaching systems. AI-based trainers could simulate key elements of coaching behavior, providing continuous, scalable, and cost-efficient support. However, current literature provides only little insights into how such systems should be designed to reproduce the motivational and relational qualities of effective human coaches (Hammes et al. 2022; Helmefalk et al. 2020). In particular, to the best of current knowledge, no scientific research has yet examined the role of anthropomorphic design in conversational AI trainers within the sports training context. Addressing this gap requires integrating insights from HCI and motivational sports psychology into the design of anthropomorphic AI coaching systems. Developing theory-driven, empirically validated design knowledge in this emerging area is crucial for transforming AI from a tool for performance optimization into a relational and motivational coach that supports athletes.

Building upon the identified research gap, it becomes evident that although AI technologies, especially CAs, are rapidly advancing across various domains, their application in sports coaching remains unclear within IS research. Existing digital solutions largely focus on data-driven performance analysis, yet little is known about how human-like and socially intelligent AI trainers could address the motivational and relational aspects of coaching. To date, research has not examined how anthropomorphic CAs influence athletes' motivation or their perceived relationship with an AI-based trainer.

Consequently, this study seeks to address this research gap by proposing design principles that establish a theoretical and empirical foundation for developing supportive and human-like AI trainers. Therefore, this study is guided by the following research question:

***RQ: To what extent do conversational, human-like AI trainers influence the motivation of athletes in training settings?***

The objective of this study is to develop and evaluate an effective AI design artifact that integrates supportive coaching behaviors with anthropomorphic cues to strengthen coach-athlete relationships and enhance athletes' motivation in sport training contexts. To address the research question, this study follows a design science research (DSR) approach (Hevner et al. 2004; Peffers et al. 2007). DSR is particularly suited to explore the design and evaluation of innovative artifacts that solve relevant problems while contributing to the theoretical knowledge base of IS research. In the context of this work, the DSR approach is used to design, implement, and evaluate a conversational AI trainer that aims to foster athletes' motivation through autonomy-supportive and human-like interaction. The goal of this research is to understand how different design choices, especially those related to anthropomorphic and social features, affect athletes' perceptions, relational experiences, and motivational outcomes when interacting with AI-based trainers. To achieve this goal, the study builds upon two kernel theories: Self-Determination Theory (SDT; Deci and Ryan 2000) and Social Presence Theory (SPT; Short et al. 1976). Combining these theoretical lenses offers a new perspective on how CAs may create supportive and motivating digital environments for athletes.

This study contributes to the fields of IS and HCI research by extending existing design knowledge on how conversational, human-like AI systems can foster motivation in sports contexts. From a theoretical perspective, the research advances the understanding of how autonomy-supportive and anthropomorphic design features influence the quality of interaction between athletes and AI trainers. By integrating SDT and SPT as kernel theories, this work develops a theory-informed set of design principles that explain how social cues can support athletes' psychological needs and therefore enhance their motivation. In doing so, it contributes to the growing body of knowledge on motivational interaction design and the application of social and psychological theories in digital sport environments. From a practical perspective, the study offers actionable insights for designers and practitioners seeking to develop intelligent training systems. The proposed design principles provide concrete guidance on how to address athletes' needs through autonomy-supportive feedback, empathetic communication, and personalized interaction. Moreover, the implementation and evaluation of the AI trainer artifact exemplify how these principles can be operationalized in practice, offering a foundation for future systems that aim to combine adaptive coaching with human-like interaction.

To answer the research question, this thesis is structured as follows. The next section provides the theoretical background by reviewing related research on motivation, autonomy-supportive coaching, and CAs, and by introducing SDT and SPT as the kernel theories guiding this study. Following this, the subsequent chapter describes the research design and methodology to derive and specify design principles for the AI trainer. The study then describes the instantiation and empirical evaluation of the proposed design artifact in a real-world sports training context. Finally, the results are discussed with regard to their theoretical and practical implications, followed by the study's limitations and suggestions for future research directions.

## 2 Background

### 2.1 Motivation

Motivation plays a crucial role in the context of physical activity and sports, as it directly influences an individual's decision to start, maintain, and invest effort in training and competition. Generally defined, motivation refers to an internal process that energizes and directs behavior toward a specific goal (Weiss and Ferrer-Caja 2002). In sports psychology, motivation is often conceptualized through a series of "why" questions (Weiss and Amorose 2008; Weiss and Williams 2004): Why do athletes engage in sports or physical activity? Why do some athletes start participating in sports for enjoyment, while others are driven by external or social factors? Why do certain people demonstrate persistence and sustained effort, while others lose interest quickly? Addressing these questions requires a deeper understanding of the underlying antecedents of motivation and the psychological, physical, and social consequences it produces.

According to Ryan and Deci (2000a) motivation is not a singular construct. Instead, individuals are moved to act by different types of motivational forces, each associated with distinct psychological experiences and behavioral outcomes. Motivation encompasses various dimensions including energy, direction, persistence, and intention, which are all essential components of goal-directed behavior. This complexity underscores why motivation has remained a central focus in psychology, as the core of biological, cognitive and social regulation. The underlying reasons for why individuals engage in, invest effort toward, and persist in a particular activity can be conceptualized along a continuum of self-determination (see Figure 1). This continuum reflects the differences in motivational regulation, which range from more externally regulated to more autonomous forms of motivation. All motivated behavior differs in terms of the perceived locus of causality, meaning whether the behavior is driven by internal intentions or external influences. Additionally, motivation varies in the degree to which actions are self-regulated. The more behavior originates from within the individual, the higher the level of autonomy involved (Deci and Ryan 1985; Ryan and Deci 2000b).

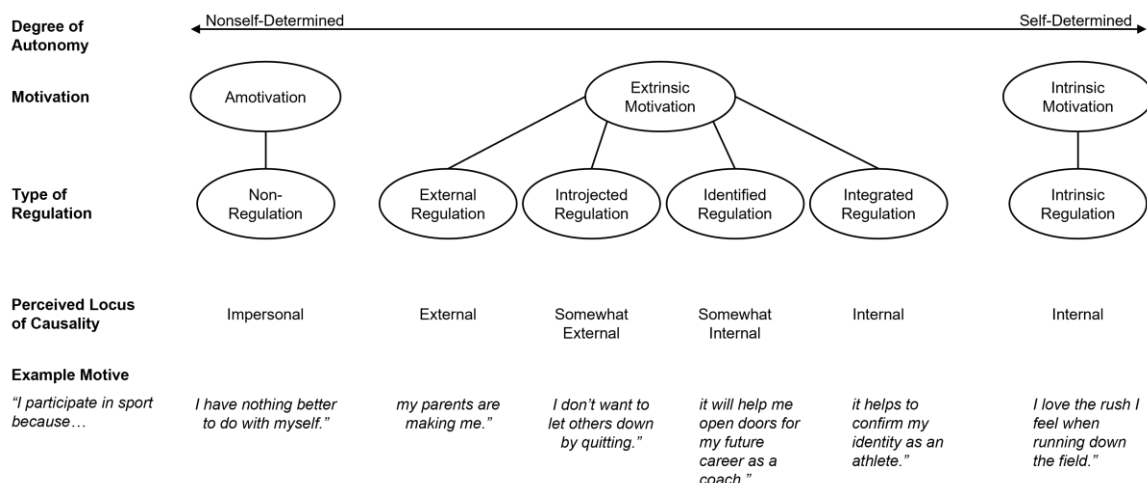


Figure 1: Self-Determination Continuum (based on: Ryan & Deci 2000b, p. 72; Weiss & Amorose 2008, p. 133 )

At one end of the continuum lies amotivation, which is characterized by a perceived absence of control or purpose. Individuals experiencing amotivation may lack the intention or motivation to act because they do not value the activity, feel incompetent, or fail to perceive a connection between their actions and expected outcomes (Ryan and Deci 2000b). Moving toward greater self-determination, extrinsic motivation refers to actions driven by outcomes that are separable from the activity itself. In such cases, the behavior is driven by instrumental purposes. For example, individuals act in order to gain external rewards or to avoid negative consequences (Teixeira et al. 2012). Ryan and Deci (2000a, 2000b) distinguish four distinct forms of extrinsic motivation, each varying in its level of autonomy: external regulation, introjected regulation, identified regulation, and integrated regulation. External regulation represents the most controlled form, in which behavior is guided by external rewards or punishments. Introjected regulation is internally controlled but still pressured, therefore behavior is driven by internalized contingencies such as guilt, shame, or ego enhancement. Though the motivation originates within the individual, it is not fully integrated with the self. Identified regulation reflects a more autonomous form, where individuals engage in an activity because they value its benefits or personal relevance. The most self-determined form of extrinsic motivation is integrated regulation. Here, the regulation is fully assimilated with one's values, goals, and identity, even though the activity itself is performed for instrumental reasons. At the far end of the self-determination continuum is intrinsic motivation, which involves engaging in an activity for the inherent satisfaction it provides. Ryan and Deci (2000b, p. 70) define intrinsic motivation as "the inherent tendency to seek out novelty and challenges, to extend and exercise one's capacities, to explore, and to learn". People experience feelings of curiosity, enjoyment, and a desire to explore and master new challenges (Teixeira et al. 2012). Therefore, intrinsic motivation is considered the most autonomous and self-sustaining form of motivation.

Research on motivation in sport and physical activity emphasizes the interaction of personal characteristics and social-environmental influences in shaping motivated behavior (Weiss and Ferrer-Caja 2002). Athletes' choices to participate, persist and invest effort in sports are rarely driven by a single reason. Rather, they are typically influenced by a complex combination of internal desires and external factors. Three common themes have been identified by Weiss and Williams (2004) as central motives for sport participation: the pursuit of physical competence, the desire for social acceptance, and the experience of enjoyment. Many athletes are motivated to develop or demonstrate physical skills, achieve fitness goals, and experience challenge. Others seek opportunities to build friendships and receive approval from peers, coaches or family members. Enjoyment, through fun, stimulation, and meaningful engagement, also plays a fundamental role. These motivated behaviors are not mutually exclusive and often involve both intrinsic and extrinsic regulatory elements. The central reasons individuals engage in voluntary physical activities such as sport is defined as one's motivational orientation (Amorose and Anderson-Butcher 2007). When athletes are driven primarily by enjoyment or personal values, such as growth or health (i.e., intrinsic motivation or identified regulation), their behavior is more self-determined. In contrast, when athletes participate due to internal pressures, such as guilt or self-worth, or external demands, like rewards or punishments, this reflects a more controlled, less autonomous form of motivational orientation (i.e., introjected or external regulation).

In the context of this study, the primary focus lies on intrinsic motivation as the most self-determined form of behavioral regulation within the SDT continuum. Nevertheless, it is important to acknowledge that athletes engage in training for a variety of reasons and may respond differently to external influences, such as an AI-based trainer. Measuring the entire motivation continuum allows the study to account for these variations while mainly focusing on intrinsic motivation, which is considered the most robust and sustainable form of motivation in sport.

## 2.2 Autonomy-Supportive Coaching

Coaching has evolved into a multifaceted discipline that draws on diverse theoretical and practical foundations. “Coaching is essentially about helping individuals regulate and direct their interpersonal and intrapersonal resources to better attain their goals” (Grant 2006, p. 153). As Ives (2008) outlines, coaching can take many different forms. These range from humanistic approaches that emphasize personal growth to behaviorist approaches that focus on changing behavior. Moreover, coaching can feature cognitive approaches aimed at developing more adaptive thinking as well as goal-oriented approaches that help individuals achieve specific outcomes. In the domain of sport, coaches play a pivotal role in shaping athletes’ experiences and development. They act not only as instructors and strategists but also as leaders, mentors, and motivational figures (Jowett 2017). The sport environment provides a highly influential context in which coaching behaviors can affect athletes’ enjoyment, long-term engagement in competitive sport (Smoll and Smith 1989), and goal-setting strategies (Smith et al. 2010). Given their central role, coaches are uniquely positioned to impact athletes’ psychological needs and motivational orientations.

Previous research has examined a variety of coach-related variables, including leadership styles (Gagné et al. 2003; Pelletier et al. 2001), behavioral strategies (Amorose and Anderson-Butcher 2015), motivational climates (Weiss and Ferrer-Caja 2002), and coach-athlete relationships (Choi et al. 2020; Jowett and Poczwardowski 2007; Kim et al. 2019), to understand their effects on athletes. Several studies conducted by Amorose and colleagues (Amorose and Anderson-Butcher 2007, 2015; Amorose and Horn 2000; Hollebeak and Amorose 2005) have investigated how athletes’ perceptions of their coaches’ leadership behavior and feedback style relate to their levels of motivation. Among these, the interpersonal style adopted by the coach is a particularly influential dimension and an effective motivational technique. Two predominant styles have been identified: an autonomy-supportive style, which fosters athlete self-initiation and engagement, and a controlling style, which relies on external pressure and directive behavior (Deci and Ryan 2000; Mageau and Vallerand 2003). Thus, while various aspects of coaching behavior can influence athletes’ motivation, a key predictor is the extent to which athletes perceive their coach as autonomy-supportive rather than controlling.

Autonomy-supportive coaching is characterized by interpersonal behaviors that support athletes’ thoughts, self-initiation, and psychological growth. Coaches who adopt an autonomy-supportive style acknowledge athletes’ perspectives, offer meaningful choices, and provide opportunities for self-regulation and independent decision-making (Deci and Ryan 1985; Mageau and Vallerand 2003). Rather than relying on authority, pressure, or external control, these coaches create environments that encourage internal motivation and personal ownership of actions (Kim et al. 2019). On the other hand, a controlling coaching style is defined by behaviors that pressure athletes to think, feel, and act according to the coach’s expectations, often through manipulative means. Controlling coaches may ignore the athletes’ input, overemphasize external rewards or punishments, or rely on conditional approval to influence behavior (Mageau and Vallerand 2003). Mageau and Vallerand (2003, p. 887) outlined several key behaviors that together form an autonomy-supportive coaching style:

- Offering athletes choices within structured guidelines and limits
- Providing athletes with a meaningful rationale for the activities and rules
- Asking about and acknowledge athletes’ feelings and emotions
- Providing the opportunity for athletes to take initiative and act independently
- Providing non-controlling performance feedback

- Avoiding overt control, guilt-induced criticism, and controlling statements, and limiting the use of tangible rewards
- Minimizing behaviors which promote ego-involvement

Empirical research has consistently demonstrated that coaches' interpersonal styles, particularly the degree to which they are autonomy-supportive or controlling, play a crucial role in shaping athletes' psychological functioning and motivational outcomes (Amorose and Anderson-Butcher 2007; Mageau and Vallerand 2003). Autonomy-supportive behaviors are repeatedly linked to a range of positive effects, including more adaptive motivational patterns (Amorose and Anderson-Butcher 2015; Gagné et al. 2003), greater self-esteem (Carpentier and Mageau 2016), stronger persistence in sport (Pelletier et al. 2001), and enhanced overall well-being (Choi et al. 2020; Kipp and Weiss 2013). For instance, Gagné et al. (2003) observed that gymnasts who perceived their coaches as autonomy-supportive and actively engaged in their development reported significantly higher levels of self-determined motivation. Similarly, Pelletier et al. (2001) demonstrated in a longitudinal study with swimmers that autonomy-supportive coaching was positively associated with intrinsic and identified regulation, while controlling behaviors correlated with more external and amotivated forms of regulation. Over time, athletes who experienced autonomy-supportive relationships showed greater persistence, whereas those with less self-determined motivation were more likely to drop out. Amorose and Anderson-Butcher (2015) further extended this line of research by analyzing the interaction of supportive and controlling behaviors. Their results indicated that the most favorable motivational profiles occurred when athletes perceived high autonomy support combined with low levels of controlling behavior. This interaction emphasizes the importance of not only promoting autonomy but also actively avoiding controlling or pressuring leadership styles. Moreover, Amorose and Horn (2000) highlighted that specific leadership behaviors, such as democratic decision-making, frequent instructional feedback, and minimal reliance on punishments, were associated with higher intrinsic motivation among collegiate athletes. These findings underscore that motivationally effective coaching is not solely about fostering choice but also about providing positive and informationally based feedback in a respectful manner.

Building on these insights, the present study explores how the principles of autonomy-supportive coaching can be translated into the design of an AI-based trainer. By incorporating key characteristics of autonomy-supportive coaching, such as providing meaningful choices, offering non-controlling feedback, acknowledging athletes' perspectives and emotions, and fostering self-initiation, the AI trainer should simulate this interpersonal style of a human coach.

### **2.3 Conversational Agents**

Traditionally, coaching in sports has been carried out by human professionals, such as personal trainers or team coaches (Deelen et al. 2018). However, the rise of digital technologies has introduced new forms of coaching support, with digital coaching systems emerging as a complementary or even alternative tool in training settings (Strunk et al. 2024). As Helmeffalk et al. (2020, p. 1266) note, digital coaching refers to "software solutions that supply the user with insight and advice based on the user's individual data". Digital coaches differ from human counterparts in several ways. While they lack emotional intelligence or interpersonal sensitivity, they offer distinct advantages in terms of precise data collection, real-time tracking, and consistent feedback delivery. Furthermore, digital coaches can serve as meaningful complements to face-to-face coaching by helping athletes adhere to training plans and reminding athletes of their goals (Helmeffalk et al. 2020).

The terminology surrounding CAs is diverse and often used inconsistently. Terms such as chatbot, virtual or digital assistant, interface agent, avatar, or autonomous agent are frequently used interchangeably, despite referring to systems with varying degrees of complexity and functionality (Luger and Sellen 2016; von der Pütten et al. 2010). This inconsistency makes it difficult to compare results across studies and hinders the development of shared understanding of these technologies (Dale 2016; Feine et al. 2019).

Lieberman (1997) describes an agent as a computer program that functions as an assistant to the user, ideally demonstrating traits associated with human intelligence, such as learning, inference, adaptability, and autonomy. Unlike conventional tools, agents act with a degree of independence and are often designed to operate in the user interface without constant supervision. Over time, the term agent, once used to describe human guides, has evolved into an established label for computer-based interfaces that exhibit human-like characteristics (Qiu and Benbasat 2009). Following this understanding, various definitions of CAs, a subset of such agent systems, capable of natural language interaction, are outlined in Table 1.

<b>References</b>	<b>Definition</b>
Weizenbaum (1966, p. 36)	“A program which makes natural language conversation with a computer possible”
Tegos et al. (2012, p. 162)	“Conversational agents which converse with humans by using natural language”
Griol et al. (2013, p. 760)	“A conversational agent is a software that accepts natural language as input and generates natural language as output, engaging in a conversation with the user”
Schuetzler et al. (2018, p. 283)	“CAs [are] user interfaces that emulate human-to-human communication using natural language processing, machine learning, and artificial intelligence”
Feine et al. (2019, p. 139)	“CA as a software-based system designed to interact with humans using natural language”

**Table 1: Definitions of Conversational Agents**

CAs are software-based systems designed to communicate with humans using natural language (Dale 2016). At their core, CAs operate as technological artifacts that enable interaction through dialog, typically to support users in completing tasks or accessing information (Araujo 2018). This core functionality positions them as communication interfaces between humans and digital systems. While the foundational idea behind CAs is not new (Dale 2016), recent advantages in AI, particularly in NLP and ML, have significantly enhanced their performance and expanded their application areas (Gregory et al. 2021). Today, modern CAs rely on LLMs like ChatGPT (OpenAI 2025b), which allow for more fluent, context-aware, and human-like communication (Schöbel et al. 2024). These technological developments have shifted CAs from simple rule-based question-answer systems to more intelligent and autonomous CAs (Feine et al. 2019). This evolution has enabled users to engage with digital systems more naturally and intuitively, improving the accessibility and usability of digital services (Behera et al. 2024). As a result, CAs are increasingly being deployed across various domains to facilitate user interactions, provide assistance, and personalize services based on user data.

Over the decades, CAs have evolved from simple rule-based systems, such as ELIZA (Weizenbaum 1966), to AI-driven tools deployed across various disciplines in the fields of computer science, IS and HCI. In recent years, CAs have gained increasing attention in both research and practice, primarily due to their potential to simulate human-like interactions and personalized communication experiences (Feine et al. 2019). Despite the growing relevance of CAs across diverse domains, there remains a notable gap in understanding the behavioral dimensions of human-agent interaction. The majority of existing studies on CAs have primarily focused on technical challenges in the domain of computer science, while neglecting the social and psychological aspects of user interaction (Schuetzler et al. 2020). Addressing this gap, recent contributions emphasize the necessity of adopting interdisciplinary perspectives that encompass not only technical but also behavioral and socio-psychological dimensions. There is a broad consensus among researchers that effective CA design requires the integration of both technical and social design considerations (Araujo 2018; Feine et al. 2019; Go and Sundar 2019). Although most CAs share similar underlying AI-based technologies, such as NLP, they vary significantly in terms of their design and intended application purposes (Dale 2016). To foster meaningful and engaging interactions, CAs should be capable of displaying expressive, authentic, and socially appropriate behaviors. Scholars argue that integrating social behaviors and human-like characteristics into agents can lead to interactions that feel more natural and emotionally resonant (Go and Sundar 2019). In response to the diverse functions CAs can serve, Bittner et al. (2019) propose that agents may assume various interactional roles, each with distinct behavioral profiles. As experts, CAs should respond to user input based on domain-specific knowledge. On the other hand, as facilitators, they take initiative to guide the interaction toward a goal, and as peers, they engage in emotional or social exchanges that emphasize group belonging over task efficiency. These roles offer a useful framework for future research on designing agents that align with different user expectations and interaction contexts.

Among various forms of CAs, chatbots represent one of the earliest and most widely recognized implementations. Over time, the term “chatbot” has become almost synonymous with CAs, although it more accurately refers to a specific subclass of CAs built for dialogic exchanges based on natural language input and output (Pfeuffer et al. 2019). According to Dale (2016, p. 813), a chatbot describes “any software application that engages in a dialog with a human using natural language”. These agents typically operate via text-based chat interfaces and leverage NLP techniques to interpret user inputs and generate semantically appropriate responses. Most modern chatbots are AI-powered and rely on predefined intent models to identify user goals and deliver tailored replies (Luger and Sellen 2016; Schöbel et al. 2024). While early chatbots followed rigid decision trees, today’s systems often build on ML architectures, enabling more nuanced, context-aware communication. This evolution aligns with the broader ambition of chatbot development: to create systems that can convincingly emulate human conversational behavior, thereby blurring the line between human and machine (Pfeuffer et al. 2019). Technological advancements have significantly expanded the capabilities of chatbots, allowing for the integration of additional interactional features. However, as Schuetzler et al. (2014) argue, introducing new features without fully understanding their communicative consequences may negatively affect user perceptions. From a user-centric design perspective, the role of chatbots extends beyond information delivery. Maedche et al. (2016) emphasize that chatbots should not only provide answers but offer proactive, adaptive, and context-sensitive support. They argue that merely enabling intelligent or interactive functionality is insufficient. For chatbots to fulfill the vision of truly intelligent assistance, they must align with user needs and context to deliver a goal-oriented and personalized experience.

CAs can be categorized into embodied and disembodied forms, depending on whether they are equipped with a virtual or physical representation. Embodied CAs typically feature human-like appearance, such as a face, body, or gestures, and are capable of engaging users through both verbal and non-verbal channels (Araujo 2018; Tegos et al. 2012). These agents may display dynamic social behaviors such as facial expressions, eye contact or body language during real-time interactions, which can enhance perceptions of social competence and presence (Schuetzler et al. 2018; Sebastian and Richards 2017). In contrast, disembodied CAs lack any visual or physical form and communicate primarily through textual or auditory channels. They typically appear as chat-based interfaces and do not possess the capability to exhibit facial behaviors (Araujo 2018). Chatbots, as disembodied agents, engage users via text-based dialogs and are commonly deployed in messaging applications or on websites. These disembodied agents interact with their users through verbal (e.g. language style) and non-verbal (e.g. blinking dots) design cues (Adam et al. 2021). While prior research has examined verbal human-like cues, such as expressing gratitude, using casual speech, or engaging in self-disclosure, these were often implemented in static or non-adaptive ways (Adam et al. 2021; Reeves and Nass 1996). Today's AI-driven chatbots are more capable of adapting these cues in real time based on user input, allowing for more flexible, content-sensitive, and emotionally resonant interactions (Schöbel et al. 2024).

This research focuses on an AI trainer conceptualized as a digital coaching system implemented through a disembodied, AI-based chatbot. As a specific type of conversational agent, the chatbot provides a text-based interface that enables natural language interaction with athletes. The focus of this study lies on the design of such AI trainers to address the behavioral and psychological dimensions of HCI. Drawing on the role typology by Bittner et al. (2019), the AI trainer combines elements of an expert, by providing sport-specific knowledge, and a facilitator, by supporting athletes in pursuing their training goals.

## 2.4 Applications of AI in Sports

Over the past decade, digitalization has affected various domains beyond its traditional application areas, including the world of sports. Although its influence in this field is still emerging, AI technologies are increasingly being integrated into athletic training, performance analysis, and strategic decision-making (Beal et al. 2019; Claudino et al. 2019). However, within the sport science research, the term AI is often used metaphorically to describe advanced, data-driven technologies, rather than being grounded in a consistent technical or theoretical framework (Hammes et al. 2022). To provide conceptual clarity, Hammes et al. (2022, p. 2) define AI in the sports context as “a loop that perceives and acts upon the world by modeling its perception, creating a deliberate plan based on that model and formulating an action, which is then exerted on the world”. This, of course, is behavior that is typically associated with intelligent agents. For the purpose of this paper, AI in terms of AI-based trainers is more broadly defined as “the ability of a machine to perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity” (Rai et al. 2019, p. iii). Despite the transformative potential of AI, IS research on its application in sports still remains limited. As Xiao et al. (2017) highlight, the digital transformation of sports presents a unique and underexplored empirical context within the IS discipline. The authors call for a unified research agenda for sports digitalization to answer questions like: what are unique design requirements for digital technologies in the sports context? Or, how can we use AI techniques to design and develop digital personal trainers/coaches for athletes? In recent years, the sports domain has increasingly integrated technologies capable of capturing extensive data from training sessions and competitive matches. These systems gather information such as player movement, health indicators, and real-time performance metrics (Beal et al. 2019).

Such data-driven insights enable both coaches and athletes to tailor training more effectively and enhance overall performance outcomes. Given the rapid progress in the field, the potential for AI applications in sports is expected to grow further, especially as evaluation research begins to inform real-world implementation and adoption in practice (Claudino et al. 2019).

Researchers have identified a wide range of application areas where AI contributes to more personalized, data-driven, and efficient management (Beal et al. 2019; Strunk et al. 2024). Various AI technologies have been successfully implemented to enhance training processes, support injury prevention, and optimize performance across multiple sports domains. Table 2 provides an overview of key AI application areas in sports.

<b>Concept</b>	<b>Description</b>	<b>References</b>
Match Outcome Prediction	AI models use historical performance data, team statistics, and game information to predict the outcome of future matches.	Bunker and Thabtah (2019)
Strategic & Tactical Decision Making	AI analyzes in-game situations and player behaviors to support coaches in planning tactics and making real-time strategic adjustments.	Bialkowski et al. (2014); Hassan et al. (2016); Shah et al. (2015)
Fantasy Sport Games	AI is used to simulate player performance and outcomes, enhancing game realism.	Goebeler et al. (2021)
Training Adaption	AI tailors training programs to the individual athletes' needs by analyzing biometric and performance data to optimize workload and recovery.	Fister jr et al. (2015); Silacci et al. (2021); Strunk et al. (2024); <i>This Study</i>
Movement Analysis & Optimization	AI captures and evaluates movement through video, image, or sensor input to detect patterns, assess technique, and correct posture in real-time.	Bialkowski et al. (2014); Mazurova et al. (2022); Wang et al. (2019)
Injury Prediction & Prevention	AI systems identify potential injury risks by processing biometric data and movement patterns, recommending preventive actions.	Claudino et al. (2019); Li and Xu (2021)

**Table 2: AI Application Areas in Sports**

A recent shift in the digitalization of sports areas has been the emergence of artificial agents that function as virtual trainers (Kettunen et al. 2024; Silacci et al. 2021). These AI-based trainers are designed to address the limitations of traditional systems by offering automated, personalized training plans derived from athletes' individual data (Beinema et al. 2021; Strunk et al. 2024). Unlike rule-based systems or conventional fitness applications, which often lack meaningful explanations and reduce feedback to basic statistics and key performance indicators (e.g., Garmin Connect or Apple Fitness), AI trainers leverage continuous data input and adaptive algorithms to tailor training in real-time (Strunk et al. 2024). Recent studies emphasize the importance of social presence and personalized interaction in these systems, showing that such features can significantly enhance athlete motivation and engagement (Beinema et al. 2021; Kettunen et al. 2024). Defined as an "artificial agent that creates personal training plans and adapts these towards a particular goal" (Strunk et al. 2024, p. 2), an AI trainer demonstrates the growing potential of intelligent agents in supporting athletic performance. In this context, early studies already underline the value of integrating motivational, interactive, and explainable design features (Fister jr et al. 2015).

The following section outlines a selection of recent AI applications in sports that illustrate these advancements and provide insights into their practical relevance and implications for this study. One of the most recent contributions in the field of AI-based trainers is the study by Strunk et al. (2024), who introduce a trust-centered design approach for AI trainers. Their research emphasized the importance of personalization, human-like interaction, explainability, and data control as central design requirements. Human-like design cues can foster trusting beliefs in athletes, while advanced NLP capabilities can improve the naturalness of coaching interaction. Beyond technological features, the authors underline the societal relevance of such systems, arguing that AI trainers offer a low-cost and highly flexible alternative for athletes with limited access to human coaching.

Wang et al. (2019) present an AI coach system that uses video-based pose estimation to provide personalized feedback on movement execution. By automatically detecting and classifying athletes' performances, the system enables athletes to refine their skills based on concrete visual feedback. A similar approach is applied by Silacci et al. (2021), who developed an AI-based virtual cycling coach. This system automatically schedules training sessions based on athletes' past performance data and provides adaptive feedback. Their findings demonstrate that such AI systems can offer training guidance that comes close to human coaching in terms of relevance and helpfulness.

From a motivational and psychological perspective, Helme Falk et al. (2020) examine how digital coaching systems impact exercise motivation. Contrary to the common assumption that gamification mechanisms drive athletes' engagement, their study finds that athletes derive more intrinsic motivation from interacting with their own training data. The study also points to the importance of satisfying basic psychological needs, which can be supported through AI-driven personalization and adaptive interfaces.

On the tactical level, AI also supports performance improvement through advanced data analytics. Hassan et al. (2016) combine game analysis software with neural networks to identify offensive tactical patterns in handball. This enables the transfer of competition-derived tactical knowledge into training practice, helping coaches design more evidence-based exercises. Similarly, Shah et al. (2015) propose an analytical platform for professional teams that enables video- and data-based analysis of individual players, groups, and entire teams. Their system supports real-time strategic decision-making and contributes to more informed coaching processes.

While recent studies have demonstrated the potential of AI systems to enhance training efficiency and personalization in sports, there remains a significant gap in understanding how design elements that emulate human social interaction affect athletes' motivation and behaviors. Most existing AI applications have focused primarily on functional aspects such as performance tracking, movement analysis, or adaptive training scheduling. However, only limited attention has been given to how human-like design elements, such as natural language use, empathy, or social responsiveness, might influence athletes' perceptions of an AI trainer and related effects. This study addresses that gap by focusing on the development of design recommendation for AI-based trainers that combine the benefits of training adaptation with the social and motivational impact of human-like design features.

## 3 Justification

### 3.1 Computers are Social Actors

The increasing use of intelligent systems in everyday life has led to a growing research interest in how users interact with these systems on a social level. A foundational theoretical framework that explains such behavior is the “Computers Are Social Actors” (CASA) paradigm developed by Reeves and Nass (1996), which has a significant impact on the field of HCI. CASA posits that people tend to respond to computers and other digital media in fundamentally social ways, even when they consciously know they are interacting with a machine. According to this theory, users mindlessly apply social norms and rules, interpersonal expectations, and behavioral scripts originally developed for human-human interaction to computer-mediated communication (Nass et al. 1994). Therefore humans will view computers as social agents and treat them as real people. This phenomenon is rooted in the automatic activation of mental models and social scripts (Nass and Moon 2000). According to Nass and colleagues (2000; 1994), the human brain evolved during a period in which only other humans exhibited social behavior. To manage social interactions, the brain developed automatic mechanisms for responding to social stimuli. When certain cues, such as interactivity, responsiveness, or verbal feedback are present, the human brain tends to interpret the interaction as social, often without conscious reflection. Thus, even minimal social stimuli from machines (e.g., polite phrasing, human-like language, conversational interface) can elicit behaviors such as politeness, reciprocity, or trust.

#### 3.1.1 Social Presence Theory

The concept of social presence was first introduced by Short et al. (1976) in the context of communication theory. Short et al. (1976, p. 65) define social presence as the “degree of salience of the other person in the interaction and the consequent salience of the interpersonal relationships”. Originally, social presence referred to the perceived sense of human contact, such as warmth, empathy, or sociability, in technology-mediated interpersonal communication. It describes how “present” a communication partner feels through a given medium and how this affects the relational quality of the interaction (Qiu and Benbasat 2009). Over time, the understanding of social presence has evolved beyond human-to-human communication. While traditional research focused on human interactions facilitated by digital media (Biocca et al. 2003), more recent studies have extended the scope of social presence to include interactions with technological artifacts as part of the HCI research (Nass and Moon 2000; Qiu and Benbasat 2009). In this context, social presence reflects the degree to which users experience social connection (e.g., warmth, sensitivity, personality, intimacy) during interactions with non-human agents.

SPT builds on the understanding that the psychological perception of another’s presence during an interaction shapes how individuals behave and relate to each other. The theory conceptualizes the salience of an interpersonal relationship as a direct function of how salient the other person appears in the interaction (Short et al. 1976). This salience is influenced by the communication medium’s capacity to convey, for example, verbal or nonverbal cues. While SPT was originally applied to human-to-human communication, its relevance has extended to interactions with artificial agents, especially in light of the CASA paradigm (Nass et al. 1994). Within this context, SPT is used to explain how users relate to non-human systems, such as CAs, by focusing on the perceived immediacy and interactivity of the system. According to Schuetzler et al. (2014), the theory predicts that as a communication partner becomes more salient, users will increasingly shift their attention to managing the social relationship with that partner. In the context of HCI, this means that the systems’ ability to project social presence can affect users’ perception of the agent as socially competent or even human-like.

Social presence is shaped by a variety of communication cues that contribute to the perceived sociability and immediacy of an interaction. According to Short et al. (1976), the degree of social presence a medium can convey is directly linked to its capacity to transmit verbal and non-verbal cues, such as tone of voice, gestures, facial expressions, and physical appearance. They originally emphasized that social presence is a “quality of the medium itself” (Short et al. 1976, p. 65), meaning some media naturally afford richer social interactions than others. Building upon this, Gunawardena and Zittle (1997) identified specific cues, such as friendliness, expertise, and expressiveness, that enhance the perception of warmth and interpersonal connection. In digital contexts, the range of available cues may be limited, particularly in text-based interfaces like chatbots. Nevertheless, certain design elements can evoke social presence even in these constrained environments. For example, cues such as human names, profile pictures, emoticons, informal language, or personalized forms of address have been shown to enhance the users’ subjective feeling of being socially connected to the system (Konya-Baumbach et al. 2023). While these human-like cues refer to the design strategy of digital systems, social presence reflects the users’ subjective perception of these agents as socially engaging partners (Short et al. 1976). Recent research suggests that social presence is not solely determined by the technological capabilities of a medium but also influenced by contextual factors and user strategies. Oh et al. (2018) point out that immersive system qualities can increase social presence, but its perception is equally shaped by individual communication patterns and the nature of the interaction task. Their systematic review highlights that contextual (e.g., social cues, identity markers) and psychological features significantly affect the perceived level of social presence. Consequently, both design decisions and situational factors play a crucial role in shaping how socially “present” a conversational agent appears to its users.

Research on social presence has increasingly explored not only its determinants but also its effects on user perceptions and behaviors (Janson 2023; Qiu and Benbasat 2009; Schuetzler et al. 2020; von der Pütten et al. 2010). Given its association with positive communication outcomes, scholars and practitioners have shown considerable interest in identifying factors that enhance social presence (Oh et al. 2018). Within the context of HCI, studies suggest that the design of CAs should incorporate characteristics of human-to-human communication in order to foster a sense of social presence. The perception of social presence has been shown to significantly affect users’ emotions, trust, and their evaluation of the interaction quality. For example, Qiu and Benbasat (2009) demonstrated that a high level of perceived social presence leads to greater enjoyment and increased trust in the system. Their experimental findings further revealed that embodiment and human voice-based communication positively influenced perceptions of social presence, which subsequently enhanced users’ intention to rely on the agent as a decision aid. Similarly, Schuetzler et al. (2020) found that the conversational skill of a chatbot, particularly its ability to produce contextually appropriate and varied responses, enhanced perceived social presence. Janson et al. (2023) further emphasize the mediating role of social presence in the relationship between human-like design elements and user satisfaction. Their findings suggest that social presence fosters trust, empathy, and overall satisfaction with the agent, which highlights its critical role in CA design. Von der Pütten et al. (2010) argue that the social influence of artificial agents is strongly linked to the degree of behavioral realism they exhibit. Their study supports the notion that users respond socially not necessarily because of the agents’ technical nature, but because of the perceived realism of its behavior.

### 3.1.2 Anthropomorphism

Anthropomorphism refers to the attribution of human-like characteristics, behaviors, emotions, or intentions to non-human agents or inanimate objects (Epley et al. 2007). The term originated from the Greek words “*anthropos*” (human) and “*morphe*” (form), and traditionally describes the human tendency to ascribe social or psychological attributes to non-human artifacts (Reeves and Nass 1996). In digital contexts, Adam et al. (2021, p. 429) define anthropomorphism as “the attribution of human-like characteristics, behaviors, and emotions to non-human agents”. This phenomenon reflects a fundamental human tendency to simplify the interpretation of unfamiliar agents by relying on human-centered knowledge structures. Individuals, either consciously or unconsciously, perceive and respond to anthropomorphic cues, assigning human traits to non-human entities (Epley et al. 2007; Pfeuffer et al. 2019).

Humans have a natural inclination to anthropomorphize non-human entities, a tendency that is shaped by both cognitive and motivational mechanisms. Epley et al. (2007) propose a three-factor model to explain why people anthropomorphize: elicited agent knowledge, effective motivation, and sociality motivation. When individuals lack knowledge about an unfamiliar agent, they are more likely to draw on anthropocentric structures to make sense of its behavior. This tendency is amplified when people are motivated to understand and predict the agents’ actions or when they experience a need for social connection. In such cases, attributing human-like characteristics, emotions, or intention to the agent serves as a cognitive shortcut to reduce uncertainty and establish a sense of familiarity (Epley et al. 2007; Janson 2023). Nass and colleagues (2000; 1994), in their work on the CASA paradigm, provided compelling experimental evidence that individuals often apply social heuristics to computers, especially when these systems exhibit social cues. For instance, users tend to respond to computers with politeness, reciprocity, or gender-based stereotypes, even when they are fully aware of the non-human nature of the system. These mindless responses emerge from overlearned social scripts that are automatically triggered when computers imitate certain human behaviors. Anthropomorphism extends beyond mere visual or auditory aspects of the interaction. It also encompasses content-level features of the interaction (Pfeuffer et al. 2019). Anthropomorphic cues, such as human-like dialogue capabilities or personalized communication can foster a sense of connection, helping users relate more naturally to technological systems.

The application of anthropomorphism has recently gained attention in the design of chatbots (Adam et al. 2021; Araujo 2018; Go and Sundar 2019; Janson 2023). Advancement in NLP and ML have significantly improved these systems’ ability to generate context-sensitive and human-like responses, thereby fostering more trustworthy and natural interactions. By incorporating anthropomorphic cues (e.g. human-like appearance, facial expression, language style, personality traits, see Chapter 3.1.3 Social Cues), chatbots are perceived as more relatable, emotionally expressive, and socially competent, which can positively influence user experience and interaction quality (Schuetzler et al. 2018). While research on branding and product design has long demonstrated that anthropomorphism can positively affect consumer attitudes and behaviors (Konya-Baumbach et al. 2023), investigations into the effectiveness of anthropomorphic features in CAs is relatively new and fragmented (Araujo 2018; Li and Suh 2022; Lu et al. 2022). Studies suggest that users’ perception of anthropomorphism is closely tied to the feeling of social presence during the interaction with a system (Schuetzler et al. 2020). Human-like characteristics can influence peoples’ judgements, increase trust and enjoyment, and lead to more favorable behavioral outcomes (Roy and Naidoo 2021). Anthropomorphism in chatbot design is particularly relevant, as people tend to seek out human-like features when engaging with systems in the absence of a real human (Epley et al. 2007). In response, IS researchers should acknowledge the impact of anthropomorphic cues on how users communicate and form relationships with non-human agents.

### 3.1.3 Social Cues

In recent years, the increasing prevalence of CAs in various digital applications has sparked growing interest in the design features that shape user perceptions and interactions. One particularly influential aspect of CA design is the integration of social cues that can trigger social responses in users and facilitate more natural, engaging interactions (Gnewuch et al. 2017). The terminology for such features varies across disciplines. Terms like human-like characteristics, anthropomorphic features, or human-like behaviors are used interchangeably, but many studies consistently demonstrate their strong influence on how users perceive and interact with CAs (Araujo 2018; Bickmore and Picard 2005; Li and Suh 2022). In the context of this study, the term social cues is used as the central design concept to describe human-like features that elicit social reactions from users during interactions with CAs. Feine et al. (2019, p. 141) define a cue of a CA as “any design feature of a CA salient to the user that presents a source of information” and a social cue as “a cue that triggers a social reaction of the user towards the emitter of the cue”. Similarly, Fogg (2002, p. 89) considers social cues as cues of computers “that elicit social responses from their human users”. These cues collectively contribute to users’ perceptions of anthropomorphism and social presence (Nass and Moon 2000).

Given that CAs are capable of using natural language and simulating human-like behavior, interactions with them often resemble interpersonal communication (Gnewuch et al. 2017). This resemblance prompts users to apply familiar social norms, such as politeness or reciprocity, even though they are aware they are interacting with a non-human entity (Nass et al. 1994). In particular, chatbots exemplify how social cues can be effectively integrated to mimic human-like interaction patterns. Studies have shown that the presence of even minimal social cues, such as informal language or self-disclosure, can be sufficient to activate users’ social cognition and evoke anthropomorphic perceptions (Adam et al. 2021; Epley et al. 2007). The goal of social cues is to create interactions that feel personal and human-like, thereby fostering emotional connection and trust between users and agents (Go and Sundar 2019). Consequently, social cues are no longer viewed as mere aesthetic enhancements but as essential components of CA design that influence user experience and behavioral outcomes (Seeger et al. 2018).

In order to systematically integrate human-like characteristics into CAs, prior research has categorized social cues according to their perceptual and functional properties. While individual studies have examined isolated features, such as facial expressions, language style, or response time, recent frameworks emphasize the importance of organizing these cues into coherent dimensions to better guide design decisions. Seeger et al. (2018) distinguish between human-identity cues, verbal cues, and nonverbal cues, while Feine et al. (2019) propose a more granular taxonomy, grouping cues into functional categories such as verbal, visual, auditory, and invisible cues. Pfeuffer et al. (2019) add a complementary dimension by highlighting mental or cognitive cues, which convey signs of intelligence such as context awareness, personalization, and dialog capability. These categories reflect different sensory channels and interaction strategies through which anthropomorphic qualities can be communicated, ranging from static appearance cues to dynamic conversational behaviors. Building on these prior conceptualizations of social cues in CA design, this study consolidates the different dimensions proposed in IS and HCI literature into an integrated framework, as listed in Table 3.

<i>Category</i>	<i>Description</i>	<i>Exemplary Cues</i>	<i>References</i>
Human Identity Cues	Human-like identity markers that convey a sense of personality in the agent.	Avatar, Name, Age, Gender	Seeger et al. (2018)
Verbal	Content and stylistic elements in written or spoken language that influence the tone and social intent of communication.	Content, Style, Emotional Expressions (Excuse, Thanking), Small Talk, Informal Language	Feine et al. (2019); Seeger et al. (2018)
Nonverbal (Visual)	Non-spoken behaviors and visual indicators that mimic human behavior or expression.	Gestures, Movements, Mimics, Emoticons, Typing Indicators, Response Time	Feine et al. (2019); Pfeuffer et al. (2019); Seeger et al. (2018)
Auditory	Sound-based signals that imitate human speech or vocal patterns.	Voice Qualities (Gender, Range, Tempo, Volume), Vocalizations (Laughing, Grunts, Yawn)	Feine et al. (2019); Pfeuffer et al. (2019)
Mental Cues (Cognitive, Behavioral, Emotional)	Indicators of cognitive processing and emotional intelligence that reflect the agents' ability to understand, adapt, and personalize interactions.	Context, Content Understanding, Emotional Intelligence, Personality, Dialogue Ability	Pfeuffer et al. (2019)

**Table 3: Categories of Social Cues**

Human identity cues represent anthropomorphic design features that convey a CA's identity through visual representation and demographic attributes. These include elements such as an avatar, name, age, gender, or ethnicity, which serve to project a recognizable human identity (Seeger et al. 2018). In line with this, Janson (2023, p. 4) conceptualize personification as the "provision of human-like cues that relate for example to a name or physical appearance". They argue that additional identifying information, such as a name or picture, enables users to better assess their interaction partner and form closer relationships (Go and Sundar 2019). Empirical evidence suggests that even minimal identity cues can influence anthropomorphic perceptions. Araujo (2018) shows that assigning a human name, such as "Emma" can enhance the perceived human-likeness of a chatbot, while Adam et al. (2021) demonstrate that using a gender-neutral name (e.g., "Alex") avoids stereotypical associations yet still signals individuality. Furthermore, the use of first-person pronouns ("I", "me", "my") communicates a self-referential identity, which has been linked to higher likability and stronger anthropomorphic attributions (Konya-Baumbach et al. 2023). Collectively, these design features convey the impression of a distinct social entity rather than a purely functional system, thereby fostering perceptions of social presence.

Verbal cues refer to all social signals expressed through written or spoken words in interactions with CAs (Feine et al. 2019). They are central to creating the impression of natural, human-like communication, especially in a text-based or voice-based interface where visual or physical embodiment is absent. Feine et al. (2019) distinguish between content cues, which relate to the primary intent expressed in a message, and style cues, which reflect the manner in which the intent is communicated. The strategic use of verbal cues can serve multiple functions. As Seeger et al. (2018) point out, word choice, sentence structure, and the way an agent refers to itself and the user all influence the "how" of a conversation. This includes relational dialogue such as small talk, greeting rituals, non-task-related questions, and personal anecdotes (Cassell and Bickmore 2003). Emotional expressions, such as congratulations, apologies, or concerns, further reinforce the agents' social presence and perceived empathy (Bickmore and Picard 2005).

In addition, verbal cues can be characterized by the use of active and direct language as well as the variability in syntax and word choice, which help maintain conversational naturalness and prevent mechanical dialogue patterns (Schuetzler et al. 2014; Seeger et al. 2018). Janson (2023) describes this as a social orientation of communication style, encompassing informal strategies and relational dialogues that convey sensitivity and warmth, including the use of acronyms to add a sensitive and extensive nuance to written communication. Empirical studies demonstrate that seemingly simple verbal elements can shape perceptions of anthropomorphism. For example Araujo (2018) shows that human-like greetings and farewells, especially when combined with a human name, can increase perceived humanness. Adam et al. (2021) highlight that small talk, such as inquiring about the users' well-being or prior chatbot experience, can reduce social distance and foster rapport. In summary, verbal cues are a critical component of anthropomorphic design, enabling CAs to transcend functional task execution and engage users on a socioemotional level. With stylistic variations designers can create interactions that feel more natural, attentive, and socially rewarding.

Nonverbal or visual cues refer to all human-like signals in CA interactions that can be perceived visually, excluding the textual content itself (Feine et al. 2019). These cues encompass observable movements, gestures, facial expressions, or other visual elements that convey emotional or cognitive states without the use of words. In the context of CAs, Seeger et al. (2018) distinguish between embodied and disembodied agents when implementing such features. Embodied CAs can employ anthropomorphic behaviors including hand gestures, gaze behavior, or facial expressions to enhance human-likeness and social presence. Disembodied CAs, by contrast, rely on alternative strategies to simulate nonverbal communication. For instance, minimalistic animations such as "typing indicators" can function as digital proxies for turn-taking behavior, signaling that the agent is formulating a response (Gnewuch et al. 2018). Similarly, the use of emoticons can convey affective expressions in text-based communication, thereby compensating for the absence of physical embodiment (Seeger et al. 2018). Pfeuffer et al. (2019) emphasize that visual anthropomorphic features, whether through software-based expressions like a smiling avatar or through hardware embodiments, can strengthen social bonding between users and agents, particularly in socially oriented interaction contexts. Consequently, nonverbal or visual cues serve as an important design dimension to simulate human-like interaction patterns even in text-only CA environments.

Auditory cues refer to design features of CAs that can be perceived through hearing, excluding the verbal content of spoken words (Feine et al. 2019). These cues include elements such as voice pitch, tone, rhythm, speed, and other paralinguistic characteristics that shape how the agents' speech is experienced by users. Beyond simple transmitting information, auditory cues contribute to the social and emotional quality of interactions by influencing perceptions of warmth, competence, and human-likeness. Auditory cues often work in combination with other modalities to create a coherent and believable representation of the agent. For instance, speech syntheses can be paired with gender-specific vocal characteristics to align with the agents' visual appearance, thereby reinforcing identity consistency (Pfeuffer et al. 2019).

Mental cues refer to the cognitive, emotional and behavioral capabilities of a CA that convey signs of intelligence, contextual awareness, and adaptive interaction. Pfeuffer et al. (2019) describe mental features as indicators that an agent can understand context, interpret content, and engage in coherent dialog. Such capabilities can be conveyed even in text-based interactions, for example, through contextually appropriate and personalized responses that give the impression of thoughtful processing. Chaves and Gerosa (2020) further categorize mental cues into three dimensions: conversational intelligence, social intelligence, and personification.

Conversational intelligence captures a CA's ability to proactively manage interaction flow, provide relevant and timely information, and maintain flexibility and consistency. Social intelligence reflects the CA's adherence to social norms, including conflict management, emotional regulation, and personalized communication. Personification, in turn, relates to the agents' perceived identity and consistent personality traits that align with user expectations and the CA's role. Empathy and adaptive feedback are also central to mental cues. For example, Adam et al. (2021) demonstrate that chatbots can enhance anthropomorphic perception by asking for self-improvement feedback and tailoring responses to a user's well-being and prior experiences. Such empathetic reactions strengthen the sense that the CA understands and cares about the user's situation. Similarly, Bickmore et al. (2010) emphasizes that engagement is a prerequisite for any system's long-term impact. Once a personal bond and goal agreement are established, users are more likely to remain engaged in ongoing interactions. Conversational skill also plays a crucial role in conveying mental cues. Schuetzler et al. (2020) highlight two important indicators: tailored responses, which provide on-topic follow-ups based on prior user statements, and response variety, which avoids repetitive phrasing. Both contribute to perceptions of attentiveness, understanding, and social presence, making users feel heard and valued. Over time, these capabilities support sustained engagement and foster stronger user-agent relationships. In sum, mental cues go beyond surface-level anthropomorphism by signaling that the CA can reason, adapt, and respond in a socially and contextually appropriate manner.

In the specific context of coaching, social cues play a pivotal role in fostering an ongoing, personalized, and trust-based interaction between the system and the user. Kamphorst (2017, p. 6) emphasized that effective e-coaching systems must be designed with a set of core functional and relational capabilities that enable them to engage in meaningful, goal-oriented exchanges. The requirements can be outlined as follows:

1. **Social ability:** the system must be able to engage in sustained, two-way conversation
2. **Credibility:** the system should be perceived as knowledgeable and trustworthy, signaling expertise that supports users' confidence in its guidance
3. **Context awareness:** the system needs an understanding of contextual factors influencing coaching
4. **Tailored interaction:** the ability to ask questions, provide feedback, and offer advice that is customized to the individuals' needs is essential
5. **Access to relevant data:** the system must integrate and process information from various data sources
6. **Proactiveness:** the system should initiate interactions to prompt reflection, encourage action, or prevent lapses in goal pursuit
7. **Behavior change modeling:** the system should operate on a structured model of behavior change that informs its strategy and interventions
8. **Support for planning:** the system needs to facilitate the formation of concrete, future-oriented intentions, helping the user set and commit to achievable goals

Social cues can positively influence a variety of CA-related outcomes, including perceptions of social presence (Adam et al. 2021; Araujo 2018; Janson 2023), trust in the CA (Cassell and Bickmore 2003; Konya-Baumbach et al. 2023), user satisfaction and empathy (Adam et al. 2021; Janson 2023), as well as long-term relationship success between a CA and a human (Araujo 2018) and user engagement (Bickmore et al. 2010; Schuetzler et al. 2020).

Janson (2023) found a significant influence of anthropomorphic design elements on social presence. Both personification and a socially oriented communication style positively affected social presence, while only communication style had a direct effect on user satisfaction. Social presence acted as a central mediator, influencing trusting beliefs, empathy perceptions, and satisfaction with the chatbot. Similarly, Adam et al. (2021) demonstrated a positive effect of verbal social cues on compliance with chatbot requests, with social presence mediating this influence. These cues increased the likelihood that users would follow a CA's request. Furthermore, Araujo (2018) showed that even minimal social cues, such as using a human name or adopting an informal language style, were sufficient to increase perceived anthropomorphism. Such cues were also relevant for disembodied agents, indicating that embodiment is not a prerequisite for human-likeness. The study further showed that these elements can strengthen emotional connection and contribute to relationship building. Moreover, Roy and Naidoo (2021) found that chatbots can be endowed with human qualities such as warmth and competence to enhance positive user experiences. Konya-Baumbach et al. (2023) confirmed that chatbot anthropomorphism has a significant positive effect on trust, purchase intention, and satisfaction, with social presence as the mediating mechanism. The research of Schuetzler et al. (2020) emphasized that higher conversational skills, characterized by variety in responses and contextually appropriate, skilled replies, make chatbots appear more human-like, socially present, and engaging. Supporting this, Bickmore et al. (2010) underlined that engagement is a prerequisite for achieving long-term interaction goals, as users must remain engaged to reach mutual objectives. Finally, Kim and Im (2023) observed that users perceive more humanness in highly intelligent but disembodied agents compared to highly intelligent agents with poorly designed appearances, suggesting that well-executed cognitive and conversational abilities can outweigh the absence of embodiment in shaping anthropomorphic perceptions.

### **3.2 Self-Determination Theory**

Self-determination theory (SDT) is a broad and evolving macro-theory of human motivation and personality that seeks to explain the initiation, persistence, and quality of human behavior by focusing on the fulfillment of fundamental psychological needs (Deci and Ryan 1985, 2000; Ryan and Deci 2000b; Ryan et al. 2009). Rooted in a humanistic perspective, SDT emphasizes self-actualization, personal growth, and the realization of human potential as central drivers of behavior. Distinct from other motivational frameworks, SDT integrates an organismic metatheory that highlights individuals' inherent growth tendencies and their evolved inner resources for personality development, behavioral self-regulation, and social functioning. The central proposition of SDT is that human motivation and well-being are profoundly shaped by the extent to which three basic psychological needs, namely autonomy, competence, and relatedness, are satisfied within a given context. These needs are considered essential and universal, functioning as psychological "nutrients" for optimal motivation, psychological health, and social development. Events or social environments that support these needs tend to foster more self-determined forms of motivation, whereas those that thwart them can undermine motivation and well-being.

SDT seeks to explain human motivation and behavior by considering individual differences in motivational orientations, the influence of social and environmental contexts, and interpersonal perceptions (Deci and Ryan 2000). In the field of sports and physical activity, SDT has become an increasingly influential framework for understanding the antecedents and processes that shape motivation (Hagger and Chatzisarantis 2008; Teixeira et al. 2012). It offers a valuable lens for investigating the environmental conditions that either foster or hinder the satisfaction of basic psychological needs. Central to SDT is the idea that the quality of motivation, as well as the mechanisms that facilitate its development, are critical for explaining why individuals initiate, persist in, and eventually disengage from various physical activities (Hagger and Chatzisarantis 2007).

Within the framework of SDT, the satisfaction of three basic psychological needs (autonomy, competence and relatedness) is considered essential for fostering high-quality, self-determined motivation and for promoting optimal functioning, well-being, and personal growth (Deci and Ryan 2000). In the sports context, engagement in training or competition can either support or hinder the realization of these needs, depending on the environment created by coaches, peers, and organizational structures (Teixeira et al. 2012).

The need for autonomy refers to the perception of being the origin of one's own behavior and making decisions in accordance with personal values and interests (Ryan and Deci 2000b). In sport settings, autonomy is supported when athletes are granted input into training decisions or strategies, and it is undermined when they feel pressured or overly controlled (Teixeira et al. 2012). The need for competence reflects the desire to interact effectively with one's environment and to experience a sense of mastery (Deci and Ryan 2000). In physical activity, experiences of competence often depend on success in challenging tasks, as well as on the quality of feedback provided by coaches. Competence is reinforced through appropriate challenges, positive and constructive information, and clear structure (Helmefalk et al. 2020). It represents a foundational driver of engagement, as it enables individuals to feel capable of managing demands and improving performance over time. The need for relatedness concerns the feeling of being connected to others, experiencing care, and having a sense of belonging within a group (Deci and Ryan 2000). In sports, this can be fostered through supportive team interactions, trust, and shared goals. Perceptions of relatedness vary with the interpersonal climate. Strong, genuine relationships strengthen this need, while isolation or exclusion can undermine it (Teixeira et al. 2012). Like any other domain, sport and exercise can be more or less conducive to satisfying these basic psychological needs. When athletes' environments actively support autonomy, competence, and relatedness, they are more likely to experience greater self-determined motivation and positive developmental outcomes. Conversely, when these needs are thwarted, motivation and well-being can be compromised.

SDT has proven to be an effective framework for explaining motivation and behavior in sports and exercise across three key domains (Hagger and Chatzisarantis 2008). First, it identifies environmental and personal antecedents, such as reward structures, feedback quality and instructional styles, that influence the satisfaction of basic psychological needs and the regulation of behavior in exercise contexts. Second, it outlines the mechanism through which these antecedents affect motivation, intentions, and perceived competence. Finally, SDT offers clear guidance for practitioners, specifying which constructs should be targeted to promote behavior change and foster long-term engagement in physical activity. A substantial body of research demonstrated how social-contextual factors, such as rewards, feedback, competitive structures, and interpersonal styles, directly influence needs satisfaction and, consequently, motivational orientation (Amorose and Anderson-Butcher 2007; Mageau and Vallerand 2003; Ryan et al. 2009). Within this framework, coaches hold a particularly influential position because they can shape many of these contextual factors. They provide performance-related feedback, administer rewards, structure training sessions, and determine the degree of athlete involvement in decision-making. Mageau and Vallerand (2003) emphasize that coaches' behaviors are among the most critical motivational influences in sport. Autonomy-supportive coaching behaviors are positively associated with the satisfaction of the three basic psychological needs and with more self-determined forms of motivation. Conversely, controlling coaching styles are linked to need thwarting and to less self-determined motives (Amorose and Horn 2000; Ryan et al. 2009). Hollembek and Amorose (2005) found that athletes' perceptions of their coaches' leadership style influenced their sense of autonomy, competence, and relatedness, which in turn predicted their intrinsic motivation. Specifically, athletes who viewed their coaches as democratic reported higher autonomy and intrinsic motivation, where those perceiving autocratic decision-making reported lower autonomy, relatedness, and intrinsic motivation.

Autonomy-supportive coaching has been operationalized through behaviors such as offering meaningful choices, explaining the rationale behind rules, acknowledging athletes' feelings, and providing opportunities for initiative and independent decision-making (Mageau and Vallerand 2003). Such practices not only fulfill the need for autonomy but also enhance competence, by providing constructive, non-controlling feedback, and relatedness, and by fostering a sense of care and connection. Amorose and Anderson-Butcher (2007) provided direct empirical evidence to support SDT's prediction that perceived autonomy support affects athletes' motivation through need satisfaction. In a sample of 518 athletes aged 13-25 from various sports, structural equation modeling revealed that perceived autonomy-supportive coaching positively predicted each of the three needs, which in turn positively predicted athletes' motivational orientation. In sum, the satisfaction of athletes' basic psychological needs is a central mechanism linking coaching behaviors to motivation. By adopting an autonomy-supportive interpersonal style, coaches can foster environments that enhance autonomy, competence, and relatedness. Such environments are more likely to produce adaptive motivational patterns, sustained engagement, and improved performance in sport.

### **3.3 Coach-Athlete Relationship**

Athletes form interpersonal relationships with a variety of individuals in sport, including teammates, parents, support staff, and coaches. Among these, the relationship with the coach holds particular significance, as it directly influences both skill development and competitive performance (Lafrenière et al. 2011). Coaches occupy a socially influential role, shaping athletes' behaviors not only through technical instruction but also through the quality of their interpersonal interactions (Choi et al. 2020). Effective coaching extends beyond the transmission of technical knowledge. Coaches are responsible for designing and delivering training sessions, providing feedback, ensuring athletes' comprehension of tasks, and fostering an environment that promotes both skill acquisition and personal growth (Mohd Kassim et al. 2020). Over the past decades, the interpersonal dynamics between coaches and athletes have attracted considerable attention in sports and exercise psychology, generating both theoretical models and empirical studies (Lafrenière et al. 2011; Smith et al. 2010; Smoll and Smith 1989). The coach-athlete relationship is now widely regarded as a central element of effective coaching, with research indicating its relevance across both individual and team sport contexts (Jowett 2017). Scholars emphasize that understanding this relationship requires examining its behavioral, affective, and cognitive dimensions, all of which contribute to the quality of interaction between coaches and athletes (Jowett and Ntoumanis 2004). Moreover, investigating its dynamic nature is essential for enhancing coaching effectiveness and for promoting athletes' physical performance, psychological well-being, and long-term engagement in sport.

A team of researchers led by Jowett (Jowett 2017; Jowett and Ntoumanis 2004; Jowett and Poczwardowski 2007) developed an integrated model of the coach-athlete relationship, drawing on principles from social psychology to conceptualize and measure its quality. Jowett and Poczwardowski (2007, p. 4) define the coach-athlete relationship as "a situation in which a coach's and an athlete's cognitions, feelings, and behaviors are mutually and causally interrelated". This definition underscores the relationship's dynamic nature, emphasizing that it is shaped over time by ongoing interpersonal exchanges, changes in emotions, thoughts, and behaviors, and the evolving demands of the sports context. Central to this model are three interpersonal dimensions: closeness, commitment, and complementarity. Closeness captures the affective bonds between coach and athlete, reflected in mutual trust, respect, liking, and appreciation. Commitment refers to the cognitive intention of both parties to maintain a close and constructive relationship over time, pursuing shared goals, values, and beliefs through open communication.

Complementarity represents the cooperative and reciprocal nature of their interactions, particularly in training and competition, encompassing behaviors such as friendliness, responsiveness, and the mutual enactment of leadership and followership roles. Together, these dimensions provide an operational framework for assessing the quality of the coach-athlete relationship. The model has become a central theoretical tool in sport psychology for understanding the interpersonal processes that underpin coaching effectiveness.

Recent research underscores the critical role of autonomy-supportive coaching in fostering high-quality coach-athlete relationships. Kim et al. (2019) found that coaches' perceptions of relationship quality, particularly in terms of closeness, commitment, and complementarity, were positively associated with autonomy-supportive behaviors and negatively associated with controlling behaviors. When coaches perceived their relationship with athletes as strong and mutually respectful, they tended to adopt more autonomy-supportive styles, while reliance on controlling strategies decreased. Similarly, Choi et al. (2020) demonstrated that autonomy-supportive coaching behaviors were significantly and positively related to the quality of the coach-athlete relationship. Such behaviors help cultivate positive emotions in athletes, which in turn strengthen emotional bonds with coaches from a future-oriented perspective. Their findings further suggested that a supportive relational climate could mitigate athlete burnout, highlighting the dual implication on performance and well-being of autonomy-supportive coaching and a high quality of coach-athlete relationship. Lafrenière et al. (2011) extended these insights by identifying autonomy-supportive behaviors as a key predictor of high-quality coach-athlete relationships as perceived by athletes. When athletes felt understood, respected, and that their perspectives were valued, they developed stronger emotional bonds and greater connectedness with their coach. Importantly, the study revealed a positive association between high-quality coach-athlete relationships and athletes' general happiness, underscoring the broader psychological benefits of such relationships beyond sport-specific outcomes. Supporting this finding, Jin et al. (2022) linked the quality of coach-athlete relationships directly to athlete satisfaction. Their results confirmed that relational quality, rooted in trust, respect, and collaborative interaction, was a strong determinant of athletes' subjective satisfaction with their sporting experience. The importance of relational quality is further supported by Mohd et al. (2020), who examined coach-athlete relationships and coaching effectiveness in team sports. They found that higher-quality relationships, characterized by commitment, closeness, and complementarity, were associated with better perceptions of coaching effectiveness. This link was evident across multiple dimensions, including motivation, technical instruction, game strategy, and character building. The study also highlighted that such relationships are essential for optimizing athlete learning, development, and performance, regardless of gender or sport type.

## 4 Methodology

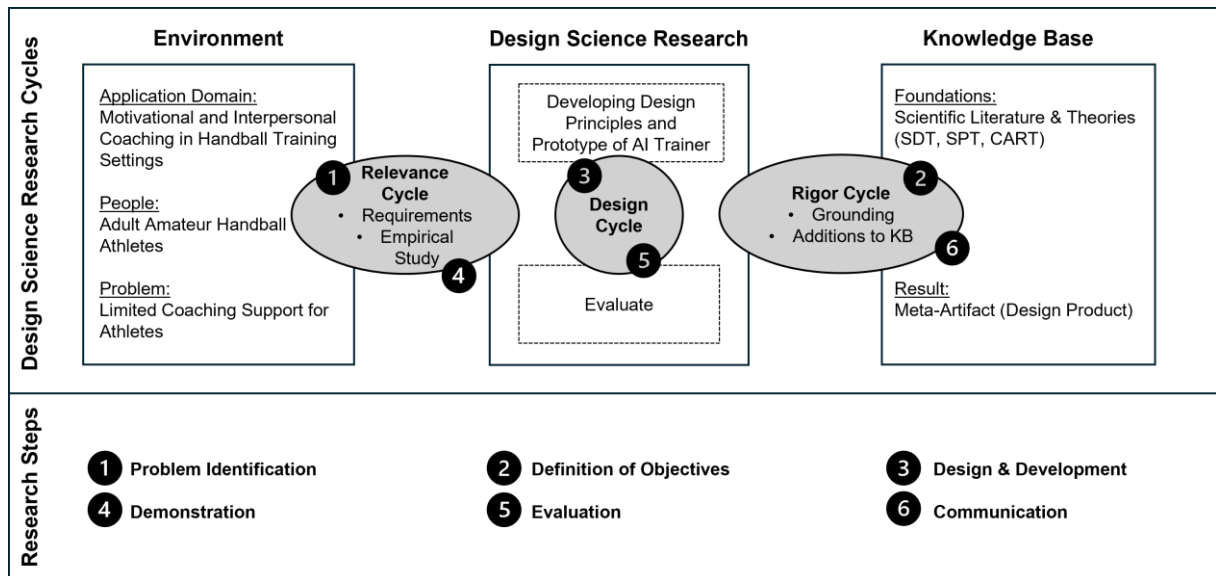
### 4.1 Design Science Research

To address the research question and develop an effective conversational AI trainer, this study adopts the DSR approach. DSR is particularly well suited for this research as it aims not only to understand a problem but to rigorously design and evaluate innovative IT artifacts that provide practical solutions in real-world contexts (Hevner et al. 2004). As such, DSR combines scientific rigor with practical relevance, making it an appropriate method for solving complex challenges that researchers and practitioners experience in their practice. According to Hevner et al. (2004), DSR focuses on the creation and evaluation of artifacts that address identified business needs and contribute to the knowledge base for the IS research discipline. Therefore, this study aims to derive generalized design implications according to Gregor and Jones (2007) and Walls et al. (1992). DSR projects typically begin with identifying a relevant business problem and theorizing the attributes of the future system. These attributes are commonly referred to as meta-requirements (Walls et al. 1992), as they capture the generic requirements that the future system should meet. Once meta-requirements have been established, researchers propose design principles (Gregor and Jones 2007) that specify how a system should be constructed to satisfy those requirements. Design principles represent an effective way to communicate such findings, as they address both technology-oriented and management-oriented audiences, as important in the context of DSR (Hevner et al. 2004). Finally, these design principles are implemented and refined through iterative cycles of development and evaluation (Hevner 2007). To support the rigorous evaluation of the artifact, this study additionally derives testable hypotheses from the underlying kernel theories. These hypotheses serve to examine whether the instantiated design principles produce the theoretically expected effects in practice (Walls et al. 1992).

To structure the research process and ensure both relevance and rigor, this study adopts the three cycle view of DSR as proposed by Hevner (2007) and applies six research steps according to Peffers et al. (2007) as displayed in Figure 2. This framework distinguishes between three interrelated research cycles: the relevance cycle, the rigor cycle, and the design cycle. The relevance cycle connects the research with the application environment and ensures practical relevance. In this study, the relevance cycle is reflected in the identification of a real-world problem, namely the lack of motivational and relational coaching support in athletic training contexts. Many athletes train without continuous access to human coaches, resulting in limited opportunities for personalized feedback, emotional support, and motivational guidance during training routines. The application domain of this research lies within the field of motivational and interpersonal coaching in sports. The environment is defined by an amateur handball club and the requirements are derived from the needs and challenges of active adult handball players who present the main stakeholder group. Moreover, the artifact is evaluated through an empirical study in a ten-day application phase with handball athletes in a real training environment, which provides feedback for further refinement.

The rigor cycle anchors the research in the existing knowledge base by drawing on scientific theories, validated design methods, and domain-specific expertise. In this project, the development of the AI trainer is informed by two established theoretical foundations: SDT and SPT. These theories guide the identification of meta-requirements and the derivation of design principles that form the conceptual basis of the artifact. In addition to these two theories, the coach-athlete relationship model (Jowett and Poczwardowski 2007) serves as a further theoretical lens, emphasizing the relational dynamics between athletes and coaches. Furthermore, methodological rigor is ensured through the use of validated measurement instruments and systematic evaluation procedures.

Finally, the design cycle represents the core iterative process of building and evaluating the artifact. This cycle encompasses the construction of a conversational AI trainer prototype. The design cycle integrates knowledge and requirements from the other two cycles and translates them into a functional artifact aimed at supporting athletes' psychological needs through autonomy-supportive interaction and human-like behavior. In this study, the design cycle included the systematic derivation of theory-grounded design principles, their translation into concrete dialogue structures and interaction patterns, and the technical implementation of a first functional prototype. In addition, testable hypotheses were derived from the underlying kernel theories to evaluate whether the instantiated design principles led to the expected motivational and relational effects in practice.



**Figure 2: Adapted DSR Process (based on: Hevner 2007, p. 88; Peffers et al. 2007, p. 54)**

To structure the DSR project, this study adopts the process model proposed by Peffers et al. (2007), which outlines six sequential research steps. These steps provide a systematic framework to guide the development, evaluation, and communication of the AI-based coaching artifact. The following section describes each step and how it was applied in the context of this study.

The study first (1) identified and outlined the problem in the introductory section (Chapter 1). This research is motivated by a lack of effective digital solutions that support and motivate athletes in sports training contexts. Current sports technologies primarily focus on data collection, performance tracking, and analytical feedback, while neglecting the motivational and relational dimensions of coaching that are crucial for sustained athlete engagement. Existing coaching technologies often fail to incorporate evidence-based strategies for autonomy-supportive communication and to build meaningful coach-athlete relationships (Strunk et al. 2024; Xiao et al. 2017). This study addresses this gap by developing an AI-based trainer that emulates human-like coaching behavior to foster athlete motivation. As a next step, this research defined the aim (2) to design a conversational AI system that supports athletes' psychological needs through personalized, autonomy-supportive interactions. The artifact is intended to simulate social presence and establish trustful relationships that align with motivational theory (Deci and Ryan 2000). In step (3), a functional prototype of the AI trainer was developed, which will be discussed in detail in Chapter 6 Design Instantiation. The design is guided by design principles derived from theoretical and empirical insights and aims to deliver anthropomorphic coaching dialogues tailored to athletes' training situations.

The artifact was demonstrated (4) in a real-world sport context, where handball athletes interacted with the system over a defined training period. This demonstration showed the system's ability to simulate autonomy-supportive coaching behavior in a digital environment. The evaluation (5) combined quantitative and qualitative methods to assess the artifact's effectiveness. A survey-based empirical study was conducted to examine changes in athletes' perceptions of motivation, psychological need satisfaction, and coach-athlete relationship quality. The results (6) of this DSR project are communicated through this scientific thesis.

## 4.2 Research Method

To address the research objectives and evaluate the effectiveness of the AI trainer, this research follows an empirical study embedded within the paradigm of DSR (Hevner et al. 2004). In line with the iterative and problem-oriented nature of DSR, the study supports the development and the evaluation of a novel IT artifact aimed at enhancing athlete motivation through autonomy-supportive and human-like interaction. Therefore, a mixed-method approach is adopted. This methodological strategy enables the integration of both quantitative and qualitative research techniques, allowing for a more comprehensive investigation of the artifact's functionality and its perceived impact (Recker 2021). The combination of standardized measurements and contextual insights ensures that hypothesis testing and in-depth understanding are achieved.

The quantitative component of the research design includes the use of structured surveys to assess the main constructs. These surveys form the basis for evaluating the theoretical model and testing predefined hypotheses regarding the relationship between perceived autonomy-supportive coaching, coach-athlete relationship quality, basic psychological needs satisfaction, social presence, and motivational outcomes. Complementing this, the qualitative component involves follow-up semi-structured interviews with selected participants. These interviews aim to explore how athletes experienced their interactions with the AI trainer, how they perceived its human-like features, and how it influenced their motivation during training. This qualitative layer enables a deeper exploration of underlying mechanisms and contributes to the refinement of theoretical and practical insights.

To empirically evaluate the proposed IT artifact, athletes completed three surveys during the ten-day evaluation phase of this study. Each survey consisted of developmentally appropriate and validated instruments to measure the main constructs. The questionnaire was divided into five sections assessing motivational orientation, psychological need satisfaction, perceived autonomy-supportive coaching behavior, coach-athlete relationship, and social presence. All constructs were assessed on a 7-point Likert scale ranging from do not agree at all (1) to very strongly agree (7), with three measurement items per construct selected for standardization and consistency. The complete list of the used measurement items is provided in Appendix A.

Athletes' motivational orientation was assessed using an adapted version of the Sport Motivation Scale II (SMS-II) by Pelletier et al. (2013), which operationalizes six distinct types of motivation along the self-determination continuum. In this study, twelve items were selected to represent intrinsic motivation, integrated regulation, identified regulation, introjected regulation, external regulation, and amotivation. Each item reflects a specific reason for engaging in sport, ranging from self-determined to controlled forms of regulation (e.g., "Because it is very interesting to learn how I can improve"; "Because people I care about would be upset with me if I didn't"). Higher scores indicate greater self-determined motivation.

Aligned with SDT (Deci and Ryan 2000), athletes' satisfaction of their three basic psychological needs, autonomy, competence, and relatedness, was measured using established sport-specific adaptations. Perceived autonomy was assessed using three items adapted from Hollembeak and Amorose (2005), which evaluate the perceived level of volition and choice in sport participation (e.g., "I have a say in what I do when participating in my sport"). Perceived competence was captured through three items by Amorose (2003), assessing athletes' self-perceptions of ability and effectiveness (e.g., "How good do you think you are at your sport?"). Finally, perceived relatedness was measured using three adjectives from the sport-oriented version of the Feelings of Relatedness Scale ((Hollembeak and Amorose 2005; Richer and Vallerand 1998), reflecting feelings of closeness and support from teammates and the coach (e.g., "supported", "understood", "bonded to them"). Each subscale demonstrated satisfactory reliability and validity in previous SDT-based studies on coaching behaviors and athlete motivation (Amorose and Anderson-Butcher 2007, 2015; Kipp and Weiss 2013).

Athletes' perceptions of autonomy-supportive behavior exhibited by the AI trainer were measured using a short version of the Sport Climate Questionnaire (Amorose and Anderson-Butcher 2007). This measure evaluates the degree to which the coach provides opportunities for choice, listens to athletes' perspectives, and acknowledges their feelings. Example items include: "I feel that my coach provides me choices and options" or "I feel understood by my coach". Responses were recorded on a 7-point Likert scale, with higher mean scores indicating stronger perceptions of autonomy support. Research by Amorose and Anderson-Butcher (2007) has demonstrated that the Sport Climate Questionnaire is reliable and valid in assessing autonomy-supportive coaching styles among high school and college athletes.

The perceived quality of the coach-athlete relationship was assessed using an adapted version of the Coach-Athlete Relationship Questionnaire (CART-Q) developed by Jowett and Ntoumanis (2004). The instrument captures the three relational components: closeness, commitment, and complementarity. Each dimension was measured with three items, such as "I feel close to my coach", "I trust my coach", and "When I am coached, I feel at ease". Higher scores indicate a stronger relationship quality. Prior research has confirmed the CART-Q's consistency, validity, and applicability across individual and team sport contexts (Choi et al. 2020; Jin et al. 2022; Kim et al. 2019).

To assess the extent to which the AI trainer was perceived as a socially engaging and human-like partner, social presence was measured using three items adapted from Gefen and Straub (2003). The items capture the perceived human warmth, sensitivity, and personalness of the interaction (e.g., "There is a sense of human contact with the AI trainer"). Higher scores reflect a greater sense of perceived humanness and interpersonal connection in athlete-coach communication.

All scales and measurement items were slightly adapted to the study context by, for example, substituting "coach" with "AI trainer" where appropriate. The survey was administrated via LimeSurvey, and all instruments were pretested with a small sample of athletes to ensure linguistic clarity and contextual appropriateness. As the study was conducted in a German handball sport club, all measurement items and construct explanations were translated into German (see Appendix A).

## 5 Design Specification

### 5.1 Kernel Theories

An essential principle of DSR is that existing theories should be leveraged within the design process in order to justify why a design is expected to work (Gregor and Jones 2007; Hevner et al. 2004). In IS design theory, kernel theories provide the theoretical foundations that govern meta-requirements and guide the formulation of designs and testable hypotheses (Walls et al. 1992). For this study, the development of an AI trainer builds upon two primary kernel theories, SDT and SPT, as well as the conceptual model of the coach-athlete relationship. Together, these theories explain the mechanisms through which autonomy-supportive AI coaching can influence athletes' motivation.

SDT (Deci and Ryan 1985, 2000) posits that human motivation is driven by the satisfaction of three basic psychological needs: autonomy (e.g. the experience of choice and volition), competence (e.g. the perception of effectiveness and mastery), and relatedness (e.g. the sense of belonging and connectedness). When these needs are fulfilled, individuals tend to display more self-determined forms of motivation, ranging from intrinsic motivation to identified regulation. Conversely, when needs are thwarted, controlled forms of motivation or amotivation prevail. In the sports context, SDT has been extensively applied to explain athletes' adherence, performance, and well-being (Ryan et al. 2009). Research has consistently shown that coaches who engage in autonomy-supportive behaviors, such as offering meaningful choices, providing rationales, encouraging initiative, and acknowledging athletes' perspectives, are more likely to satisfy athletes' psychological needs (Amorose and Horn 2000; Mageau and Vallerand 2003). For example, Amorose (2007) demonstrated that high school and college athletes who perceived their coaches as more autonomy-supportive reported higher satisfaction of their needs and more self-determined motivational orientations. Their findings demonstrated that perceived autonomy-support from coaches positively predicted athletes' perceptions of autonomy, relatedness, and competence. In turn, all three needs significantly predicted motivational orientation. Crucially, the direct path from perceived autonomy-support to motivational orientation was not significant, indicating a fully mediated relationship. This means that the effect of autonomy-supportive coaching on athletes' motivation was entirely explained by the extent to which athletes' basic psychological needs were satisfied. While these findings provide strong evidence for the role of SDT in human coaching contexts, they have yet to be extended to the domain of AI-based coaching systems. Building on Amorose's model (2007), the present study investigates whether an AI trainer, designed to interact in an autonomy-supportive manner, can similarly influence athletes' perceptions of autonomy, competence, and relatedness, and thereby foster more self-determined forms of motivation. By transferring this well-established mechanism from human coaches to an AI trainer, this research seeks to advance the application of SDT in digital sport environments and provide insights into the potential of conversational AI to act as a motivational coach. SDT as a kernel theory therefore justifies why an AI trainer should be designed to act in an autonomy-supportive manner.

As a complementary conceptual lens, the coach-athlete relationship model (Jowett and Ntoumanis 2004) emphasized the quality of the interpersonal bond between coach and athlete, which is characterized by three dimensions: closeness (e.g., mutual trust, respect, and emotional connection), commitment (e.g., dedication to maintain the relationship over time), and complementarity (e.g., cooperative and responsive interaction). Together, these three dimensions capture the affective, cognitive, and behavioral facets of a high-quality coach-athlete relationship.

While SDT-based studies such as Amorose and Anderson-Butcher (2007) have demonstrated that autonomy-supportive coaching influences athletes' need satisfaction and motivational orientation, they did not consider the quality of the coach-athlete relationship as a mediating mechanism. In contrast, Jowett's framework (Jowett and Ntoumanis 2004; Jowett and Poczwardowski 2007) highlights that athletes' experiences in sport are not only shaped by the satisfaction of psychological needs but also by the perceived quality of their interpersonal bond with the coach. Thus, the coach-athlete relationship model introduces an additional relational layer that may explain how autonomy-supportive behaviors translate into positive psychological and motivational outcomes. To date, empirical studies on the coach-athlete relationship have been conducted exclusively with human coaches (Choi et al. 2020; Jin et al. 2022; Mohd Kassim et al. 2020). It remains an open question whether athletes are able to perceive dimensions such as closeness, commitment, and complementarity in interactions with an AI trainer, which this study aims to explore. The present study addresses this gap by integrating the coach-athlete relationship model into the SDT framework. Specifically, it proposes that autonomy-supportive coaching behaviors by an AI trainer will enhance athletes' perceptions of closeness, commitment, and complementarity, thereby strengthening the coach-athlete relationship. This relational quality, in turn, is expected to mediate the effects of autonomy-supportive coaching on the satisfaction of basic psychological needs, which ultimately shape athletes' motivational orientation.

While SDT addresses what drives motivation, SPT explains how digital communication media can influence relational and motivational outcomes. SPT (Short et al. 1976) defines social presence as the degree to which a person perceives another as a "real" social entity during mediated interactions. Media with high social presence are more capable of fostering trust, empathy, and relational closeness than media with low social presence (Oh et al. 2018). In the context of AI-driven conversational systems, SPT has been widely adopted to explain why users often respond socially to artificial agents (Gunawardena and Zittle 1997; Konya-Baumbach et al. 2023; Nass and Moon 2000). Social cues such as natural language, empathetic responses, personalization, and memory of past interactions increase perceived social presence, which in turn strengthens relational bonds between user and system (Feine et al. 2019; Go and Sundar 2019; Janson 2023). In this study, SPT serves as a kernel theory by explaining why athletes may experience an AI trainer as a socially present coach. Through the deliberate integration of social design elements, the AI trainer is expected to elicit stronger perceptions of social presence. In this study, it is assumed that higher perceived social presence of the AI trainer will influence the quality of the coach-athlete relationship, thereby strengthening athletes' perceptions of closeness, commitment, and complementarity.

In summary, the kernel theories applied in this study establish the theoretical foundation for the design and expected functioning of the AI trainer. SDT explains why autonomy-supportive coaching behaviors should foster motivation by satisfying athletes' basic psychological needs for autonomy, competence, and relatedness. The coach-athlete relationship model complements this perspective by highlighting the mediating mechanisms through which autonomy-supportive behaviors are likely to unfold their effects. Finally, SPT provides the rationale for why athletes may perceive an AI trainer as a socially meaningful partner, and why such perceptions are expected to strengthen the quality of the coach-athlete relationship. By integrating these theoretical perspectives, the study extends prior research from human coaching contexts to AI-based systems.

## 5.2 Meta-Requirements

In DSR, the derivation of meta-requirements (MRs) represents a central step in building design knowledge (Hevner et al. 2004). Meta-requirements define the general conditions that an information system should fulfill in order to address the identified problem and achieve the intended goals (Walls et al. 1992). They are formulated at a conceptual level, describing what a system should do rather than how it should be implemented. According to Hevner (2007), this step corresponds to theorizing the essential attributes of a future system, grounded in the problem context and in relevant kernel theories. In this study, the meta-requirements are derived from the interplay of SDT, SPT and the coach-athlete relationship model, each representing a crucial mechanism for fostering motivation, relational quality, and perceived humanness in digital coaching.

Motivation is one of the most decisive factors for participation and persistence in sport. Research shows that athletes commonly engage in physical activity to pursue competence, build social acceptance, and experience enjoyment (Weiss and Williams 2004). These motives align with the three basic psychological needs defined by SDT: autonomy, competence, and relatedness (Deci and Ryan 2000; Ryan et al. 2009). When these needs are satisfied, athletes are more likely to display self-determined motivational orientations, which are associated with higher persistence, performance, and engagement (Hollembek and Amorose 2005; Teixeira et al. 2012). In contrast, environments that frustrate these needs foster amotivation or controlled forms of regulation, undermining athletes' intrinsic engagement. An AI trainer that aims to increase motivation must be designed to actively support the satisfaction of these three psychological needs during training. Therefore, the first requirement is defined as:

**MR1:** *The AI trainer should foster athletes' motivation by supporting the satisfaction of the three basic psychological needs (autonomy, competence, and relatedness) in the context of physical activity.*

Autonomy-supportive coaching is a central mechanism through which athletes' motivation can be enhanced (Amorose and Horn 2000). Research shows that this interpersonal style adopted by a coach fosters athletes' self-initiation, engagement, and psychological growth, whereas a controlling style often undermines motivation and well-being (Deci and Ryan 2000; Mageau and Vallerand 2003). By promoting self-determined forms of motivation, autonomy-supportive coaching has been identified as an effective motivational technique that contributes to greater self-esteem, stronger persistence, and overall well-being (Amorose and Anderson-Butcher 2007). As a result, the following requirement is formulated:

**MR2:** *The AI trainer should demonstrate autonomy-supportive behaviors.*

The quality of the coach-athlete relationship plays a crucial role in shaping athletes' experiences in sport (Lafrenière et al. 2011). Studies have shown that strong relationships between coaches and athletes are associated with higher satisfaction, greater engagement, and more positive motivational outcomes (Kim et al. 2019; Smith et al. 2010). The relational bond does not only affect how athletes perform but also how they feel supported, connected, and committed within their sporting environment. As such, the interpersonal dynamic between coach and athlete represents a powerful determinant of long-term participation and well-being (Jowett and Poczwardowski 2007). The relational qualities of closeness, commitment, and complementarity provide the basis for trust and cooperation and strengthen the impact of motivational support (Jowett and Ntoumanis 2004). Hence, the third requirement is derived as follows:

**MR3:** *The AI trainer should foster a high quality coach-athlete relationship by enabling athletes to perceive closeness, commitment, and complementarity in their interactions.*

Social presence has been identified as a critical factor in shaping how users perceive and interact with CAs (Janson 2023; Nass et al. 1994). Prior research shows that when a system conveys human-like qualities through social cues, users are more likely to experience the agent as a socially present and relatable partner (Kim and Im 2023; Qiu and Benbasat 2009). Such perceptions influence the depth of engagement, the level of trust established, and the extent to which users respond socially to the system (Go and Sundar 2019; Konya-Baumbach et al. 2023). Therefore, the requirement is defined as:

**MR4:** *The AI trainer should employ social cues to increase perceived social presence and humaneness.*

Together, these four meta-requirements specify the foundational attributes that an AI trainer must fulfill to act as a motivationally effective, autonomy-supportive, and human-like coach. MR1 and MR2 draw primarily on SDT to ensure that the system promotes psychological need satisfaction and self-determined motivation, while MR3 and MR4 build upon the coach-athlete relationship model and SPT to translate relational and social mechanisms into digital interaction. Collectively, they provide the conceptual link between the underlying kernel theories and the practical design objectives of the AI trainer, establishing the theoretical foundation for the subsequent formulation of design principles.

### 5.3 Design Principles

Design principles (DPs) represent prescriptive knowledge that guides how an artifact should be constructed to fulfill previously defined meta-requirements. While meta-requirements specify what a system must achieve, design principles provide actionable recommendations on how these requirements can be implemented (Gregor and Jones 2007; Walls et al. 1992). In line with DSR, design principles can be understood as statements that guide or constrain design actions to ensure that the artifact contributes to the intended outcomes. They serve both researchers and practitioners by providing knowledge about how the new system should be built in order to fulfill the identified meta-requirements (Hevner et al. 2004).

Allowing athletes to actively participate in training-related decisions has been shown to be a powerful factor in fostering motivation (Mageau and Vallerand 2003). Research demonstrates that when athletes are given meaningful opportunities to contribute to the direction of their training, they are more likely to experience a sense of volition, self-initiation, and personal growth (Ryan and Deci 2000b). In sport contexts, such participation supports athletes in aligning their activities with personal values and interests, which in turn strengthens their engagement and persistence over time (Teixeira et al. 2012). Athletes who perceive independent decision making report greater self-determined motivation (Amorose and Anderson-Butcher 2007). These results suggest that providing choice within structured boundaries is essential for creating an empowering motivational climate. For an AI trainer, enabling athletes to influence training decisions is therefore critical. Through tailored options, adaptive interaction, and recognition of individual preferences, the system can promote a perception of autonomy. Thus, this study proposes:

**DP1:** *Provide athletes with opportunities to contribute to training decisions so that they experience a sense of autonomy in their physical activity.*

The way feedback is provided plays a central role in athletes' motivation and learning. Studies consistently show that athletes who receive positive, respectful, and informationally based feedback are more likely to feel competent and motivated to improve their performance (Amorose and Horn 2000; Mageau and Vallerand 2003). In contrast, controlling statements, guilt-inducing criticism, or excessive use of external rewards can undermine intrinsic motivation and foster ego-involvement, leading to lower persistence and well-being (Amorose and Anderson-Butcher 2007; Deci and Ryan 2000).

Effective feedback therefore requires a balance between providing clear structure and avoiding behaviors that signal external control. Perceptions of competence are reinforced when athletes experience success in appropriately challenging tasks and when progress is recognized in a constructive way. Research highlights that competence thrives on specific, non-controlling performance feedback that emphasizes progress and mastery rather than comparison or punishment (Weiss and Williams 2004). Athletes are more likely to accept feedback from systems they perceive as knowledgeable and reliable, which strengthens their confidence in the guidance provided (Bittner et al. 2019; Kamphorst 2017). For an AI trainer, this implies that feedback must go beyond simple performance tracking. It should deliver constructive, non-controlling guidance that reinforces competence and mastery while avoiding judgmental or demotivating language. By combining domain-specific knowledge with adaptive communication, the AI trainer can establish credibility and provide athletes with feedback that is both trustworthy and motivating. Thus, this study proposes:

**DP2:** *Provide clear and constructive feedback on athletes' progress and performance while avoiding controlling statements so that they perceive increased competence and mastery.*

Feeling connected and socially accepted is a fundamental source of motivation in sport. Athletes often strive not only for physical competence but also for belonging, recognition, and trust within their team and with their coach (Ryan et al. 2009; Weiss and Williams 2004). Empirical evidence highlights that shared goals, mutual trust, and cooperative responsiveness are essential conditions for fostering persistence, well-being, and long-term adherence in physical activity (Teixeira et al. 2012). When such interaction patterns are present, athletes are more likely to feel socially integrated and valued, which strengthens both their commitment and their performance. Trust-centered design approaches, supported by social cues, can significantly enhance athletes' willingness to engage with AI trainers (Strunk et al. 2024). An AI trainer should act as a facilitator that guides interactions, builds cooperation, and fosters a sense of joint responsibility (Bittner et al. 2019). Such facilitation translates into establishing transparent communication, reinforcing shared objectives, and responding cooperatively to athletes' inputs. This combination creates a relational foundation that not only increases social acceptance but also enhances motivation through the perception of being connected and supported. Thus, this study proposes:

**DP3:** *Provide interaction patterns that emphasize trust, shared goals, and cooperative responsiveness so that athletes feel socially connected and accepted.*

Athletes' motivation and relational quality are strongly influenced by whether their feelings and perspectives are acknowledged during interactions. Research in sport psychology highlights that coaches who actively recognize athletes' emotions and viewpoints foster greater trust, understanding, and motivational commitment (Amorose and Anderson-Butcher 2007; Mageau and Vallerand 2003). Such acknowledgment signals respect and care, which helps athletes feel supported rather than controlled (Deci and Ryan 1985). By contrast, neglecting or dismissing athletes' perspectives can weaken the relational bond and undermine intrinsic motivation. Perceived support during digital interactions is strengthened when agents respond in ways that validate users' input and emotions (Qiu and Benbasat 2009). These relational cues enhance trust and positively influence how users evaluate the quality of the interaction. For an AI trainer, this means that responses cannot remain purely functional or task-oriented but must also reflect a sensitivity to the athletes' emotional state and perspectives. Providing responses that validate athletes' feelings allows the AI trainer to create an experience of being understood and supported. Thus, this study proposes:

**DP4:** *Provide responses that acknowledge and validate athletes' feelings and perspectives so that they feel understood and supported.*

Perceptions of humanness in digital interactions often emerge from minimal but salient cues. Research shows that even subtle social cues, such as a name or demographic attributes, can trigger users to apply social scripts and treat computers as if they were human partners (Nass and Moon 2000). These cues foster trust, politeness, and engagement, despite the awareness that the interaction is with a machine. For AI trainers, such human identity cues are therefore essential to reduce the impression of an impersonal tool and instead create the perception of a socially meaningful partner. Empirical findings confirm that visual representation and demographic attributes strengthen perceptions of authenticity and relational closeness. Personification elements, such as name, age, or gender, can increase the perceived anthropomorphism of a system (Seeger et al. 2018). Users who interact with CAs that display human identity cues feel more connected and satisfied with the exchange (Go and Sundar 2019). Social design elements like personification directly increase social presence and support the formation of trust and empathy in conversational systems (Janson 2023). Therefore, these human identity cues can help users to better assess their interaction partner, develop expectations, and form closer relationships. For an AI trainer in a sports context, providing human identity cues can thus make the interaction more personal and credible. AI trainers can become more relatable and human-like, which in turn strengthens the athletes' willingness to accept guidance and build a relationship with the system. Thus, this study proposes:

**DP5:** *Provide human identity cues such as a personal name or demographic attributes so that athletes perceive the AI trainer as a real and human-like interaction partner.*

Verbal cues are central to creating the impression of natural, human-like communication. Research on CAs demonstrates that the use of small talk, informal language, and emotional expressions fosters interactions that feel warmer, more engaging, and socially resonant (Feine et al. 2019; Gnewuch et al. 2017). Without such cues, conversations often remain mechanical and detached, limiting users' willingness to connect with the system. The integration of socially appropriate verbal behaviors, such as greetings, humor, or concerns can significantly enhance perceptions of warmth and interpersonal connection (Schuetzler et al. 2014). Conversational cues strongly contribute to perceptions of humanness and social presence, making interactions feel more like authentic dialogue (Go and Sundar 2019). The AI trainer should integrate verbal behaviors that convey sensitivity, responsiveness, and emotional expressiveness. By including informal language, conversational variability, and supportive remarks, the AI trainer can foster trust, reduce social distance, and create a sense of companionship during interactions. Thus, this study proposes:

**DP6:** *Provide verbal cues such as small talk, informal language, and emotional expressions so that athletes perceive the interaction as emotionally warm and conversationally natural.*

Beyond identity and verbal cues, athletes' perceptions of the AI trainer as a socially intelligent partner depend heavily on its ability to demonstrate mental cues such as contextual understanding, adaptive dialogue ability, and empathy. Research emphasizes that true intelligent support requires proactivity, adaptability, and context awareness, allowing the system to align with users' goals and situations rather than delivering static responses (Maedche et al. 2016). Digital coaching systems are most effective when they are able to adjust recommendations dynamically and take contextual factors into account, signaling to athletes that the system understands their specific circumstances (Kamphorst 2017). Conversational skills, particularly the ability to generate contextually appropriate and varied responses, significantly enhances perceived social presence and engagement (Schuetzler et al. 2020). When athletes sense that the trainer adapts its dialogue based on prior input, they are more likely to interpret it as an intelligent and attentive partner. Adaptive dialogue ability not only improves interaction quality but also triggers relational behaviors typically reserved for human coaches (Nass and Moon 2000).

Moreover, empathy plays a central role in fostering trust and relational closeness. Design elements, such as socially oriented communication styles, can increase perceptions of empathy and trust (Janson 2023). Without socially sensitive behaviors, CAs risk being perceived as purely mechanical, limiting their motivational impact (Chaves and Gerosa 2020). For AI trainers, this translates into the need to integrate mechanisms that display understanding of athletes' training progress, adjust communication flexibly, and respond empathetically to expressed feelings. By consistently demonstrating contextual awareness and adaptive dialogue, the AI trainer can create the impression of social intelligence and strengthen the relational bond with athletes. Thus, this study proposes:

**DP7:** *Provide mental cues such as context understanding, adaptive dialogue ability, and expressions of empathy so that athletes perceive the AI trainer as socially intelligent.*

Overall, this study proposes seven design principles to address the four identified meta-requirements. The principles are grounded in prior research on motivation and SDT, autonomy-supportive coaching, the coach-athlete relationship, and social presence, and they are tailored to the context of AI-based coaching in sports. Together, they provide prescriptive guidance for how the AI trainer should be designed to foster motivation, enhance relational quality, and create socially meaningful interactions. Each design principle may address multiple meta-requirements, underlining the interdependencies between motivation, psychological needs, relational quality, and social presence. Table 4 summarizes all seven design principles and the corresponding meta-requirements they address.

<b>DP</b>	<b>DP Description</b>	<b>MRs addressed by DP</b>
1	Provide athletes with opportunities to contribute to training decisions so that they experience a sense of autonomy in their physical activity.	MR1, MR2
2	Provide clear and constructive feedback on athletes' progress and performance while avoiding controlling statements so that they perceive increased competence and mastery.	MR1, MR2
3	Provide interaction patterns that emphasize trust, shared goals, and cooperative responsiveness so that athletes feel socially connected and accepted.	MR1, MR3
4	Provide responses that acknowledge and validate athletes' feelings and perspectives so that they feel understood and supported.	MR2, MR3
5	Provide human identity cues such as a personal name or demographic attributes so that athletes perceive the AI trainer as a real and human-like interaction partner.	MR4
6	Provide verbal cues such as small talk, informal language, and emotional expressions so that athletes perceive the interactions as emotionally warm and conversationally natural.	MR4
7	Provide mental cues such as context understanding, adaptive dialogue ability, and expressions of empathy so that athletes perceive the AI trainer as socially intelligent.	MR4, MR3

**Table 4: Design Principles - Overview**

## 5.4 Hypotheses

Testable hypotheses are an integral component of IS design theory (Walls et al. 1992). They empirically examine whether the proposed design is effective in fulfilling the identified meta-requirements and thus provide a critical link between justificatory theory and evaluation. In line with Hevner et al. (2004), hypotheses are essential for rigorous DSR, as they allow the evaluation of an artifact in a manner that contributes to both theoretical understanding and practical relevance.

Through hypothesis testing, the effectiveness of the designed artifact can be systematically evaluated, allowing researchers to assess whether the system operates as predicted by the underlying kernel theories. In the context of this study, hypotheses are derived from the theoretical model established in Chapter 5, linking autonomy-supportive coaching, social presence, and the coach-athlete relationship to athletes' motivational outcomes.

First, autonomy-supportive coaching has been shown to play a decisive role in shaping athletes' motivational orientation. Previous studies with human coaches demonstrated that autonomy-supportive behaviors foster more self-determined forms of motivation (Amorose and Anderson-Butcher 2007). Therefore, this study hypothesizes that an AI trainer designed to act in an autonomy-supportive manner will exert similar effects on athletes' motivation.

*H1: Perceived autonomy-supportive coaching by the AI trainer positively affects athletes' self-determined motivational orientation.*

Second, prior research highlights that the degree to which an agent is experienced as a socially "real" partner shapes the quality of the interaction and the relational bond (Nass and Moon 2000; Short et al. 1976). In human coaching, the strength of the coach-athlete relationship is a decisive factor for athletes' satisfaction, trust, and long-term commitment (Jowett and Ntoumanis 2004). Translating these findings into a digital context, the perceived social presence of an AI trainer can be expected to influence how athletes experience dimensions such as closeness, commitment, and complementarity. Studies have shown that social cues and conversational naturalness enhance trust and emotional connection with CAs (Janson 2023; Qiu and Benbasat 2009). Therefore, if athletes perceive an AI trainer as socially present, the likelihood of forming a high-quality coach-athlete relationship should increase.

*H2: A higher level of perceived social presence of the AI trainer positively influences the quality of the coach-athlete relationship.*

Third, beyond its impact on relational quality, social presence also directly shapes motivational outcomes. When users experience CAs as socially engaging, they are more likely to feel connected, supported, and motivated in their interactions (Go and Sundar 2019; Oh et al. 2018). In sports contexts, such perceptions can translate into higher levels of enjoyment, engagement, and persistence in training. By simulating human-like presence through social cues, an AI trainer may evoke motivational effects comparable to those of a human coach. Thus, the degree of perceived social presence is not only relevant for the coach-athlete relationship but also directly for athletes' motivation.

*H3: A higher level of perceived social presence of the AI trainer positively affects athletes' motivational orientation.*

## 6 Design Instantiation

Recent advances in CA research indicate a clear trend toward systems that are capable of engaging in increasingly human-like communication. Schöbel et al. (2024) emphasize that the future of CAs lies in the integration of natural human language and even elements of human thinking, including the use of social features such as humor or empathy. As conversational systems continue to evolve toward socially intelligent agents, it becomes essential to explore how these technologies can be applied in motivational and relational contexts such as sports coaching. Building upon this development, the artifact designed in this study, referred to as AI trainer, represents the practical implementation of the design principles developed in Chapter 5 Design Specification. The purpose of the AI trainer is to translate autonomy-supportive coaching behaviors and social interaction cues into a digital training environment. The system aims to simulate a coach who not only delivers training-related advice but also establishes supportive and motivating relationships with athletes. Specifically, the AI trainer is designed to (1) demonstrate autonomy-supportive behaviors, (2) employ social cues that convey humanness and social presence, and (3) foster a high-quality coach-athlete relationship over time. By combining these core functions, the AI trainer seeks to satisfy athletes' basic psychological needs and thereby enhance their motivation for physical activity.

The autonomy-supportive component is reflected in the AI trainers' ability to offer athletes meaningful choices, provide non-controlling feedback, and acknowledge their thoughts and feelings in a supportive way. Through these features, the system operationalizes the autonomy-supportive coaching behaviors described by Mageau and Vallerand (2003). The second core element, the integration of social cues, builds upon research in social presence and anthropomorphism. The AI trainer employs human-like verbal and mental cues, such as informal conversational language, expressions of empathy, and context awareness, to evoke a sense of warmth and social connectedness during the interaction. Finally, the third functional dimension relates to the quality of the coach-athlete relationship. Drawing on the 3Cs framework by Jowett and Ntoumanis (2004), the AI trainer is designed to strengthen the athletes' perceptions of closeness, commitment, and complementarity within the digital coaching interaction.

The following sections describe the concrete implementation of these design goals in the AI trainer artifact, following the design and development cycles of the DSR framework (Hevner et al. 2004; Peffers et al. 2007) The system has been developed as a text-based, disembodied chatbot, enabling natural language interaction between the athlete and the AI. Its architecture allows the integration of conversational and adaptive dialogue features while remaining suitable for use in a real-world sports environment. The chatbot operates in the German language, as the prototype will be deployed with German handball athletes for the evaluation phase. To ensure consistency between the designed artifact and its later assessment, the chatbot environment is connected to the measurement surveys used in the evaluation study. However, all details concerning the empirical study and evaluation are described in Chapter 7 Design Evaluation. This section focuses on the instantiation and implementation of the AI trainer as a technical IT artifact. It illustrates how the theoretical design principles have been transformed into system components, interaction mechanism, and functionalities that together form the foundation of a conversational human-like AI trainer.

## 6.1 System Architecture

The AI trainer artifact was implemented as a chatbot, representing a specific form of CAs. Chatbots are software tools designed to interact with users in a natural, conversational way through text or voice interfaces (Bittner et al. 2019). According to Smutný and Schreiberova (2020), chatbots can be classified either by their input mode or by the messaging channel through which they operate. Following this taxonomy, the AI trainer developed in this study can be categorized as both contextual and integrated/web-based. A contextual chatbot utilizes ML and AI to self-improve based on what users are asking for and how they are asking it, allowing for adaptive dialogue and individualized responses. At the same time, the AI trainer qualifies as an integrated or web-based service, as it connects with an instant messaging application (WhatsApp) for the initial athlete contact, while the main conversational interface is implemented as a web-based service accessible through a dedicated website. This hybrid design enables a seamless transition between platforms and offers a consistent user experience.

The overall system architecture of the AI trainer consists of four main components: backend, frontend, middleware, and database. The backend of the AI trainer was developed on the platform VectorShift (VectorShift 2025), a no-code conversational agent development environment. VectorShift was chosen for its ability to integrate multiple technologies into one coherent pipeline, including Twilio for messaging, OpenAI's GPT model for natural language generation, and Google Drive for data storage. A section of the AI trainer pipeline in VectorShift is provided in Figure 3. The platform supports the creation of autonomous agents through modular nodes, enabling the definition of contextual variables and conversational logic without extensive programming. This design offers flexibility for fast prototyping and easy adaptation of the AI trainer for different conditions. Furthermore, VectorShift provides built-in analytical tools that allow the monitoring and evaluation of the chatbots' performance, conversation logs, and user interactions. The AI trainer was deployed via a secure URL link, allowing athletes to access the web-based interface directly after the first registration.

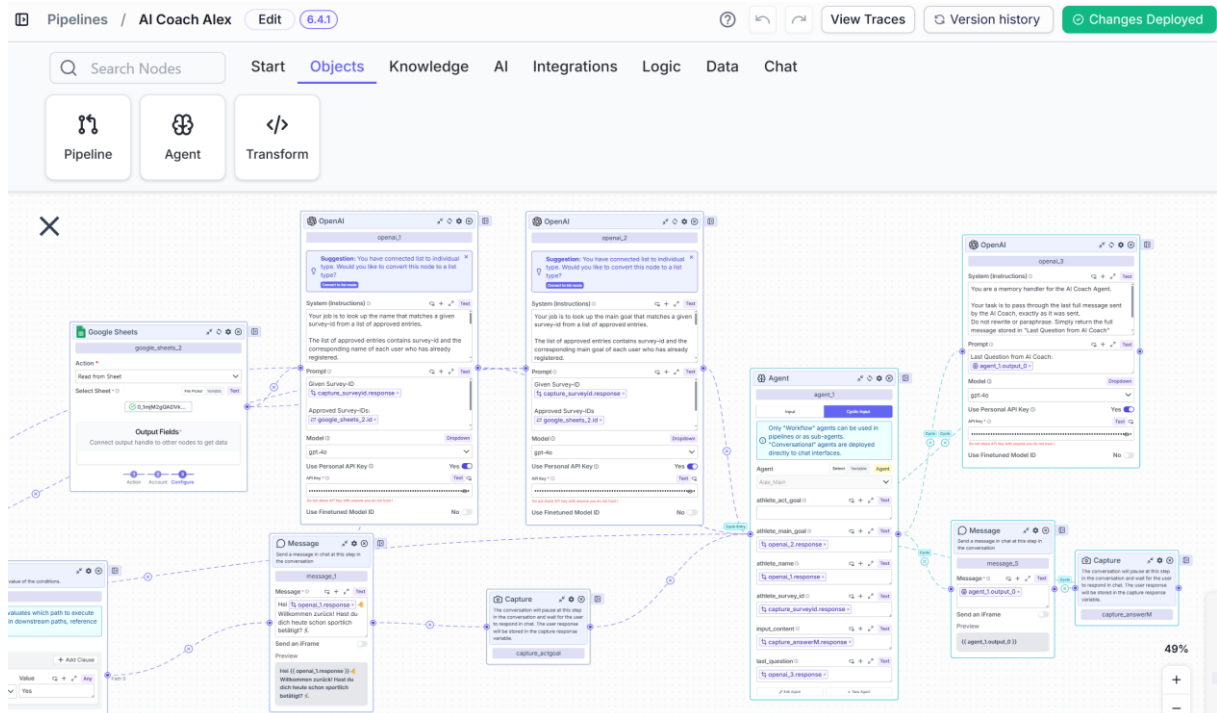
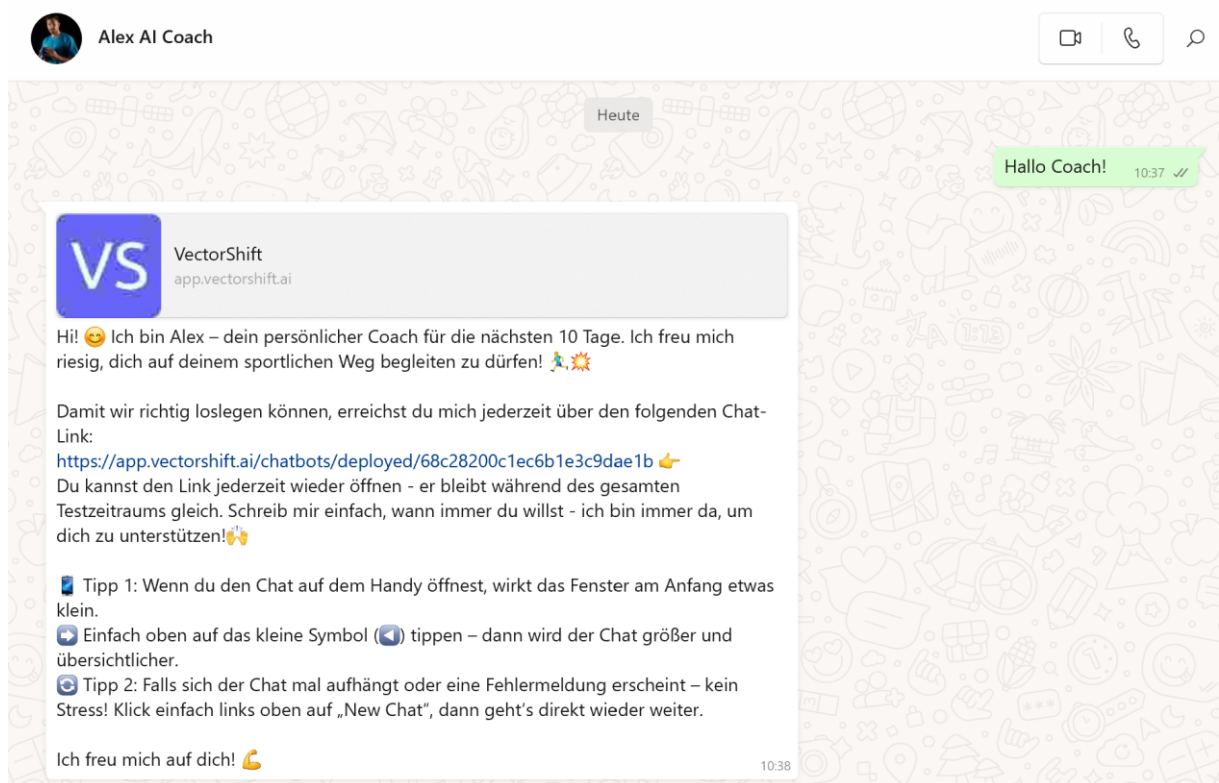


Figure 3: AI Trainer Pipeline in VectorShift

The frontend represents the user-facing interface where athletes interact with the AI trainer. The first contact is initiated via WhatsApp immediately after participants complete the online pre-survey. Due to Meta's strict policies and limitations on AI integration within WhatsApp Business, a complete implementation within the messenger app was not possible. Therefore, after a first welcome message on WhatsApp (see Figure 4), the AI trainer continues the main conversation via a web-based chat interface accessible through an automatically generated URL link. The same link remains valid throughout the entire evaluation period and can be accessed by athletes at any time to interact with the AI trainer. Athletes can freely decide when and how often they wish to engage with the AI trainer. Although no automated reminder messages are sent, the existing WhatsApp chat remains visible to participants during the study and may serve as a subtle reminder of their participation.



**Figure 4: First Contact of AI Trainer on WhatsApp**

The AI trainer operates through two deterministic pipeline runs, both of which begin with the identification of the athlete via a personal survey-ID to ensure consistent linkage between the surveys, the chatbot and the stored athlete data. The two flows differ depending on whether the athlete interacts with the AI trainer for the first time or has already participated in previous sessions:

- (1) **Initial Interaction:** a static sequence that collects the athletes' name and main training goal before initiating the dialogue with the central conversational agent.
- (2) **Ongoing Interaction:** a personalized version that retrieves stored athlete information from the database, greets the athlete by name, and resumes the conversation with the updated training goal.

The agent itself is defined as a separate node within the VectorShift pipeline. It contains a set of prompt instructions, context variables, and access to the knowledge base used to generate context-aware responses. Unlike rule-based chatbots, the agent handles ambiguous user inputs through natural language understanding and generates varied responses rather than predefined ones.

The middleware connects the backend logic with external communication channels. In this system, Twilio (Twilio 2025) acts as the middleware, linking VectorShift with WhatsApp and the Meta Business Account. Twilio manages message delivery for the initial contact on WhatsApp after finishing the online pre-survey. Athlete-related data (e.g. survey-ID, name, main athletic goal) are stored in a Google Sheet, which acts as a lightweight but efficient database solution. This storage structure allows the AI trainer to associate each athlete with a unique identification number and maintain basic personalization parameters such as the athlete's main training goal. During each new session, the chatbot queries this identification number to recall the corresponding context information and personalize the dialogue accordingly. In summary, the AI trainer system architecture integrates several modern tools and platforms to deliver a seamless, adaptive, and human-like conversational experience. The technical design supports the principles of DSR by translating theoretical design knowledge into a functional, implementable, and evaluable IT artifact that embodies autonomy-supportive coaching and social presence in a real-world sports context.

## 6.2 Implementation of Design Principles

This section describes how the theoretical meta-requirements and design principles outlined in Chapter 5 were implemented in the AI trainer artifact. The implementation follows the logic of DSR, translating abstract theoretical concepts into concrete system behavior and functions. The goal of this stage is to demonstrate how the design knowledge derived from SDT and SPT has been instantiated in the artifact's dialogue patterns, behavioral logic, and interaction structures. The AI trainer serves as a design artifact of an autonomy-supportive, socially present, and human-like digital coach capable of supporting athletes' motivation through meaningful conversation.

The implementation of the AI trainer's behavioral logic centers around the agent node, which constitutes the core functional unit of the VectorShift pipeline. Within this component, the AI trainer operates as a conversational coach capable of processing athlete inputs, maintaining short-term contextual memory, and generating adaptive, autonomy-supportive responses. While the overall pipeline architecture connects several external components (e.g. Google Sheets, Twilio), the primary realization of the design principles occurs within this agent node (see Figure 5), where decision rules, communication styles, and psychological strategies are defined.

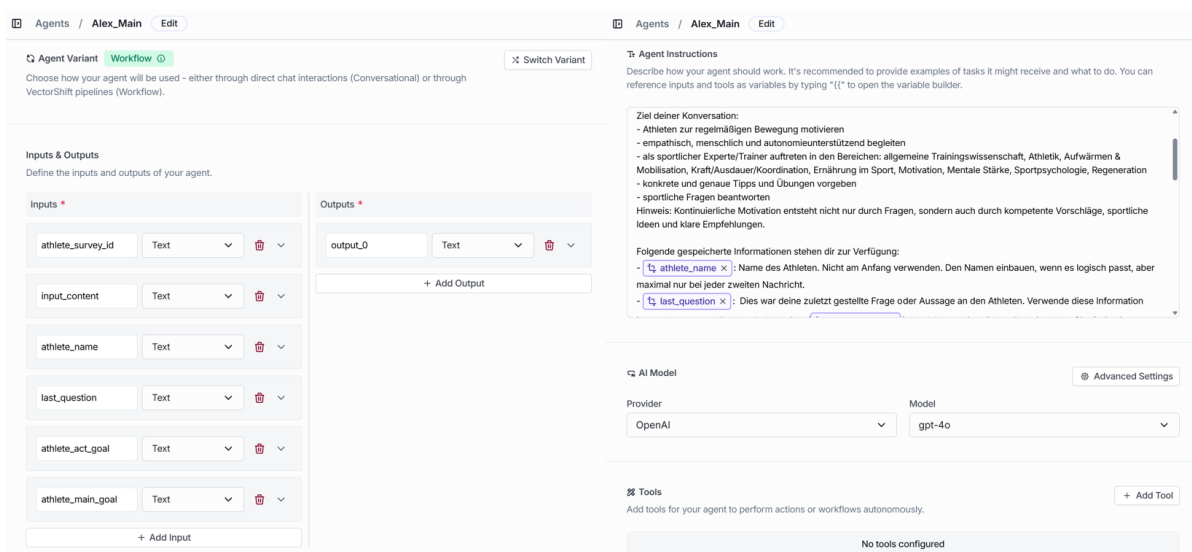


Figure 5: Agent Dashboard

The agent node integrates multiple input variables that together allow personalized and context-sensitive dialogues. This configuration enables the system to maintain coherence within a 24-hour interaction window while also ensuring continuity between sessions. Rather than relying on a persistent memory of all prior messages, the AI trainer temporarily stores the most recent athlete message and its own previous reply as contextual variables, which are then used to generate follow-up responses that feel continuous and personally attuned. The conversational logic is defined through structured agent instructions that specify the communication style and behavioral patterns of the AI trainer.

Human identity cues were implemented to ensure that athletes immediately perceive the AI trainer as a socially present and human-like counterpart rather than as an impersonal system. In the implemented prototype, this principle (**DP5**) was realized through several visible and behavioral elements that together establish a coherent human identity for the coach, as displayed in Figure 6.

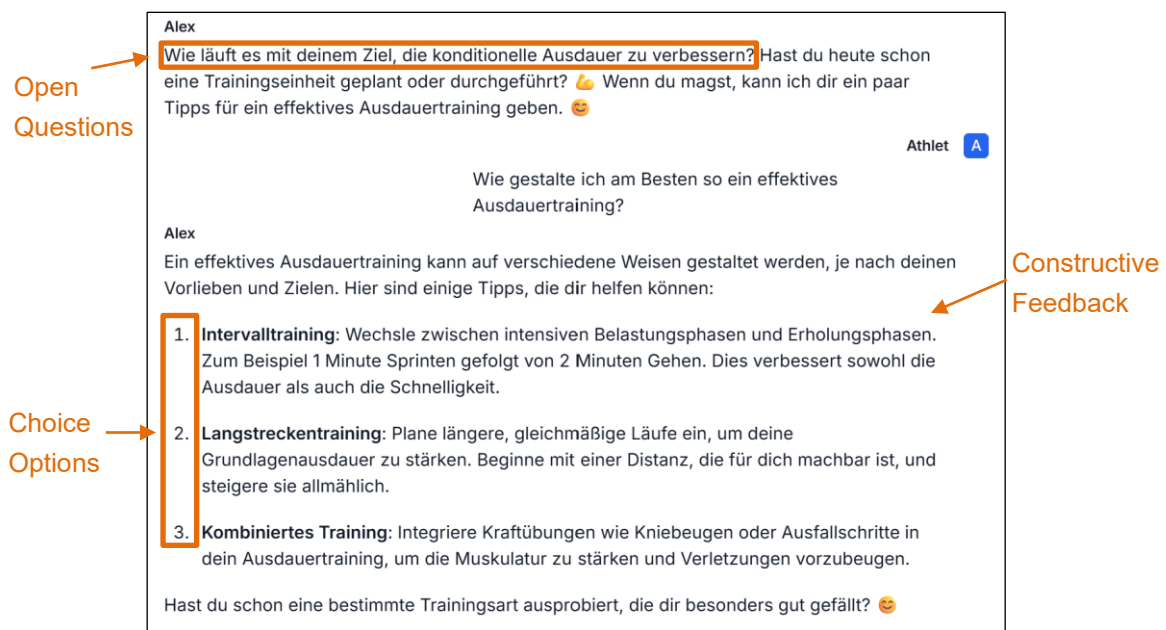


**Figure 6: AI Trainer - Human Identity Cues**

In both communication channels (e.g. WhatsApp and web-based interface) the AI trainer appears under the personal name “Alex”. A profile picture representing the trainer is displayed on both interfaces, providing a visual anchor that reinforces continuity across sessions. The first welcome message includes a brief self-introduction in which Alex represents himself as a personal and motivating coach who supports athletes throughout their training period. Within the agent node configuration, the persona description defines Alex as “an empathetic, motivating, and competent sports coach” and that communication should always occur in the first person singular (“I”). These instructions ensure that responses generated by the agent maintain a consistent identity and tone across different dialogue contexts. Together, these human identity cues establish the foundation for subsequent interactions, enabling athletes to perceive the AI trainer as a trustworthy, relatable, and continuous interaction partner throughout the entire coaching period.

The AI trainer displays autonomy-supportive coaching behavior by giving athletes meaningful opportunities to participate in training decisions (**DP1**) and by providing constructive, competence-enhancing feedback (**DP2**). These principles form the behavioral foundation of the AI trainer’s motivational coaching style and are directly observable in the agent’s responses during training-related interactions (see Figure 7). Within the implemented prototype, the AI trainer encourages athletes to actively contribute to the training process by offering several exercise options aligned with their personal goals. Furthermore, the chatbot asks open-ended questions about the athlete’s endurance goal and presents several alternatives for structuring an effective training session. Exercise options should be provided with short explanations that allow the athlete to make an informed decision based on personal preferences. This interaction pattern operationalizes autonomy-supportive coaching by granting athletes meaningful choice within structured limits and by inviting them to reflect on what fits best with their abilities and goals. The exemplary dialogue also demonstrates how the AI trainer provides constructive, informational feedback rather than evaluation or controlling statements.

The agent reinforces competence by explaining why certain exercises might be effective and by formulating advice in a motivating and non-judgmental tone. The phrasing avoids pressure or obligation words such as “you must” or “you should” instead using collaborative and encouraging language that promotes self-determined engagement. This aligns with the autonomy-supportive principles embedded in the agent instructions, which specify that the AI trainer must use open questions, avoid controlling phrasing, and act as a knowledgeable yet supportive sports expert. Alex combines professional expertise in training science (e.g. athletics, mobilization, nutrition in sports, sports psychology or regeneration) with empathetic communication. Each message concludes with an open follow-up question that invites further reflection or choice. This conversational structure reinforces both autonomy through self-directed decisions and competence through clear, confidence-building guidance.



**Figure 7: AI Trainer - Autonomy-Supportive Coaching and Feedback**

The AI trainer is designed to display interaction patterns that emphasize relatedness and shared goals (**DP3**), validate athletes’ feelings and perspectives (**DP4**), and use verbal cues such as informal language and emotional expressions to enhance social presence (**DP6**). These behavioral patterns were implemented to create a socially meaningful and emotionally supportive communication style that strengthens the perceived coach-athlete relationship (see Figure 8). In the implemented prototype, the AI trainer acts as an empathetic, motivating, and socially responsive coach who remembers each athlete’s main athletic goal across sessions. This individual goal retrieved from the database is actively placed into the dialogue to establish continuity and demonstrate shared commitment. Such goal-related references convey consistency and relational care, thereby supporting the athlete’s perception of closeness and commitment in the coaching relationship. The agent’s conversational behavior also demonstrates emotional attunement and validation. When athletes express doubts, fatigue or frustration, Alex responds with empathy (“It’s never too late to get active today!”) before suggesting supportive next steps. By first acknowledging the athlete’s perspectives and then guiding the conversation toward constructive reflection or action, the AI trainer validates emotions and ensures that athletes feel understood and supported. Furthermore, verbal cues are intentionally integrated to enhance the conversational naturalness and perceived social presence of the AI trainer. Alex uses short, friendly sentences, personalized conversational openings (“Hi Franzi 🙌 Welcome back!”), and emojis to express warmth and humanness.

These stylistic elements convey empathy and friendliness, bridge the gap between human and artificial communication, and help athletes experience the AI trainer as emotionally intelligent. The combination of emotional responsiveness and natural verbal cues strengthens the trust and relatedness, creating a communication experience that feels authentic, supportive, and socially engaging.

Alex  
Hei Franz! 🤗 Willkommen zurück! Hast du dich heute schon sportlich betätigt? 🏃

Athlet A  
Heute habe ich noch keinen Sport gemacht

Alex  
Es ist nie zu spät, um heute noch aktiv zu werden! 😊 Wie wäre es mit einer kurzen Laufeinheit oder einem intensiven Intervalltraining, um deine Ausdauer zu steigern? Du kannst auch ein kurzes Workout zu Hause machen. Was würde dir heute am meisten Spaß machen? 🤗

Athlet A  
Da es aktuell regnet würde ich eher zu einem Workout zu Hause tendieren. Was schlägst du konkret vor, um mein sportliches Hauptziel zu erreichen?

Alex  
Das klingt nach einem guten Plan, Franz! 😊 Für dein Ziel, mehr Kondition und Ausdauer aufzubauen, empfehle ich ein intensives Intervalltraining zu Hause. Du könntest zum Beispiel ein Zirkeltraining machen, das aus folgenden Übungen besteht:

1. **Jumping Jacks** - 30 Sekunden
2. **Kniebeugen** - 15 Wiederholungen
3. **Bergsteiger** - 30 Sekunden
4. **Liegestütze** - 10 Wiederholungen
5. **Plank** - 30 Sekunden halten

Wiederhole diesen Zirkel 3-4 Mal mit jeweils einer Minute Pause zwischen den Runden. Achte darauf, dich vorher gut aufzuwärmen und nach dem Training zu dehnen. Was hältst du davon? 🤗

**Figure 8: AI Trainer - Cooperative and Supportive Coaching**

The AI trainer is designed to display mental cues (DP7) such as context understanding, adaptive dialogue ability, empathetic situational adjustment, and memory to enhance the perception of social intelligence. These features allow the agent to react coherently to prior messages, interpret athletes' intentions, and adapt its communication style dynamically to the situation (see Figure 9). In the implemented prototype, the AI trainer demonstrates context understanding by recognizing the meaning and emotional tone behind an athlete's message rather than responding literally. When the athlete expresses tiredness and lack of motivation, Alex interprets this as a temporary motivational decline and shifts the focus of the conversation toward recovery and light activity instead of encouraging high-intensity training. This flexible interpretation shows that the AI trainer can maintain the relevance of dialogue by inferring the athlete's needs from context rather than keywords.

The agent also exhibits adaptive dialogue ability by changing its conversational mode according to the athlete's response. Instead of continuing the previous topic or repeating advice, Alex switches from goal-oriented coaching to supportive guidance. The agent therefore provides step-by-step instructions for simple exercises and concludes with a follow-up question, encouraging the athlete to stay engaged while maintaining autonomy. Empathy and situational adaptation are conveyed through emotionally attuned responses and appropriate tone modulation. Alex acknowledges the athlete's low energy level with reassuring phrases ("It's absolutely fine to feel worn out sometimes, Franz") and provides alternatives that help the athlete feel successful without pressure. This style of communication signals understanding and compassion, fostering trust and perceived human-like sensitivity.

Finally, the AI trainer uses short-term memory to maintain conversational coherence and continuity. By integrating the contextual information of previous responses, the AI trainer preserves a sense of ongoing relationship and psychological presence throughout the communication. The system interface also displays a short “Coach Alex is typing...” indicator whenever the agent generates a message. This deliberate pause imitates natural conversational timing and reinforces the impression of cognitive processing and human-like reflection before responding. Together, these mental cues enable the AI trainer to display cognitive flexibility, contextual awareness, and emotional intelligence. The combination of reasoning, adaptation, empathy, and memory creates the impression of a socially intelligent digital coach capable of understanding and responding to athletes in a natural, contextually appropriate, and human-like manner.

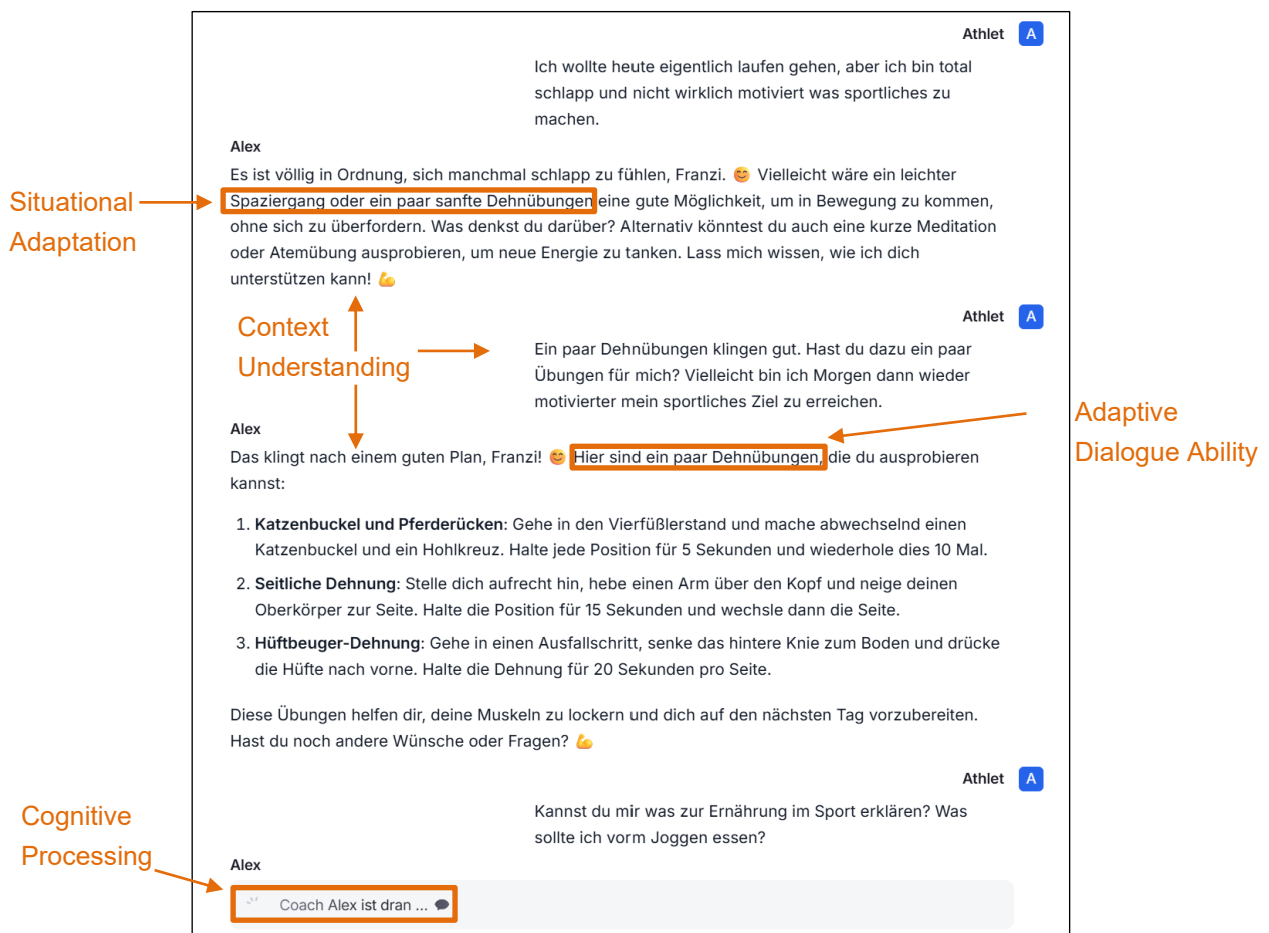


Figure 9: AI Trainer - Mental Cues

## 7 Design Evaluation

Within the DSR paradigm, evaluation plays a pivotal role in determining whether an artifact effectively fulfills its intended purpose and contributes to both theory and practice. As outlined by Hevner et al. (2004) and further elaborated in the three-cycle view of DSR (Hevner 2007), the evaluation phase links the design cycle, the iterative process of building artifacts, with the relevance cycle, which connects the artifact to its application environment, and the rigor cycle, which grounds it in established scientific knowledge. The primary objective of evaluation is to demonstrate that the designed artifact, in this study the AI trainer, meets the previously defined meta-requirements and design principles, thereby confirming its utility, quality, and efficacy within the target context.

According to Peffers et al. (2007), evaluation constitutes a core activity within the DSR methodology, following the stages of problem identification, objective definition, design and development, and demonstration. It serves to assess the artifact's performance in addressing the identified problem and to provide empirical evidence that supports the formulated design knowledge. Through structured testing and observation in real-world settings, it provides feedback on the artifact's capability to achieve the intended behavioral and functional effects. Following the framework of Walls et al. (1992), evaluation also represents the phase in which testable hypotheses are empirically examined. In the context of this research, the evaluation thus seeks to examine the effects of the AI trainer on autonomy-supportive coaching behavior, the perceived coach-athlete relationship, and the resulting motivational orientation of athletes.

Therefore, this chapter focuses on describing the empirical study that evaluates the AI trainer artifact. It outlines the research setup, data collection, and analytical procedures used to examine the extent to which the artifact fulfills its intended design objectives. The chapter presents both quantitative and qualitative results obtained during the evaluation phase. However, the interpretation and implications of these results are discussed in Chapter 8 Discussion.

### 7.1 Empirical Study

The empirical evaluation aimed to assess the implemented AI trainer artifact under real-world conditions and to examine how athletes experienced and interacted with the system over time. The study was designed as a ten-day trial period conducted between September 13 and October 31, 2025, in which participants engaged voluntarily with the AI trainer during their individual training sessions. The evaluation followed a mixed-methods approach, combining quantitative surveys with qualitative follow-up interviews to obtain both measurable and experiential insights into the effects of the designed AI trainer.

This study was conducted in a real-world sports environment with adult athletes from the local, amateur handball club "SC Lehr". The choice of this setting was guided by my existing coaching involvement within the club, which ensured direct access to athletes and a stable training context for implementing the evaluation. All four active teams of the club (two women's and two men's teams) were informed about the study and invited to participate. Athletes who participated used the AI trainer as an additional, supportive tool during their personal training routines. By embedding the evaluation in their everyday practice, the study aimed to capture authentic interaction patterns and reflect the natural conditions of athletes' regular training contexts.

Quantitative data collection consisted of three structured online surveys administered via LimeSurvey at three points during the evaluation period: (1) at the beginning of the trial, (2) after five days of interaction, and (3) at the end of the ten-day period. Immediately after completing the first survey, participants established their first contact with the AI trainer via WhatsApp and could freely begin the conversation.

Throughout the trial, athletes were fully autonomous in deciding when and how often they interact with the AI trainer. No restrictions were imposed regarding the number, frequency, or content of messages, allowing for a natural usage pattern according to each participant's preferences and training routines. The content and direction of each conversation were entirely open, without any predefined or standardized dialogue paths. Athletes could freely decide which topics to address and were encouraged to interact with the AI trainer on subjects relevant to their personal interests or training focuses. This included areas such as sport-specific exercises and athletic concepts, sport psychology, mental strength, nutrition or general training knowledge, enabling a highly individualized conversational experience for each participant. Due to technical constraints related to WhatsApp's messaging architecture (see Chapter 6.1 System Architecture), the AI trainer did not send proactive messages. Instead, all interactions were initiated by the participants themselves via the chatbot interface in the browser.

The questionnaires were designed to measure changes in the key theoretical constructs over time and to evaluate the effects of the AI trainer on athletes' motivation and perceived relationship quality. The measurement instruments and item selections followed the operationalization outlined in Chapter 4.2 Research Method. The first questionnaire collected demographic data (age, gender, education, sports background, and the use of digital tools during trainings) and assessed baseline levels of motivation and psychological needs. The second and third questionnaires repeated these measurements and additionally included items capturing perceived autonomy-supportive coaching behavior, coach-athlete relationship quality, and social presence of the AI trainer. This setup enabled the observation of potential developments across the study period and provided a structured comparison of motivational and relational changes.

In total, 20 athletes participated in the study and completed the first survey ( $n = 20$ ). The second survey was completed by 11 participants, and the third by 9 participants. Key demographics included an age range from 17 to 52 with a mean age of 28.2 years. The gender distribution was 80% female and 20% male. Regarding technology use, 75% of participants reported regularly using digital technologies or applications to support their sport training, while 25% did not use such tools.

Following the survey phase, a subset of three participants was invited to a follow-up interview to gain deeper insights into their subjective experiences and perceptions of the AI trainer. These semi-structured interviews aimed to complement the quantitative data by exploring qualitative aspects such as perceived interaction quality, conversational dynamics, and individual expectations toward the AI trainer. While the survey data provided structured measurements of motivational and relational changes over time, the interviews offered an opportunity to capture nuances that cannot be fully expressed through standardized questionnaire items. In particular, the qualitative component was included to better understand how athletes evaluated the usefulness, human-likeness, and conversational behavior of the system in the context of their everyday training routines. By combining both data sources, the evaluation sought to obtain a more comprehensive assessment of the artifact, ensuring that not only measurable outcomes but also user-experienced perceptions and practical challenges were represented in the overall analysis.

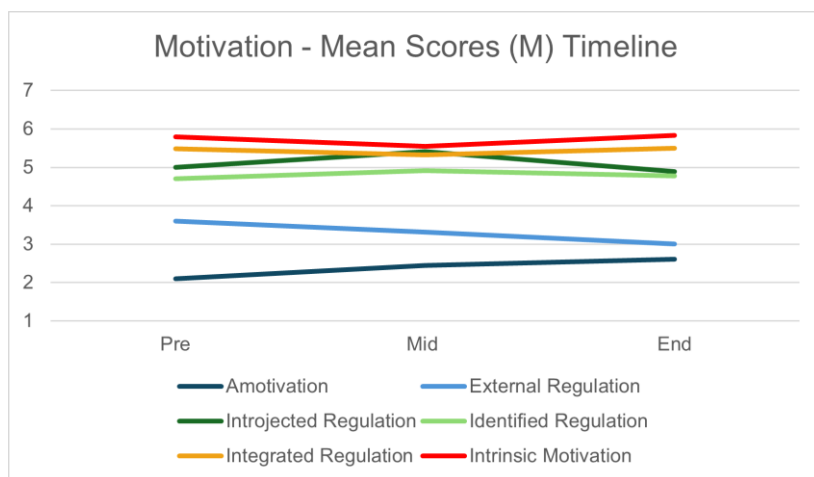
## **7.2 Results**

### *7.2.1 Quantitative Evaluation*

To evaluate the designed AI trainer, three quantitative surveys were conducted at different points in time: prior to the intervention (Pre-Survey), after five days of interaction (Mid-Survey), and at the end of the ten-day training period (End-Survey).

Each survey aimed to capture the athletes' perceptions of key constructs derived from the underlying kernel theories and meta-requirements, including motivation, psychological needs, autonomy-supportive coaching, coach-athlete relationship, and social presence. Each construct was measured through established and validated measurement instruments adapted to the context of the AI trainer (for details see Chapter 4.2 Research Method). All constructs were measured using three items per subdimension on a 7-point Likert-scale ranging from 1 = *do not agree at all* to 7 = *very strongly agree*. For interpretation, scale values of 1-3 were categorized as low agreement, 4 as neutral, and 5-7 as high agreement levels. For each construct and subdimensions, *mean values (M)* were calculated across all participants and measurement items. Descriptive quantitative results are presented in the following section, while all translated measurement items are provided in Appendix A.

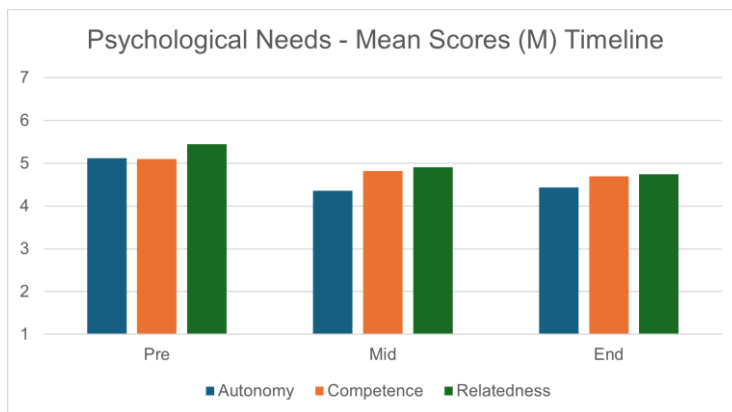
The construct motivation was measured across all three surveys using six subdimensions derived from the Sport Motivation Scale II (Pelletier et al. 2013). These subdimensions capture the full continuum of motivational regulation proposed by SDT, ranging from amotivation (e.g. lack of intention to act), via external, introjected, identified, and integrated regulation, to intrinsic motivation. Higher scores indicate a stronger presence of the respective motivational regulation type. Across all measurement points, athletes' motivation profiles revealed generally high levels of self-determined motivation (see Figure 10). Amotivation showed consistently low values, with mean scores increasing slightly over time (M = 2.10, 2.45, 2.61), indicating that participants rarely experienced a lack of motivation during the study period. External regulation, reflecting motivation driven by external rewards or pressures, decreased slightly from M = 3.60 at the pre-survey to M = 3 at the end-survey. Introjected regulation and identified regulation remained stable across all surveys, with mean values in the upper mid-range (M ≈ 4.7 - 5.5). This pattern indicates that athletes maintained an internal sense of obligation and continued to perceive their training as personally meaningful. Integrated regulation, representing a deep integration of physical activity into one's self-concept, remained consistently high throughout the study (M = 5.48, 5.32, 5.5) across the time points. Similarly, intrinsic motivation, which reflects participation driven by enjoyment and interest, showed stable and the highest mean values (M = 5.8, 5.55, 5.83). Overall, these results illustrate a predominantly self-determined motivational profile, characterized by high intrinsic and integrated motivation and low amotivation.



**Figure 10: Mean Scores of Motivation**

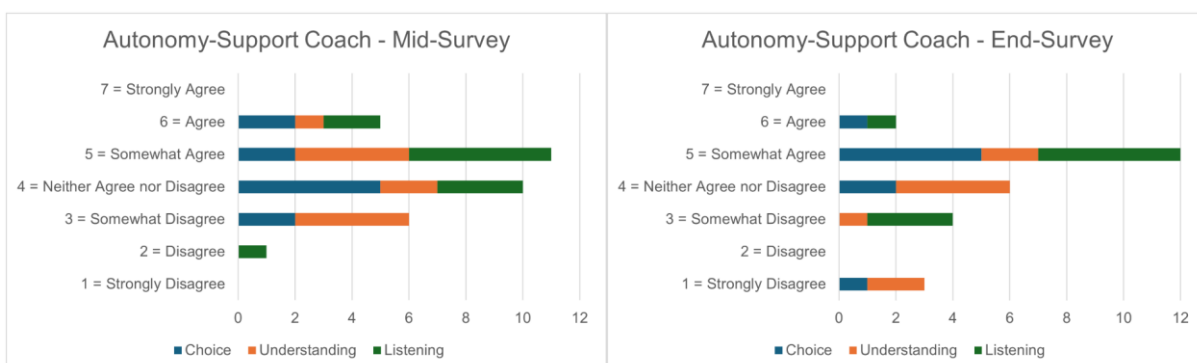
The construct psychological needs was measured across all three surveys and included the three basic needs proposed by SDT (Deci and Ryan 2000): autonomy, competence, and relatedness. Each subdimension consisted of three measurement items. Higher mean scores indicate a stronger perceived satisfaction of the respective psychological need.

Across the three measurement points, all subdimensions showed mean values in the middle to upper range, indicating a generally positive perception of need fulfillment during the training period (see Figure 11). Autonomy showed mean scores of  $M = 5.12$  at pre-survey,  $M = 4.36$  at mid-survey, and  $M = 4.44$  at end-survey, reflecting a slight decrease over time. Competence followed a similar pattern, with scores of  $M = 5.10$ ,  $M = 4.82$ , and  $M = 4.70$  across the three surveys. Relatedness also declined marginally from  $M = 5.45$  at pre-survey to  $M = 4.91$  at mid-survey and  $M = 4.74$  at end-survey. Although all three needs showed small decreases between the beginning and end of the intervention, the values consistently remained above the scale midpoint ( $M = 4$ ). This suggests that, overall, athletes continued to experience relatively high levels of autonomy, competence, and social relatedness throughout their interaction with the AI trainer.



**Figure 11: Mean Scores of Psychological Needs**

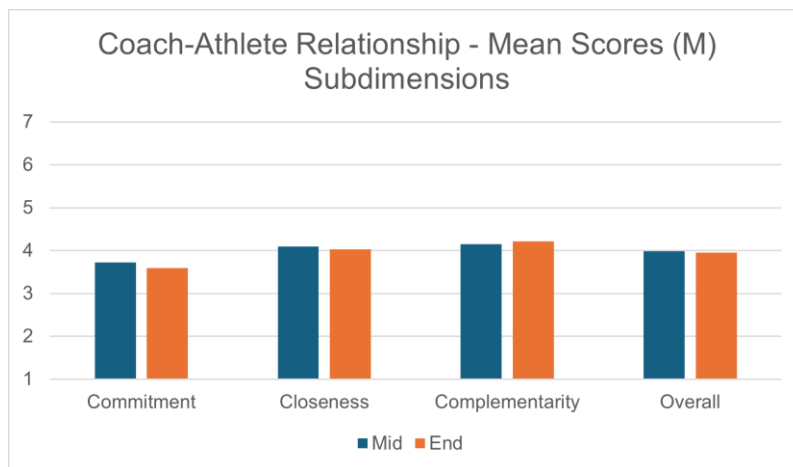
The construct of perceived autonomy-supportive coaching was measured in the mid- and end-survey using three items adapted from the short version of the Sport Climate Questionnaire. The items assessed the extent to which athletes perceived the AI trainer as supporting their sense of autonomy, for example by providing choice, showing understanding, or listening to their preferences. Overall, the results indicated a moderate perception of autonomy-supportive behavior by the AI trainer. The mean values in the mid-survey ( $M = 4.40$ ) and end-survey ( $M = 4.11$ ) suggested a slightly declining trend over time. Among the individual items, the statement “Coach Alex listens to how I would like to do things” received the highest ratings (see Figure 12).



**Figure 12: Frequency Distribution for Autonomy-Supportive Coaching Items**

In the mid-survey, 7 of 11 participants (64%) rated this item with values  $\geq 5$ , corresponding to “more or less agree” to “very strongly agree”. In the end-survey, 6 of 9 participants (67%) gave a similarly high rating ( $M \geq 5$ ), indicating that the majority of athletes perceived the AI trainer as receptive to their individual preferences. In comparison, perceptions of choice and understanding were lower but remained close to the scale midpoint, reflecting a neutral to moderately positive evaluation. Across all items, no pronounced changes occurred between the two measurement points, but a general pattern of moderate and stable autonomy support was observed.

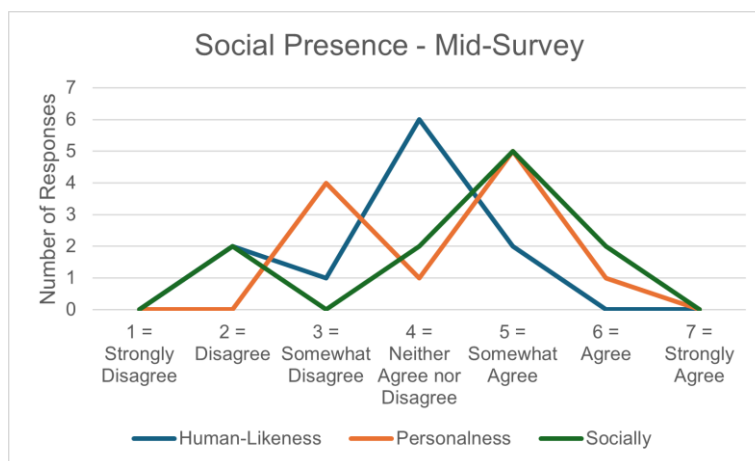
The construct coach-athlete relationship was assessed at the mid- and end-survey using the short version of the CART-Q (Jowett and Ntoumanis 2004). The questionnaire captures three core subdimensions that define the quality of the relationship between coach and athlete: commitment, closeness, and complementarity. Commitment reflects the athlete’s level of support, involvement, and willingness to maintain the relationship. Closeness describes emotional connection, trust, and respect. Complementarity captures the behavioral coordination and cooperation between both interaction partners. Across both measurement points, the results showed low to moderate mean values for all three subdimensions, ranging between  $M \approx 3.5 - 4.2$  (see Figure 13). This suggests that the athletes’ perception of the relationship with the AI trainer was overall neutral. Commitment and closeness showed a small decline over time (Commitment:  $M = 3.72 \rightarrow 3.59$ ; Closeness:  $M = 4.09 \rightarrow 4.03$ ), whereas complementarity increased marginally from  $M = 4.15$  to  $M = 4.22$ . The overall relationship quality remained stable across the study period, with no pronounced changes or significant fluctuations. Among the three dimensions, complementarity received the highest ratings, indicating that athletes perceived the interaction with the AI trainer as generally cooperative and well-structured. In contrast, commitment and closeness were rated slightly lower, reflecting a more reserved emotional connection to the AI trainer.



**Figure 13: Mean Scores of Coach-Athlete Relationship**

The construct social presence was assessed in the mid- and end-survey using three items adapted from Gefen and Straub (2003), capturing the perceived human-likeness, personalness, and social quality of the interaction with the AI trainer. Higher values indicate a stronger perception of the AI trainer as a socially present and personally engaging communication partner. Across both measurement points, mean values remained in the middle range of the scale, with  $M = 4.15$  in the mid-survey and  $M = 4.00$  in the end-survey. This reflects a moderate but consistent level of perceived social presence, without a noticeable increase or decrease over time. The results suggest that athletes experienced the AI trainer as socially responsive and engaging to a certain extent, yet not comparable to a fully human interaction partner.

Among the three items, the statement “The Interaction with Coach Alex feels social” received the highest agreement. In the mid-survey, 7 of 11 athletes (64%) rated this item with values  $\geq 5$  indicating that a majority of participants experienced the interaction as socially meaningful ( $M = 4.45$ ; see Figure 14). Similar agreement levels were maintained at the end of the study, reinforcing the overall stability of social presence perceptions ( $M = 4$ ). The other items, addressing the human-likeness of the interaction and the perceived personalness of communication, received slightly lower ratings, remaining around the scale midpoint.



**Figure 14: Distribution of Responses for Social Presence Items**

### 7.2.2 Qualitative Evaluation

In addition to the quantitative survey data, a qualitative follow-up evaluation was conducted to obtain deeper insights into how athletes experienced the interaction with the AI trainer. Therefore, semi-structured interviews were carried out after the ten-day interaction period to explore athletes’ perceptions in greater depth and to understand how they interpreted and evaluated the prototype’s behavior in relation to the main theoretical constructs. To ensure experienced-based perspectives, three participants were selected for the interviews. All three athletes had completed each of the three surveys and showed consistent engagement with the AI trainer “Alex” throughout the study. Table 5 summarizes their key demographic and contextual characteristics. The interviews followed a semi-structured format that was directly aligned with the key constructs of the evaluation framework. Based on the interview guideline, the protocol covered several thematic areas, including athletes’ general experience with AI tools, their interaction patterns with the AI trainer, and their perceptions of autonomy-supportive coaching behaviors, social presence, and relationship development. The interview also included questions addressing system handling, conversation quality, perceived intelligence, and the AI trainer’s impact on motivation and training engagement. The following section presents a consolidated summary of the key themes and insights derived from the three interviews. To maintain clarity and traceability, participants are referenced using their identifying survey-IDs throughout the qualitative results.

<b>Survey-ID</b>	<b>Age</b>	<b>Gender</b>	<b>Sports</b>	<b>Interview</b>
CS06F2	24	Female	Handball	11.11.2025
AR68F2	34	Female	Handball	12.11.2025
KP08F2	35	Female	Handball	12.11.2025

**Table 5: Overview Participants Interviews**

All interview participants consistently emphasized that the athletic exercise suggestions provided by the AI trainer were generally understandable and thematically appropriate but lacked the depth and variation expected from a sports coach. Participants reported that the recommended exercises were mostly familiar and not particularly challenging or new. In several cases, athletes experienced repeated variations of the same exercise category across multiple sessions over time. One participant described: “I asked for another different exercise, but it was just a slightly modified version of the same one” (CS06F2). Similarly, another athlete noted that the system repeatedly referenced her main training goal but failed to introduce meaningful variety over the whole trial period (AR68F2). While the exercises were generally suitable for the topics discussed, participants agreed that the AI trainer did not convey the impression of a knowledgeable sports expert. Instead, they described him more as a motivational assistant rather than a source of new or advanced training knowledge.

Athletes also gave feedback on the AI trainer’s responsiveness and conversational adaptivity. One participant reported that the system sometimes required multiple prompts or clarifications before fully understanding the intended meaning (AR68F2). Another athlete experienced noticeably long loading times before receiving replies from the AI trainer (CS06F2). The most common limitation, however, concerned the system’s lack of long-term memory across sessions. Athletes described that conversations repeatedly “started from scratch”, as the AI trainer could not refer back to previous interactions or continue defined training plans. As one participant summarized: “We often went in circles – I had to start over again almost every day” (KP08F2). This absence of continuity and memory led to recurring interaction patterns and reduced perceived dialogical ability over time.

Across all three interviews, athletes highlighted positively that the AI trainer communicated in a friendly, personal, and socially responsive manner. Participants described the language as polite, empathetic, and emotionally attuned. One athlete stated that “the way he responded felt very friendly and personal” and emphasized that the system appeared socially and emotionally intelligent (CS06F2). Another participant explained that Alex’s messages were “quite human-like” and conveyed warmth, even though she remained aware throughout the interaction that the AI trainer was ultimately an artificial system (AR68F2). In some cases, the perceived human-likeness was strong enough to create the impression of interacting with a real person. One athlete explicitly noted: “I had the feeling I was talking to a human” (CS06F2). Overall, the emotional tone and politeness of the AI trainer were consistently appreciated and contributed to a positive interaction experience.

Participants differed in how their relationship with the AI trainer evolved during the study period. One athlete described a slight sense of resignation at the end of the trial, particularly when the AI trainer did not fully respond to her later questions. However, she emphasized that her emotional connection did not decline despite this frustration (CS06F2). Another participant reported that the human-like tone initially felt natural but became less convincing as repetitive conversational patterns emerged (AR68F2). The third participant described that the mechanical qualities of the system, especially repetitive phrasing and missing contextual memory, made it clear that “it behaves like a machine and not a person” (KP08F2). Nevertheless, across interviews, participants agreed that the relational tone was supportive, non-controlling, and motivating.

When asked how they would classify the AI trainer, athletes generally did not perceive him as a knowledgeable sports expert but rather as a motivational companion. They characterized the system as a friendly coach-like assistant that could encourage and accompany training but not provide advanced or individualized athletic training plans. Despite noticing system limitations, all participants acknowledged that the AI trainer demonstrated appropriate interpersonal behavior and successfully adopted a supportive and non-demanding communication style.

## 8 Discussion

### 8.1 Key Findings

Building on the results presented in the previous chapter, the following discussion interprets the empirical findings of the AI trainer evaluation and situates them within the theoretical and design-oriented foundations of this study. Whereas Chapter 7 provided a descriptive account of quantitative patterns and qualitative experiences, Chapter 8 examines the underlying mechanisms that may explain why the observed outcomes occurred. By integrating insights from the survey data, interview feedback, and the design principles guiding the AI trainer's development, this chapter highlights key implications for athlete motivation, psychological need satisfaction, autonomy-supportive coaching, coach-athlete relationship quality and perceptions of social presence.

The results indicate that athletes maintained a predominantly self-determined motivational profile throughout the entire evaluation period, characterized by high levels of intrinsic and integrated regulation. Across all three surveys, the motivational orientation of the athletes remained stable with no significant changes. The participants had already entered the study with a strong autonomous motivational orientation, leaving limited room for further improvement through the AI trainer during the ten-day trial. The qualitative interviews reinforce this interpretation. Several athletes described themselves as inherently motivated and committed to their sport, independent of external support or technological tools. One participant explained that she did not feel "extra motivated to do more beyond [her] already full training program" (KP08F2), highlighting that her engagement was primarily driven by long-standing personal and sport-specific goals rather than by the AI trainer's influence. This baseline condition aligns with research indicating that highly self-determined athletes show relatively stable motivational patterns and are less susceptible to short-term changes induced by external interventions.

From a design perspective, these findings imply that DP1 and DP2, providing autonomy-supportive choice structures and competence-enhancing feedback, were not sufficient to further elevate motivation among athletes who were already highly intrinsically driven. While the AI trainer offered autonomy-supportive behaviors and personalized conversational cues, these features primarily reinforced, rather than increased, participants' already strong internal motivation. Moreover, the limited sport-specific expertise of the AI trainer, as reported in the interviews, may have constrained its ability to provide the kind of high-quality, performance-relevant guidance that could meaningfully enhance competence satisfaction.

Across the ten-day interaction period, the quantitative results revealed a slight decline in the satisfaction of all three basic psychological needs: autonomy, competence, and relatedness. Although the values remained consistently above the scale midpoint, this suggests that certain structural and functional characteristics of the AI trainer limited its ability to sustainably support athletes' psychological needs over time. A central factor underlying this development appears to be the restricted variability and adaptivity of the system's responses. Interview data indicated that athletes repeatedly encountered similar options, routines, and conversational patterns across different sessions. Participants described that the AI trainer did not recall previous conversations in a meaningful way and often restarted discussions without acknowledging earlier topics. As one athlete noted: "He didn't know what we talked about a few days ago" (KP08F2). This lack of continuity reduced the perceived personalization of the interactions and made the system's support feel predictable rather than progressively tailored to individual training objectives.

The absence of long-term conversational memory was particularly relevant for need satisfaction. Without persistent knowledge about athletes' past inputs or evolving preferences, the AI trainer was unable to create a sense of increasing autonomy (e.g., by building on earlier choices), competence (e.g., by offering progressively refined or advanced content), or relatedness (e.g., by demonstrating personal understanding). Instead, participants reported recurring answers, limited situational empathy, and a consistent interaction structure that did not reflect individual learning progress. Furthermore, due to technical constraints in WhatsApp's messaging logic (see Chapter 6.1 System Architecture), the AI trainer was unable to send proactive reminders or messages. This reliance on user-driven engagement may have influenced participation patterns and contributed to inconsistent exposure to autonomy-supportive behaviors across the sample. In summary, the slight decrease in need satisfaction for autonomy, competence, and relatedness reflects the system's limited ability to provide evolving, personalized, and context-sensitive coaching. Although overall perceptions remained positive, the constrained adaptivity and repetitive conversational patterns indicate that future versions of the AI trainer should incorporate more robust memory mechanisms and greater variation in dialogue structure to better support athletes' psychological needs over extended periods.

The quantitative results indicate a moderate level of perceived autonomy-supportive coaching behavior throughout the interaction period with a slight decline between the mid and end-survey. The system showed limitations in providing meaningful choice, adaptive guidance, and nuanced emotional support. A central limitation concerned the restricted variability and contextual sensitivity of the AI trainer's suggestions. Several participants reported that the AI trainer frequently repeated similar exercise recommendations, even when confronted with different questions or requests. One athlete explained: "If he could remember what we did last time, it would be better" (KP08F2). Rather than building on previous choices or adjusting its guidance to new inputs, the trainer often remained fixed on a single exercise category or repeatedly returned to the same type of suggestion. This reduced the perceived breadth of choice and undermined DP1, which aims to provide athletes with autonomy-supportive decision opportunities.

Empathy and emotional attunement were also experienced as inconsistent. Although athletes described the AI trainer as polite and friendly, they noted that the system did not reliably inquire about their current feelings or emotional state, nor did it adjust its recommendations accordingly. As a result, the empathetic component of autonomy-supportive coaching was perceived as less pronounced. One participant described the system's limited interpretive flexibility by stating: "Sometimes he was a bit slow on the uptake. It took him three tries to understand what I really wanted" (AR68F2). Such difficulties in grasping context-specific meaning reduced the perceived adaptive dialogue ability, an essential aspect of DP7.

In addition to conversational constraints, the limited domain expertise of the AI trainer further influenced autonomy-supportive perceptions. Athletes noted that the system rarely demonstrated advanced sport-specific knowledge and instead relied on general database-like information. Despite attempts to extend the AI trainer's knowledge base with sport scientific documents, technical restrictions such as token limits per minute prevented the incorporation of deeper expertise. This limitation affected the AI trainer's perceived competence and credibility, as repeated or overly generic recommendations reduced athletes' confidence in the system's coaching abilities. Overall, the findings suggest that while the AI trainer succeeded in offering responsive and respectful interactions, it provided only partial support for autonomy-related mechanisms due to its limited adaptivity, insufficient variety in coaching strategies, and restricted domain expertise. These constraints highlight the need for enhanced memory structures, more dynamic dialogue models, and richer sport-specific knowledge to fully realize the intent of DP1, DP2, and especially DP7.

The findings regarding the perceived coach-athlete relationship showed generally low to moderate levels across the ten-day interaction period, with mean values slightly below the scale midpoint. These results suggest that while athletes experienced the AI trainer as cooperative and respectful, the relational depth needed to establish a strong, trust-based relationship did not fully materialize. This aligns with interview statements indicating that athletes did not view the AI trainer as a true sport expert or as a relational counterpart similar to a human coach. Participants frequently emphasized that exercise suggestions were often too simple or repetitive, and therefore did not reflect advanced expertise or individualized progression. One athlete articulates this by stating: “Questions were answered correctly in terms of subject matter, but the depth of content was the problem” (CS06F2).

A key factor influencing relational perceptions was the absence of proactive communication. Due to WhatsApp’s system architecture, the AI trainer was unable to initiate conversations, resulting in a fully athlete-driven interaction dynamic. This limited the development of perceived commitment, a core dimension of the 3Cs model (Jowett and Ntoumanis 2004), because athletes did not experience the AI trainer as an actively involved or invested agent. Instead, commitment remained low and even declined slightly over time, reflecting the absence of reciprocal engagement or shared responsibility for the training process.

Perceived closeness followed a similar pattern. While athletes characterized the AI trainer as friendly, polite, and emotionally safe, with one stating that “I never felt uncomfortable” (AR68F2), these interpersonal qualities did not translate into stronger affective bonds. Emotional closeness requires continuity, shared experiences, and personalized responses, all of which were constrained by the AI trainer’s limited memory and repetitive conversational structure. As a result, although the AI trainer fulfilled basic interpersonal expectations (DP6), the system remained at a functional rather than relational level.

Complementarity, however, emerged as the strongest relational dimension. Athletes consistently described the AI trainer as cooperative, supportive, and responsive in tone and behavior, indicating that DP3 and DP4, fostering cooperation and acknowledging athletes’ perspectives, were partially successful. Nevertheless, the lack of individualized expertise and long-term adaptation hindered the development of trust. Without credible, progressively refined sport-specific input, athletes were hesitant to rely on the trainer for training decisions or performance guiding. Moreover, the short intervention period limited opportunities for relational growth, as building commitment and closeness typically requires extended and varied interactions.

The results regarding perceived social presence show a moderate yet stable pattern across the trial period. Athletes generally experienced the AI trainer as socially engaging and human-like to a certain degree, but not to the extent that it could be mistaken for a human counterpart. This aligns with interview statements describing a sense of partial human-likeness, while also clearly recognizing machine-like limitations. Social presence was likely moderated by athletes’ prior experience with LLMs. As LLM-based systems such as ChatGPT have rapidly become a part of our daily lives, participants entered the study with elevated expectations and were already familiar with conversational AI conventions. Consequently, the “novelty bonus” was diminished. As one athlete noted, she did not perceive the AI trainer as particularly intelligent because “he didn’t even remember what we talked about a few days ago” (KP08F2).

Technically, the text-based format also restricted key components of social presence. Without nonverbal cues such as tone of voice, facial expressions, or gestures, the AI trainer relied exclusively on linguistic strategies (DP5 - DP7) to convey humanness and warmth. While human identity cues (e.g., name, personal address) and polite, friendly language contributed to positive impressions, they were insufficient to elicit stronger forms of social presence. Athletes consistently framed the interaction as helpful but not deeply immersive or emotionally rich.

To complement the construct-based interpretations of the evaluation results, the design principles (DP1 - DP7) are systematically assessed to determine the extent to which they were perceived in the implemented AI trainer, as described in Table 6. This reflexive analysis links the empirical findings directly to the intended design logic of the artifact and highlights where the prototype successfully fulfilled the design principles, where only partial implementation occurred, and where technical or conceptual constraints hindered full realization.

<b><i>Design Principles</i></b>	<b><i>Fulfillment</i></b>	<b><i>Explanation Based on Evaluation</i></b>
<b>DP1:</b> Autonomy-supportive through meaningful choice	Partially fulfilled	Athletes reported some choice options, but the system often repeated similar exercise suggestions and did not adapt choices across sessions. Missing long-term memory and demonstrating limited exercise variation reduced perceived autonomy and prevented more personalized decision pathways.
<b>DP2:</b> Competence-enhancing and non-controlling feedback	Partially fulfilled	Feedback was perceived as friendly and non-controlling but lacked depth and individualized progression. Limited sport-specific expertise and generic explanations restricted competence enhancement.
<b>DP3:</b> Cooperative, trust-building interaction patterns	Partially fulfilled	Athletes described the AI trainer as respectful, safe, and cooperative. However, trust and shared-goal alignment remained low due to limited expertise and repetitive suggestions. Lack of proactive engagement weakened commitment and long-term relational development.
<b>DP4:</b> Acknowledging and validating athletes' feelings	Partially fulfilled	The trainer demonstrated a polite and supportive tone, but emotional attunement was inconsistent. The system rarely asked about athletes' feelings or contextual states, leading to insufficient emotional validation.
<b>DP5:</b> Human identity cues for perceived humanness	Fully fulfilled	The use of a personal name ("Coach Alex"), conversational framing, and human-like language established a basic sense of humanness. Participants recognized the trainer as a social agent.
<b>DP6:</b> Verbal, informal, and emotional cues for warmth	Mostly fulfilled	Athletes consistently described the interaction as friendly, polite, and emotionally safe. However, the purely text-based format limited the richness of affective expression.
<b>DP7:</b> Adaptive dialogue ability and social intelligence	Not fulfilled	The AI trainer lacked long-term context understanding, repeated responses across sessions, misunderstood queries, and did not exhibit sustained empathy. Limited memory, a restricted knowledge base, repetitive patterns, and no personalized adaptation prevented meaningful social intelligence.

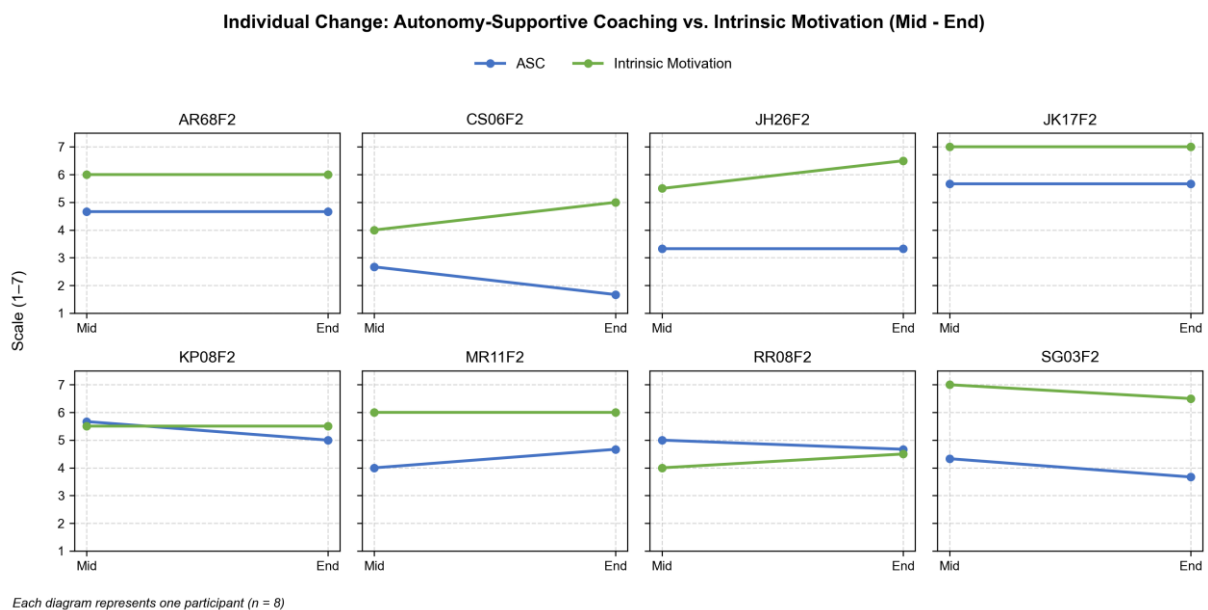
**Table 6: Design Principles - Assessment**

## 8.2 Hypotheses Testing

In addition to the construct-based interpretation of results presented in the previous section, this study also evaluated the three theory-driven hypotheses defined in Chapter 5.4 Hypotheses. Within the DSR paradigm, hypothesis testing serves as a mechanism to assess whether the designed artifact produces the theoretically expected effects in its intended context of use (Walls et al. 1992).

While DSR does not primarily aim at statistical generalization, it emphasizes the empirical grounding of design theory by examining whether kernel-theoretical assumptions manifest in observable system behavior (Hevner et al. 2004). To enable a consistent and comparable assessment of change patterns, hypothesis testing was based exclusively on the subset of 8 participants who completed all three surveys (pre-, mid-, and end-survey). This ensured that longitudinal developments could be evaluated within individuals rather than across incomplete samples. As in previous analyses, participants are referred to by their survey-IDs.

H1 proposed that higher levels of perceived autonomy-supportive coaching by the AI trainer would positively influence athletes' motivational orientation. The individual change trajectories displayed in Figure 15 show that autonomy-supportive coaching values remained in the moderate range across mid and end measurements, with several athletes demonstrating slight declines rather than improvements. At the same time, intrinsic motivation remained consistently high and stable among all participants, with no substantial fluctuations between the two survey points. A comparison of autonomy-supportive coaching behaviors and intrinsic motivation patterns reveals no clear or systematic relationship between the development of perceived autonomy support and changes in intrinsic motivation. For example, athletes such as CS06F2 or RR08F2 showed increases in intrinsic motivation despite declining or stable autonomy supportive coaching perceptions, whereas others (SG03F2) exhibited simultaneous declines in both constructs. Overall, the data do not support H1, as no measurable positive effect of autonomy-supportive coaching on intrinsic motivation was observed in this short-term intervention.

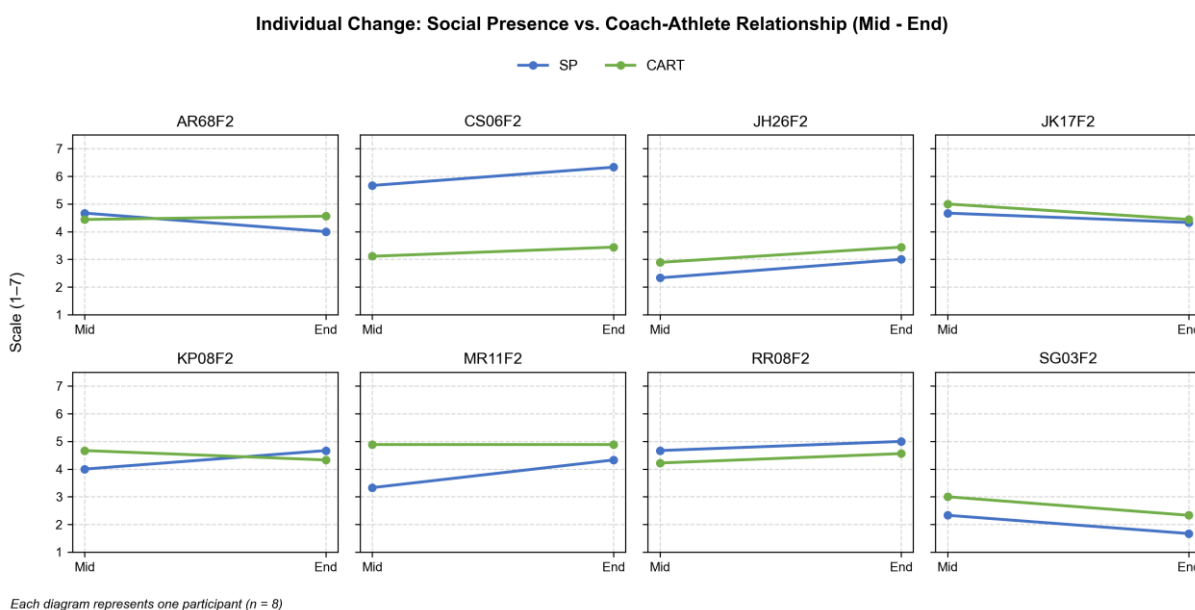


**Figure 15: Hypothesis 1 - Evaluation**

A central reason for the absence of this effect lies in the athletes' pre-existing motivational profile. All participants entered the study with already high levels of intrinsic and integrated regulation, leaving little room for additional motivational enhancement. This ceiling effect aligns with SDT, which emphasizes that improvements in autonomous motivation typically emerge when individuals experience a meaningful increase in autonomy, competence, and relatedness, conditions that are more influential among less self-determined athletes. Furthermore, although the AI trainer was experienced as moderately autonomy-supportive, the level of autonomy support was insufficient to trigger additional motivational gains. As identified in the results, athletes perceived the AI trainer's support as friendly but limited in variation, contextual sensitivity, and depth.

These characteristics may have contributed to a relatively stable but not motivationally transformative experience. According to SDT, sustained and authentic autonomy-supportive interactions, typically unfolding over longer periods, are required to meaningfully strengthen intrinsic motivation. A ten-day interaction window with a moderately autonomy-supportive AI agent was therefore unlikely to yield substantial motivational changes. In sum, the data do not confirm H1. While the AI trainer succeeded in maintaining a generally positive motivational climate, the combination of already highly self-determined athletes and moderate, but not deeply personalized autonomy support did not lead to measurable increases in intrinsic motivation.

H2 proposed that higher levels of perceived social presence would positively influence the quality of the coach-athlete relationship. On average, social presence increased slightly ( $M = 3.96 \rightarrow 4.17$ ), while the coach-athlete relationship remained essentially stable ( $M = 4.03 \rightarrow 4.00$ ). Both constructs can be categorized into a moderate perception level. The individual trajectories illustrated in Figure 16 reveal substantial variability across athletes. Three participants showed parallel increases in both social presence and relationship quality (namely CS06F2, JH26F2, RR08F2), suggesting a potential positive association. One athlete (MR11F2) experienced an increase in social presence while the relationship with the AI trainer remained constant. Two athletes (JK17F2, SG03F2) showed slight declines in both variables, and two displayed opposite development patterns (AR68F2, KP08F2). This indicated that the relationship between social presence and coach-athlete relationship is not uniform across individuals and does not manifest in a consistent linear trend.

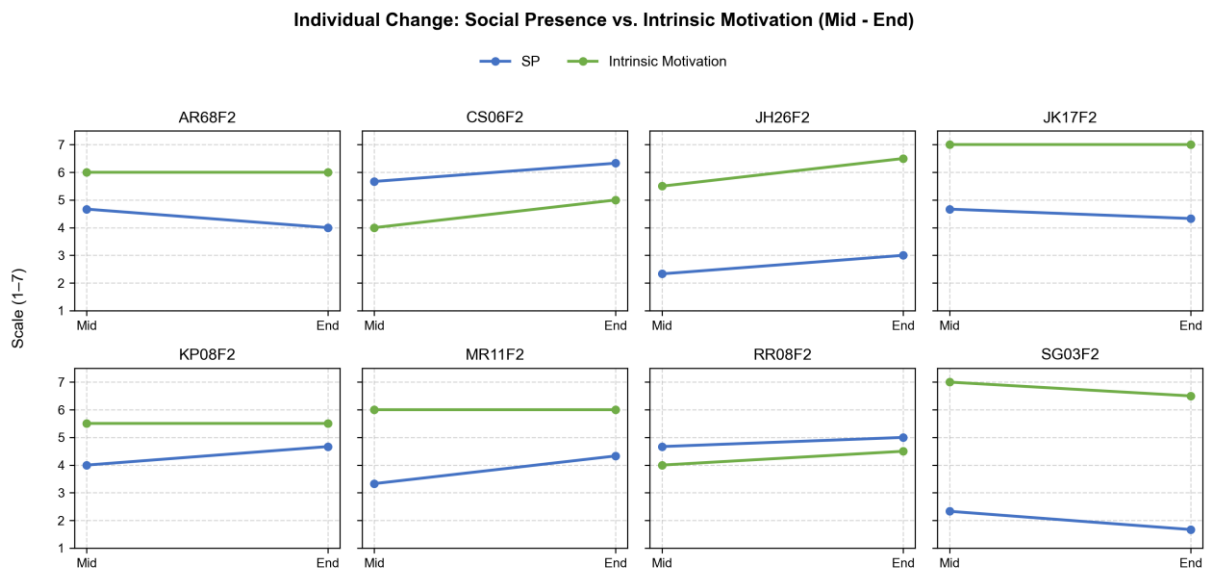


**Figure 16: Hypothesis 2 - Evaluation**

Despite this variability, the data show a weak tendency in line with H2: athletes who reported higher or increasing social presence also displayed slightly higher relationship scores. Conversely, those with decreasing social presence exhibited small reductions in relationship quality. These patterns suggest that social presence may serve as a facilitating factor for relational perceptions, but it does not appear to be sufficient on its own to meaningfully enhance relationship quality. The qualitative findings support this interpretation. Although athletes described the AI trainer as polite, friendly, and socially engaging, they also emphasized that deeper relational qualities, such as trust, emotional closeness, and shared goals, are strongly associated with human coaching expertise and emotional authenticity.

From a design perspective, these findings indicate partial support for H2. Social presence is a relevant contributor to relational perceptions, but its impact is constrained when other relational foundations remain limited. Enhancements to social cues and adaptive communication strategies may strengthen social presence and thereby provide a stronger relational basis.

H3 proposed that higher levels of perceived social presence would positively affect athletes' motivational orientation, with a particular focus on intrinsic motivation. The descriptive data show a slight increase in the mean values of both constructs, although at different baseline levels. Social presence remained within a moderate range, while intrinsic motivation reflected an already highly self-determined motivation. The individual change trajectories displayed in Figure 17 indicate a nuanced but directionally consistent pattern. Three athletes (namely CS06F2, JH26F2, RR08F2) showed parallel increases in both social presence and intrinsic motivation. Two additional athletes reported a small increase in social presence while their intrinsic motivation remained stably high (KP08F2, MR11F2). Another two participants showed slight decreases in social presence but stable motivation levels (AR68F2, JK17F2), and only one athlete exhibited a simultaneous decline in both constructs (SG03F2). Importantly, none of the athletes showed a contradictory pattern in which increasing social presence was associated with a decrease in intrinsic motivation.



**Figure 17: Hypothesis 3 - Evaluation**

This finding is further supported by the qualitative data. Several athletes reported that the AI trainer prompted them to think more about training or occasionally perform suggested exercise, even if the system did not fundamentally alter their motivational levels. One athlete stated: "I didn't exercise more because of Alex, but I did think more about training" (CS06F2). Another participant explained that she performed some of the exercises recommended by the AI trainer, although her engagement was driven partly by curiosity about how the system would respond (AR68F2). These statements indicate that social presence may act as a supportive motivational cue, but not as a primary driver of behavioral change. Motivation in sport is influenced by numerous contextual factors, including training schedules, team dynamics, and personal well-being, which likely overshadow the impact of short-term-digital interactions. The ten-day duration of the study, combined with moderate levels of social presence and the absence of deeper emotional bonding, may also have been insufficient to generate substantial motivational gains.

Overall, the findings partially support H3. While social presence appears to be a relevant and directionally positive factor for motivational processes, its effect remains modest in this context. Higher levels of social presence did not lead to decreases in intrinsic motivation and were often associated with stable or slightly increasing motivation. However, without more sustained interaction, stronger relational cues, and deeper emotional engagement, social presence alone is insufficient to meaningfully elevate already high levels of intrinsic motivation.

The overarching research question guiding this study was to examine the extent to which conversational, human-like AI trainers influence the motivation of athletes in training settings. Based on the combined quantitative and qualitative findings, the influence of the AI trainer on athletes' motivation can be characterized as stabilizing rather than enhancing. Across all participants, intrinsic and integrated motivation remained consistently high throughout the ten-day evaluation period. No substantial increases in motivational orientation were observed, and the hypothesis-driven analyses confirmed that neither autonomy-supportive coaching nor perceived social presence exerted a strong or systematic effect on intrinsic motivation.

The qualitative findings suggest several reasons for this outcome. First, athletes entered the study with an already pronounced self-determined motivational profile, leaving limited potential for further enhancement. In this context, the AI trainer served primarily as a supportive companion rather than a transformative motivational agent. Second, while the system displayed human-like characteristics such as friendliness, politeness, and conversational warmth, its limited adaptivity, lack of long-term memory, and repetitive response patterns constrained its ability to deliver the type of deep, personalized, and evolving interaction known to foster motivational gains over time. Third, participants emphasized that their motivation in sport is shaped by long-term personal goals, team commitments, and embodied training experiences, dimensions that cannot be fully replicated by a short-term, text-based conversational agent. Taken together, conversational, human-like AI trainers can support and maintain athletes' motivation but exert only limited influence on increasing motivation. With more advanced adaptivity, richer sport-specific knowledge, proactive engagement, and longer-term use, future versions of such AI trainers may hold greater potential to actively enhance motivational processes in athletic settings.

### **8.3 Implications for Theory and Practice**

This study provides several implications for theory and practice by advancing scientific knowledge on human-AI interaction in sports contexts and by offering concrete guidance for the design of future AI-based training systems. From a theoretical perspective, the research contributes to current discussions in IS research, particularly those examining how AI-based systems can be designed to support complex social and motivational processes (Schöbel et al. 2024; Strunk et al. 2024). Positioned at the intersection of sport science and HCI, the study extends existing knowledge on conversational AI by demonstrating how autonomy-supportive communication and social cues can be meaningfully integrated into a text-based coaching system. In doing so, it responds to recent calls for research that emphasizes the need to better understand the integration of anthropomorphism in HCI (Konya-Baumbach et al. 2023; Li and Suh 2022). Moreover, the findings address an existing research gap in IS literature by illustrating how human-like interaction features can be operationalized in sports-specific scenarios, a context that has been largely unexplored so far. The study thus contributes to the scientific knowledge base by offering theory-inspired, empirically informed design knowledge for a new class of AI-based coaching systems.

This study offers several theoretical implications by examining how established motivational and relational theories translate into the design and functioning of conversational AI trainers in sport. First, the findings contribute to SDT by demonstrating that autonomy-supportive communication can be simulated by an AI system and is perceived by athletes to some extent. Participants acknowledged elements such as empathetic responses, acknowledgement of feelings, and the provision of choices, features that align with human autonomy-supportive coaching behaviors described in SDT-based sport research (Amorose and Anderson-Butcher 2007; Hollembek and Amorose 2005). However, the effects predicted by SDT, namely increased psychological need satisfaction and more self-determined motivational orientations (Deci and Ryan 2000), were only marginal or absent. Despite slight positive trends, neither autonomy, competence, relatedness need satisfaction nor intrinsic motivation showed substantial improvement. This divergence suggests that while an AI system can reproduce surface-level autonomy-supportive cues, the full SDT mechanisms observed with human coaches may require deeper personalization, sport-specific expertise, and consistency. Thus, the results nuance existing assumptions in SDT by showing that autonomy-supportive communication alone does not automatically elicit the motivational effects described in traditional sport coaching contexts.

Second, the study advances SPT by demonstrating that anthropomorphic features in sports AI-systems, such as an informal and natural language conversation style, can evoke moderate feelings of social presence and interpersonal closeness. This confirms theoretical expectations that human-like cues foster warmth and relational engagement (Araujo 2018; Feine et al. 2019; Nass and Moon 2000). Several athletes described the interaction as “human-like” or “as if talking to a person”, supporting the idea that social presence can arise even in text-based sport coaching. However, social presence did not uniformly increase across all participants, and its effects did not translate into substantial motivational changes. In addition, the absence of contextual continuity, limited memory, and repeated dialogue patterns disrupted the relational flow. This highlights that social presence is not merely a function of anthropomorphic cues but depends on the AI’s ability to sustain coherent, context-sensitive interactions.

Third, the results contribute to the theoretical understanding of the coach-athlete relationship by examining whether the 3Cs model (Jowett and Ntoumanis 2004) can emerge in interactions with an AI coach. The findings suggest partial support for this assumption. Elements of closeness appeared through warm, respectful, and validating communication. Complementarity emerged when exercises or recommendations aligned with athletes’ preferences or needs. Commitment, a dimension typically built through long-term memory and shared history, remained weak due to technical limitations such as missing long-term memory and repetitive interaction loops. These results indicate that AI systems may be capable of initiating relational dynamics but struggle to maintain them in ways comparable to human coaches. This challenges conventional assumptions in sports psychology that relationship quality fundamentally requires physical presence and offers a new perspective on how relational processes might unfold in human-AI coaching dyads.

Finally, the study contributes to the emerging field of sports informatics by empirically illustrating that athletes value motivational and social qualities in digital systems, not just performance analytics. Prior research has criticized existing technologies for being only data-driven and lacking social presence or interpersonal support (Rapp and Tirabeni 2018; Strunk et al. 2024). The findings align with this critique: participants appreciated empathetic communication and conversational warmth but consistently noted limitations in sport-specific expertise and adaptivity. As such, the study expands the theoretical discourse by highlighting that effective AI coaching requires an integrated approach that combined motivational communication with advanced domain knowledge and adaptive, memory-driven dialogue capabilities.

From a practical perspective, the results provide valuable insights for the development and deployment of AI trainers in real-world sports settings. The evaluation demonstrates that state-of-the-art conversational AI technology is capable of supporting athletes through motivating, personalized, and socially engaging interactions. The prototypical implementation illustrates how autonomy-supportive coaching behaviors and human-like cues can be translated into a functional system. These insights are relevant for practitioners, developers, and sports organizations seeking to implement AI trainers, as the evaluation offers concrete evidence regarding which design features are perceived as supportive and which areas require further advancement.

In line with the goals of DSR, the artifact itself forms an additional practical contribution. It provides a working example of how design principles can be realized in practice and yields actionable insights for developers of comparable applications (Peppers et al. 2007). Practitioners benefit from the evaluated prescriptive knowledge embedded in the design principles, which can help to guide the development of more adaptive, socially intelligent, and motivationally effective AI systems. Furthermore, the findings show that athletes are generally open to using AI tools as part of their training routines, highlighting the potential of such systems to complement human coaches. Rather than replacing human expertise, AI trainers can serve as a scalable form of additional support that reinforces daily training habits and provides motivational input between regular coaching sessions.

## **8.4 Limitations**

Despite its contributions, this study has some limitations that should be acknowledged. These limitations inform the interpretation of the findings and highlight important avenues for future research. The empirical evaluation was conducted with a relatively small and homogeneous sample. All participants were adult handball athletes competing at an amateur performance level, with the majority being female. This narrow participant group creates a specific interaction environment that does not reflect the diversity of the broader sports population. Athletes from other disciplines, particularly non-team sports, or individuals without structured sports backgrounds may experience AI-based coaching differently. The limited sample size also restricted the capacity to detect meaningful variations in motivational responses or interaction patterns, making it difficult to generalize the findings beyond the immediate study context.

Furthermore, the study did not employ a control group, such as athletes interacting with a human coach or with a less anthropomorphic version of the conversational system. As a result, it remains unclear whether the observed effects can be attributed to the AI trainer itself, to the novelty of the technology, or to the specific social cues embedded in the system. Comparative study designs would allow for stronger conclusions regarding the added value of human-like design elements and autonomy-supportive communication relative to existing coaching practices.

Another limitation concerns the short duration of the intervention. The evaluation period of ten days provides only a snapshot of how athletes respond to an AI-based coaching system in the early stages of interaction. Short-term impressions may be strongly influenced by novelty effects, curiosity, or initial engagement that may not persist over time. Because coaching relationships and motivational patterns develop gradually, longitudinal research is needed to understand whether AI trainers can sustain perceived autonomy support, social presence, and relational closeness over extended periods.

In addition, the study relied entirely on self-report instruments to assess motivational outcomes, psychological needs, relationship quality, and social presence. Although standardized questionnaires provide validated measurement approaches, they remain susceptible to distortions such as social desirability, response biases, fluctuating mood states, or inaccurate self-assessment.

Behavioral or physiological indicators, interaction logs, or performance-related measures could complement self-reported data to offer a more comprehensive assessment of athletes' experiences. This further limits the ability to draw firm conclusions about the hypothesized links between autonomy-supportive AI coaching, psychological need satisfaction, and motivational orientation.

Beyond methodological issues, the artifact itself exhibits several technical limitations that influenced the user experience. The AI trainer lacked robust context awareness and long-term memory, which resulted in fragmented dialogue continuity. Athletes frequently experienced the system as "starting over" in new sessions, which weakened perceptions of relational commitment and personalization. The system also had limited adaptive dialogue capabilities, making it difficult to respond meaningfully to complex or nuanced input. This restricted its ability to behave like a socially intelligent coach who integrates previous interactions into further recommendations. Additionally, the AI trainer displayed only basic sport-scientific knowledge, which reduced athletes' confidence in its expertise. Participants noted that the exercise suggestions lacked depth, variation, and progressive structure. This limitation hindered the full implementation of several design principles, particularly those requiring meaningful feedback, tailored skill development, and collaborative goal-setting. The system was also purely reactive, initiating no proactive check-ins or reminders, an important aspect of authentic coaching behavior. These technical constraints were partly due to limitations of the underlying platforms (WhatsApp and VectorShift), which do not support persistent states, user profiling, or advanced multimodal interaction.

Finally, the study did not examine potential negative consequences of using AI-based trainers, such as overreliance on technology, potential misinterpretation of advice, reduced human contact, or data privacy concerns. These risks must be considered carefully before AI trainers are implemented at scale in sports environments. In summary, the concept of an AI-athlete relationship, inspired by traditional coach-athlete relationship research, is still theoretically underdeveloped and lacks a validated framework for digital contexts.

## **8.5 Further Research**

Building on the findings and limitations of this study, several promising avenues for further research emerge. As sports informatics is still a comparatively young and rapidly evolving field within IS research, ongoing technological advancements continuously introduce new opportunities for applying AI in sports contexts. Consequently, future research is encouraged to expand and refine the design knowledge generated in this study and to explore the broader potential of AI-based coaching systems.

A first direction concerns the empirical testing and validation of the proposed design principles in more diverse settings. Since the evaluation was conducted mainly within a single sport and with a relatively homogeneous sample, future studies should examine the applicability of the design principles across contrasting sport environments, including individual sports, team sports with different tactical demands, and varying performance levels such as youth, amateur and elite athletes. Validating the effectiveness of autonomy-supportive and human-like AI coaching in different populations would strengthen the generalizability of the results and help identify context-specific adaptations of the design principles. Relatedly, future research should draw on larger samples and extend the duration of intervention period. Longitudinal studies would allow researchers to investigate whether the motivational and relational effects observed in this study persist over time or transform into more stable patterns of human-AI interaction. Such designs could also examine whether AI trainers meaningfully influence athletes' training adherence or performance development, further dependent variables that were not assessed within this study.

Another research direction involves systematically varying anthropomorphism and social presence. Experimental research comparing low-, medium-, and high-anthropomorphic AI trainers could provide more precise insights into which human-like cues are most effective for which user groups and sport contexts. Similarly, contrasting AI coaching with human coaching or hybrid human-AI coaching formats would help to determine whether and under which conditions AI trainers supplement, complement, or approximate the motivational and social qualities of human coaches. This is particularly relevant for addressing the overarching question of whether AI trainers could partially replace certain coaching functions or whether their role remains primarily supportive.

From a design science perspective, the meta-requirements and design principles identified in this study should be further refined through additional DSR iterations. Future cycles of design, demonstration, and evaluation could incorporate more extensive feedback from athletes and coaches to sharpen the alignment of the design principles with practical coaching processes. Larger-scale DSR studies would allow a more systematic investigation of how adaptive dialogue models, richer sport-scientific knowledge bases, long-term conversational memory, and proactive communication capabilities influence athletes' perceptions and outcomes. Technical advancements such as integrating wearables data, contextual sensor inputs, or multimodal communication (e.g. audio, video analysis) could unlock new forms of personalized coaching and further improve the validity of AI training systems.

Finally, the design knowledge generated in this study offers opportunities for transfer to adjacent sport-related application domains. AI systems could support human coaches by analyzing match data, generating training plans, or evaluating player performance. Similarly, real-time AI coaching applications using video-based technique analysis, motion tracking, or automated feedback could extend the concept of AI trainers beyond text-based interactions. Exploring these emerging use cases not only broadens the relevance of conversational and anthropomorphic AI in sport but also opens new interdisciplinary research opportunities at the intersection of IS, sport science, and HCI.

## 9 Conclusion

This thesis aimed to explore how conversational, human-like AI trainers can be designed to foster athletes' motivation in training settings. Building on SDT and SPT as kernel theories, the study developed theory-informed meta-requirements and a concise set of seven design principles that guided the creation of autonomy-supportive and human-like AI trainers. Based on these theoretical foundations and insights from sports psychology and IS research, this study presented the first steps toward designing a conversational AI trainer that interacts in a socially meaningful, supportive, and motivationally informed way. The design principles were instantiated in the development of Coach "Alex", a text-based conversational agent, which operationalizes human-like interaction patterns and autonomy-supportive behaviors. The artifact was evaluated in a real-world setting with handball athletes using a mixed-method approach, combining quantitative measures of autonomy support, psychological needs, motivation, coach-athlete relationship, and social presence with qualitative insights from interviews.

The evaluation revealed several important insights. The AI trainer was able to convey a moderate sense of social presence and to provide interactions that athletes perceived as friendly, respectful, and non-controlling. While the AI trainer implemented parts of autonomy-supportive coaching, its overall coaching behavior remained limited by technical constraints such as missing long-term memory, restricted adaptivity, and shallow sport-specific expertise. Although some athletes experienced moments of social connectedness with the AI trainer, the overall quality of the coach-athlete relationship remained modest and did not systematically improve over time. Athletes' motivational orientation, initially already highly self-determined, remained largely stable throughout the study. Hypotheses linking social presence to relationship quality and motivation received partial support, indicating that human-like cues can contribute to positive perceptions but are not sufficient to produce strong motivational or relational effects on their own yet.

Despite the valuable insights gained through this study, the findings must be interpreted within the boundaries of its methodological scope. The evaluation was limited to a short interaction period, a small athlete sample, and an early-stage prototype. These constraints may limit the strength and generalizability of the observed effects and prevent definitive conclusions about long-term motivational outcomes.

In summary, the findings suggest that conversational AI trainers can play a supportive, stabilizing role in athletes' motivational experience, but in their current form cannot replicate the depth, adaptivity, or long-term influence of human coaches. Nevertheless, this study provides a first step toward establishing design guidelines for AI trainers that integrate psychological theory with social interaction design in sports contexts. By systematically deriving theory-informed design principles and evaluating an initial software artifact, the thesis contributes to the emerging research on AI-based systems in sports informatics.

## References

- ACSM. (2024). ACSM Worldwide Fitness Trends 2025: Future Directions of the Health and Fitness Industry. *American College of Sports Medicine*.
- Adam, M., Wessel, M., & Benlian, A. (2021). AI-based Chatbots in Customer Service and their Effects on User Compliance. *Electronic Markets*, 31 (2), pp. 427-445.
- Amorose, A. (2003). Reflected Appraisals and Perceived Importance of Significant others' Appraisals as Predictors of College Athletes' Self-Perceptions of Competence. *Research Quarterly for Exercise and Sport*, 74 (1), pp. 60-70.
- Amorose, A., & Anderson-Butcher, D. (2007). Autonomy-Supportive Coaching and Self-Determined Motivation in High School and College Athletes: A Test of Self-Determination Theory. *Psychology of Sport and Exercise*, 8 (5), pp. 654-670.
- Amorose, A., & Anderson-Butcher, D. (2015). Exploring the Independent and Interactive Effects of Autonomy-Supportive and Controlling Coaching Behaviors on Adolescent Athletes' Motivation for Sport. *Sport, Exercise, and Performance Psychology*, 4 (3), pp. 206-218.
- Amorose, A., & Horn, T. S. (2000). Intrinsic Motivation: Relationships with Collegiate Athletes' Gender, Scholarship Status, and Perceptions of Their Coaches' Behavior. *Journal of Sport and Exercise Psychology*, 22 (1), pp. 63-84.
- Araujo, T. (2018). Living Up to the Chatbot Hype: The Influence of Anthropomorphic Design Cues and Communicative Agency Framing on Conversational Agent and Company Perceptions. *Computers in Human Behavior*, 85 (1), pp. 183-189.
- Beal, R., Norman, T. J., & Ramchurn, S. D. (2019). Artificial Intelligence for Team Sports: A Survey. *The Knowledge Engineering Review*, 34 (28), pp. 1-37.
- Behera, R., Bala, P., & Ray, A. (2024). Cognitive Chatbot for Personalised Contextual Customer Service: Behind the Scene and beyond the Hype. *Information Systems Frontiers*, 26 (3), pp. 899-919.
- Beinema, T., op den Akker, H., van Velsen, L., & Hermens, H. (2021). Tailoring Coaching Strategies to Users' Motivation in a Multi-Agent Health Coaching Application. *Computers in Human Behavior*, 121 (1).
- Bialkowski, A., Lucey, P., Carr, P., Yue, Y., Sridharan, S., & Matthews, I. (2014). *Large-Scale Analysis of Soccer Matches using Spatiotemporal Tracking Data*. IEEE International Conference on Data Mining, Shenzhen, China.
- Bickmore, T., & Picard, R. (2005). Establishing and Maintaining Long-Term Human-Computer Relationships. *ACM Transactions on Computer-Human Interaction*, 12 (2), pp. 293-327.

- Bickmore, T., Schulman, D., & Yin, L. (2010). Maintaining Engagement in Long-term Interventions with Relational Agents. *Applied Artificial Intelligence*, 24 (6), pp. 648-666.
- Biocca, F., Harms, C., & Burgoon, J. (2003). Towards A More Robust Theory and Measure of Social Presence: Review and Suggested Criteria. *Presence: Teleoperators and Virtual Environments*, 12 (5), pp. 456-480.
- Birnstiel, S., Steinkamp, L., Dümler, B., & Morschheuser, B. (2024). *Designing Gamification for Team Sports: Mapping of the Problem Space and Design Recommendations*. Thirty-Second European Conference on Information Systems (ECIS 2024), Paphos, Cyprus.
- Bittner, E., Oeste-Reiß, S., & Leimeister, J. M. (2019). *Where is the Bot in our Team? Toward a Taxonomy of Design Option Combinations for Conversational Agents in Collaborative Work*. Hawaii International Conference on System Sciences (HICSS), Maui, Hawaii, USA.
- Bouton, M. E. (2014). Why Behavior Change is Difficult to Sustain. *Preventive Medicine*, 68 (1), pp. 29-36.
- Bunker, R. P., & Thabtah, F. (2019). A Machine Learning Framework for Sport Result Prediction. *Applied Computing and Informatics*, 15 (1), pp. 27-33.
- Carpentier, J., & Mageau, G. (2016). Predicting Sport Experience During Training: The Role of Change-Oriented Feedback in Athletes' Motivation, Self-Confidence and Needs Satisfaction Fluctuations. *Journal of sport & exercise psychology*, 38 (1), pp. 45-58.
- Cassell, J., & Bickmore, T. (2003). Negotiated Collusion: Modeling Social Language and its Relationship Effects in Intelligent Agents. *User Modelling and User-Adapted Interaction*, 13 (1), pp. 89-132.
- Chaves, A. P., & Gerosa, M. A. (2020). How Should My Chatbot Interact? A Survey on Social Characteristics in Human–Chatbot Interaction Design. *International Journal of Human–Computer Interaction*, 37 (8), pp. 729-758.
- Choi, H., Jeong, Y., & Kim, S.-K. (2020). The Relationship between Coaching Behavior and Athlete Burnout: Mediating Effects of Communication and the Coach–Athlete Relationship. *International Journal of Environmental Research and Public Health*, 17 (22), pp. 1-17.
- Claudino, J. G., Capanema, D. d. O., de Souza, T. V., Serrão, J. C., Machado Pereira, A. C., & Nassis, G. P. (2019). Current Approaches to the Use of Artificial Intelligence for Injury Risk Assessment and Performance Prediction in Team Sports: a Systematic Review. *Sports Medicine - Open*, 5 (28).
- Dale, R. (2016). The Return of the Chatbots. *Natural Language Engineering*, 22 (5), pp. 811-817.
- Deci, E., & Ryan, R. (1985). *Intrinsic Motivation and Self-Determination in Human Behavior*. New York:Plenum Press.

- Deci, E., & Ryan, R. (2000). The "What" and "Why" of Goal Pursuits: Human Needs and the Self-Determination of Behavior. *Psychological Inquiry*, 11 (4), pp. 227-268.
- Deelen, I., Ettema, D., & Kamphuis, C. B. M. (2018). Sports Participation in Sport Clubs, Gyms or Public Spaces: How Users of Different Sports Settings Differ in their Motivations, Goals, and Sports Frequency. *PLOS ONE*, 13 (10).
- Elshan, E., & Ebel, P. (2020). *Let's Team Up: Designing Conversational Agents as Teammates*. International Conference on Information Systems, India.
- Epley, N., Waytz, A., & Cacioppo, J. (2007). On Seeing Human: A Three-Factor Theory of Anthropomorphism. *Psychological Review*, 114 (4), pp. 864-886.
- Falala-Séchet, C., Antoine, L., Thiriez, I., & Bungener, C. (2019). *Owlie: A Chatbot that Provides Emotional Support for Coping with Psychological Difficulties*. Proceedings of the 19th ACM International Conference on Intelligent Virtual Agents, Centre National de la Recherche Scientifique (CNRS).
- Feine, J., Gnewuch, U., Morana, S., & Maedche, A. (2019). A Taxonomy of Social Cues for Conversational Agents. *International Journal of Human-Computer Studies*, 132 (1), pp. 138-161.
- Fister jr, I., Fister, K., Suganthan, P., Perc, M., & Fister, I. (2015). Computational Intelligence in Sports: Challenges and Opportunities within a new Research Domain. *Applied Mathematics and Computation*, 262 (1), pp. 178-186.
- Fogg, B. J. (2002). *Computers as Persuasive Social Actors. Persuasive Technology: Using Computers to Change What We Think and Do*. San Francisco, CA, USA: Morgan Kaufmann Publishers.
- Følstad, A., Brandtzaeg, P., Feltwell, T., Law, E., Tscheligi, M., & Luger, E. (2018). *Chatbots for Social Good*. Proceedings of the ACM CHI Conference on Human Factors in Computing Systems, Montreal, Canada.
- Gagné, M., Ryan, R., & Bargmann, K. (2003). Autonomy Support and Need Satisfaction in the Motivation and Well-Being of Gymnasts. *Journal of Applied Sport Psychology*, 15 (4), pp. 372-390.
- Gefen, D., & Straub, D. (2003). Managing User Trust in B2C E-Services. *e-Service Journal*, 2 (2), pp. 7-24.
- Gnewuch, U., Morana, S., Adam, M., & Maedche, A. (2018). *Faster Is Not Always Better: Understanding the Effect of Dynamic Response Delays in Human-Chatbot Interaction*. European Conference on Information Systems (ECIS), Portsmouth, United Kingdom.
- Gnewuch, U., Morana, S., & Maedche, A. (2017). *Towards Designing Cooperative and Social Conversational Agents for Customer Service*. Proceedings of the 38th International Conference on Information Systems (ICIS), Seoul, South Korea.

- Go, E., & Sundar, S. S. (2019). Humanizing Chatbots: The Effects of Visual, Identity and Conversational Cues on Humanness Perceptions. *Computers in Human Behavior*, 97 (1), pp. 304-316.
- Goebeler, L., Standaert, W., & Xiao, X. (2021). *Hybrid Sport Configurations: The Intertwining of the Physical and the Digital*. Hawaii International Conference on System Sciences (HICSS), Maui, Hawaii, USA.
- Grant, A. M. (2006). An Integrative Goal-Focused Approach to Execute Coaching. In D. R. Stober & A. M. Grant (Eds.), *Evidence Based Coaching Handbook: Putting Best Practices to Work for your Clients* (pp. 153-192). New York: John Wiley & Sons.
- Gregor, S., & Jones, D. (2007). The Anatomy of a Design Theory. *Journal of the Association for Information Systems*, 8 (5), pp. 312-335.
- Gregory, R. W., Henfridsson, O. L. A., Kaganer, E., & Kyriakou, S. H. (2021). The Role of Artificial Intelligence and Data Network Effects for Creating User Value. *Academy of Management Review*, 46 (3), pp. 534-551.
- Griol, D., Carbó, J., & Molina, J. M. (2013). An Automatic Dialog Simulation Technique to Develop and Evaluate Interactive Conversational Agents. *Applied Artificial Intelligence*, 27 (9), pp. 759-780.
- Gunawardena, C., & Zittle, F. (1997). Social Presence as a Predictor of Satisfaction Within a Computer-Mediated Conferencing Environment. *American Journal of Distance Education*, 11 (3), pp. 8-26.
- Hagger, M., & Chatzisarantis, N. (2007). *Intrinsic Motivation and Self-Determination in Exercise and Sport*. APA PsycInfo: Human Kinetics.
- Hagger, M., & Chatzisarantis, N. (2008). Self-determination Theory and the Psychology of Exercise. *International Review of Sport and Exercise Psychology*, 1 (1), pp. 79-103.
- Hammes, F., Hagg, A., Asteroth, A., & Link, D. (2022). Artificial Intelligence in Elite Sports—a Narrative Review of Success Stories and Challenges. *Frontiers in Sports and Active Living*, 4 (1).
- Hassan, A., Ramadan, W., Schrapf, N., & Tilp, M. (2016). Evaluation of tactical training in team handball by means of artificial neural networks. *Journal of Sports Sciences*, 35 (7), pp. 642-647.
- Helmeffalk, M., Marcusson, L., & Sell, A. (2020). "Who cares about fireworks?" - A Study on Digital Coaching, Gamification and Exercise Motivation. Hawaii International Conference on System Sciences (HICSS), Maui, Hawaii, USA.
- Hevner, A. (2007). A Three Cycle View of Design Science Research. *Scandinavian Journal of Information Systems*, 19 (2), pp. 87-92.

- Hevner, A., March, S., Park, J., & Ram, S. (2004). Design Science in Information Systems Research. *MIS Quarterly*, 28 (1), pp. 75-105.
- Hobert, S. (2019). *Say Hello to 'Coding Tutor'! Design and Evaluation of a Chatbot-based Learning System Supporting Students to Learn to Program*. Proceedings of the 40th International Conference on Information Systems (ICIS), Munich, Germany.
- Hollembek, J., & Amorose, A. (2005). Perceived Coaching Behaviors and College Athletes' Intrinsic Motivation: A Test of Self-Determination Theory. *Journal of Applied Sport Psychology*, 17 (1), pp. 20-36.
- Horn, T. S. (1985). Coaches' Feedback and Changes in Children's Perceptions of their Physical Competence. *Journal of educational psychology*, 77 (2), pp. 174-186.
- Ives, Y. (2008). What is 'Coaching'? An Exploration of Conflicting Paradigms. *International Journal of Evidence Based Coaching and Mentoring*, 6 (2), pp. 100-113.
- Janson, A. (2023). How to Leverage Anthropomorphism for Chatbot Service Interfaces: The Interplay of Communication Style and Personification. *Computers in Human Behavior*, 149 (1).
- Jin, H., Kim, S., Love, A., Jin, Y., & Zhao, J. (2022). Effects of Leadership Style on Coach-Athlete Relationship, Athletes' Motivations, and Athlete Satisfaction. *Frontiers in Psychology*, 13 (1), pp. 1-14.
- Jowett, S. (2017). Coaching Effectiveness: The Coach-Athlete Relationship at its Heart. *Current Opinion in Psychology*, 16 (1), pp. 154-158.
- Jowett, S., & Ntoumanis, N. (2004). The Coach–Athlete Relationship Questionnaire (CART-Q): Development and Initial Validation. *Scandinavian journal of medicine & science in sports*, 14 (4), pp. 245-257.
- Jowett, S., & Poczwardowski, A. (2007). Understanding the Coach-Athlete Relationship. In S. Jowett & D. Lavelle (Eds.), *Social Psychology in Sport* (pp. 3-14). Champaign, IL: Human Kinetics.
- Kamphorst, B. (2017). E-Coaching Systems: What they are, and what they aren't. *Personal and Ubiquitous Computing*, 21 (1), pp. 1-8.
- Kettunen, E., Kari, T., Critchley, W., & Frank, L. (2024). Critical Experiences with Sport and Wellness Technology Digital Coach – Differences between Young Adults and Young Elderly. *Behaviour & Information Technology*, 43 (12), pp. 3010-3026.
- Kim, I., Lee, K., & Kang, S. (2019). The Relationship between Passion for Coaching and the Coaches' Interpersonal Behaviors: The Mediating Role of Coaches' Perception of the Relationship Quality with Athletes. *International Journal of Sports Science & Coaching*, 14 (4), pp. 463-470.
- Kim, J., & Im, I. (2023). Anthropomorphic Response: Understanding Interactions between Humans and Artificial Intelligence Agents. *Computers in Human Behavior*, 139 (11), pp. Article Number 107512.

- Kipp, L., & Weiss, M. (2013). Social Influences, Psychological Need Satisfaction, and Well-Being Among Female Adolescent Gymnasts. *Sport, Exercise, and Performance Psychology*, 2 (1), pp. 62-75.
- Konya-Baumbach, E., Biller, M., & Janda, S. (2023). Someone Out There? A Study on the Social Presence of Anthropomorphized Chatbots. *Computers in Human Behavior*, 139 (4), pp. Article 107513.
- Lafrenière, M.-A. K., Jowett, S., Vallerand, R. J., & Carbonneau, N. (2011). Passion for Coaching and the Quality of the Coach–Athlete Relationship: The Mediating Role of Coaching Behaviors. *Psychology of Sport and Exercise*, 12 (2), pp. 144-152.
- Lembcke, T.-B., Diederich, S., & Brendel, A. B. (2020). *Supporting Design Thinking Through Creative and Inclusive Education Facilitation: The Case of Anthropomorphic Conversational Agents for Persona Building*. 28th European Conference on Information Systems (ECIS), Marrakesh, Morocco.
- Li, B., & Xu, X. (2021). Application of Artificial Intelligence in Basketball Sport. *Journal of Education, Health and Sport*, 11 (7), pp. 54-67.
- Li, M., & Suh, A. (2022). Anthropomorphism in AI-enabled Technology: A Literature Review. *Electronic Markets*, 32 (1), pp. 2245-2275.
- Lieberman, H. (1997). *Autonomous Interface Agents*. ACM SIGCHI Conference on Human Factors in Computing Systems, CHI 97.
- Lu, L., McDonald, C., Kelleher, T., Lee, S., Chung, Y. J., Mueller-Bryson, S., Vielledent, M., & Yue, C. A. (2022). Measuring Consumer-Perceived Humanness of Online Organizational Agents. *Computers in Human Behavior*, 128 (3), pp. Article 107092.
- Luger, E., & Sellen, A. (2016). *"Like Having a Really Bad PA": The Gulf between User Expectation and Experience of Conversational Agents*. Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, San Jose, California, USA.
- Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., Hinz, O., Morana, S., & Söllner, M. (2019). AI-Based Digital Assistants: Opportunities, Threats, and Research Perspectives. *Business & Information Systems Engineering*, 61 (4), pp. 535-544.
- Maedche, A., Morana, S., Schacht, S., Werth, D., & Krumeich, J. (2016). Advanced User Assistance Systems. *Business & Information Systems Engineering*, 58 (5), pp. 367-370.
- Mageau, G., & Vallerand, R. (2003). The Coach–Athlete Relationship: A Motivational Model. *Journal of Sports Sciences*, 21 (1), pp. 883-904.
- Mazurova, E., Standaert, W., Penttinen, E., & Tan, F. T. C. (2022). Paradoxical Tensions Related to AI-Powered Evaluation Systems in Competitive Sports. *Information Systems Frontiers*, 24 (3), pp. 897-922.

- McTear, M. (2017). The Rise of the Conversational Interface: A New Kid on the Block? In J. F. Quesada, F. J. M. Mateos, & T. L. Soto (Eds.), *Future and Emerging Trends in Language Technology. Machine Learning and Big Data* (pp. 38-49). Cham:Springer.
- Mohd Kassim, A. F., Abdullah, W., Md Japilus, S., & Yusri, A. (2020). Coach-Athlete Relationship and Coaching Effectiveness in Team Sports Athletes. In M. Hassan (Ed.), *Enhancing Health and Sports Performance by Design* (pp. 451-462). Singapore:Springer.
- Nass, C., & Moon, Y. (2000). Machines and Mindlessness: Social Responses to Computers. *Journal of Social Issues*, 56 (1), pp. 81-103.
- Nass, C., Steuer, J., & Tauber, E. R. (1994). *Computers are Social Actors*. Proceedings of the ACM CHI Conference on Human Factors in Computing Systems, New York, USA.
- Oh, C. S., Bailenson, J. N., & Welch, G. F. (2018). A Systematic Review of Social Presence: Definition, Antecedents, and Implications. *Frontiers in Robotics and AI*, 5 (1).
- OpenAI. (2025a). *ChatGPT-5*. Retrieved 26.11.2025 from <https://openai.com/de-DE/index/introducing-gpt-5/>
- OpenAI. (2025b). *ChatGPT - Overview* Retrieved 26.11.2025 from <https://openai.com/chatgpt/overview/>
- Peppers, K., Tuunanen, T., Rothenberger, M., & Chatterjee, S. (2007). A Design Science Research Methodology for Information Systems Research. *Journal of Management Information Systems*, 24 (3), pp. 45-77.
- Pelletier, L., Fortier, M., Vallerand, R., & Brière, N. (2001). Associations Among Perceived Autonomy Support, Forms of Self-Regulation, and Persistence: A Prospective Study. *Motivation and Emotion*, 25 (4), pp. 279-306.
- Pelletier, L. G., Rocchi, M. A., Vallerand, R. J., Deci, E. L., & Ryan, R. M. (2013). Validation of the Revised Sport Motivation Scale (SMS-II). *Psychology of Sport and Exercise*, 14 (3), pp. 329-341.
- Pfeuffer, N., Benlian, A., Gimpel, H., & Hinz, O. (2019). Anthropomorphic Information Systems. *Business & Information Systems Engineering*, 61 (4), pp. 523-533.
- Qiu, L., & Benbasat, I. (2009). Evaluating Anthropomorphic Product Recommendation Agents: A Social Relationship Perspective to Designing Information Systems. *Journal of Management Information Systems*, 25 (4), pp. 145-182.
- Rai, A., Constantinides, P., & Sarker, S. (2019). Next-Generation Digital Platforms: Toward Human–AI Hybrids. *MIS Quarterly*, 43 (1), pp. iii-ix.

- Rapp, A., & Tirabeni, L. (2018). Personal Informatics for Sport: Meaning, Body, and Social Relations in Amateur and Elite Athletes. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 25 (3), pp. 1-30.
- Recker, J. (2021). *Scientific Research in Information Systems: A Beginner's Guide* (2nd ed.). Cham:Springer.
- Reeves, B., & Nass, C. (1996). *The Media Equation: How People Treat Computers, Television, and New Media Like Real People*. New York:Cambridge University Press.
- Richer, S. F., & Vallerand, R. (1998). Construction and Validation of the Relatedness Feeling Scale. *Revue Européenne de Psychologie Appliquée*, 48 (2), pp. 129-137.
- Roy, R., & Naidoo, V. (2021). Enhancing Chatbot Effectiveness: The Role of Anthropomorphic Conversational Styles and Time Orientation. *Journal of business research*, 126 (2), pp. 23-34.
- Ryan, R., & Deci, E. (2000a). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, 25 (1), pp. 54-67.
- Ryan, R., & Deci, E. (2000b). Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. *American psychologist*, 55 (1), pp. 68-78.
- Ryan, R., Williams, G., Patrick, H., & Deci, E. (2009). Self-Determination Theory and Physical Activity: The Dynamics of Motivation in Development and Wellness. *Hellenic Journal of Psychology*, 6 (1), pp. 107-124.
- Schöbel, S., Schmitt, A., Benner, D., Saqr, M., Janson, A., & Leimeister, J. M. (2024). Charting the Evolution and Future of Conversational Agents: A Research Agenda Along Five Waves and New Frontiers. *Information Systems Frontiers*, 26 (2), pp. 729-754.
- Schuetzler, R., Grimes, G. M., & Giboney, J. (2020). Impact of Chatbot Conversational Skill on Engagement and Perceived Humanness. *Journal of Management Information Systems*, 37 (3), pp. 875-900.
- Schuetzler, R., Grimes, G. M., Giboney, J. S., & Nunamaker Jr, J. F. (2018). *The Influence of Conversational Agents on Socially Desirable Responding*. Hawaii International Conference on System Sciences (HICSS), Maui, Hawaii, USA.
- Schuetzler, R., Grimes, M., Giboney, J., & Buckman, J. (2014). *Facilitating Natural Conversational Agent Interactions: Lessons from a Deception Experiment*. International Conference on Information Systems, Auckland.
- Sebastian, J., & Richards, D. (2017). Changing Stigmatizing Attitudes to Mental Health via Education and Contact with Embodied Conversational Agents. *Computers in Human Behavior*, 73 (2), pp. 479-488.

- Seeger, A.-M., Pfeiffer, J., & Heinzl, A. (2018). *Designing Anthropomorphic Conversational Agents: Development and Empirical Evaluation of a Design Framework*. 39th International Conference on Information Systems, San Francisco.
- Shah, F., Kretzer, M., & Mädche, A. (2015, 13-16.12.2015). *Designing an Analytics Platform for Professional Sports Teams*. International Conference on Information Systems, Fort Worth, United States.
- Short, J., Williams, E., & Christie, B. (1976). *The Social Psychology of Telecommunications*. London:Wiley.
- Silacci, A., Taiar, R., & Caon, M. (2021). Towards an AI-Based Tailored Training Planning for Road Cyclists: A Case Study. *Applied Sciences*, 11 (1).
- Smith, A., Ntoumanis, N., & Duda, J. (2010). An Investigation of Coach Behaviors, Goal Motives, and Implementation Intentions as Predictors of Well-Being in Sport. *Journal of Applied Sport Psychology*, 22 (1), pp. 17-33.
- Smoll, F. L., & Smith, R. E. (1989). Leadership Behaviors in Sport: A Theoretical Model and Research Paradigm. *Journal of applied social psychology*, 19 (18), pp. 1522-1551.
- Smutný, P., & Schreiberova, P. (2020). Chatbots for Learning: A Review of Educational Chatbots for the Facebook Messenger. *Computers & Education*, 151 (5), pp. Article 103862.
- Strunk, J., Nissen, A., & Smolnik, S. (2024). *Getting Trust in Shape: Towards an Athlete-Centered Design Approach for AI-Based Trainers*. Thirty-Second European Conference on Information Systems (ECIS 2024), Paphos, Cyprus.
- Tegos, S., Demetriadis, S., & Tsiatsos, T. (2012). *Using a Conversational Agent for Promoting Collaborative Language Learning*. International Conference on Intelligent Networking and Collaborative Systems, IEEE.
- Teixeira, P. J., Carraça, E. V., Markland, D., Silva, M. N., & Ryan, R. M. (2012). Exercise, Physical Activity, and Self-Determination Theory: A Systematic Review. *International Journal of Behavioral Nutrition and Physical Activity*, 9 (1).
- Twilio. (2025). *Business Messaging API*. Retrieved 26.11.2025 from <https://www.twilio.com/en-us/messaging>
- VectorShift. (2025). *The Fastest Way to Build AI Apps and Workflows*. Retrieved 26.11.2025 from <https://vectorshift.ai/>
- von der Pütten, A. M., Krämer, N. C., Gratch, J., & Kang, S.-H. (2010). "It doesn't matter what you are!" Explaining Social Effects of Agents and Avatars. *Computers in Human Behavior*, 26 (6), pp. 1641-1650.
- Walls, J., Widmeyer, G., & El Sawy, O. (1992). Building an Information System Design Theory for Vigilant EIS. *Information Systems Research*, 3 (1), pp. 36-59.

- Wang, J., Qiu, K., Peng, H., Fu, J., & Zhu, J. (2019). *AI Coach: Deep Human Pose Estimation and Analysis for Personalized Athletic Training Assistance*. Proceedings of the 27th ACM International Conference on Multimedia, Nice, France.
- Weiss, M. R., & Amorose, A. J. (2008). Motivational Orientations and Sport Behavior. In T. S. Horn (Ed.), *Advances in Sport Psychology* (3rd ed., pp. 115-154). Champaign, IL:Human Kinetics.
- Weiss, M. R., & Ferrer-Caja, E. (2002). Motivational Orientations and Sport Behavior. In T. S. Horn (Ed.), *Advances in Sport Psychology* (2nd ed., pp. 101-184). Champaign, IL:Human Kinetics.
- Weiss, M. R., & Williams, L. (2004). The Why of Youth Sport Involvement: A Developmental Perspective on Motivational Processes. In M. R. Weiss (Ed.), *Developmental Sport and Exercise Psychology: A Lifespan Perspective* (pp. 223-268). Morgantown, WV, US:Fitness Information Technology.
- Weizenbaum, J. (1966). ELIZA—A Computer Program for the Study of Natural Language Communication between Man and Machine. *Communications of the ACM*, 9 (1), pp. 36-45.
- Xiao, X., Tan, F. T. C., Lim, E. T., Henningsson, S., Vatrapu, R., Hedman, J., Tan, C. W., Clemenson, T., Mukkamala, R. R., & Van Hillegersberg, J. (2017). *Sports Digitalization: An Overview and a Research Agenda*. 38th International Conference on Information Systems ICIS 2017.

## Appendix A: Measurement Items of Constructs

<b>Construct</b>	<b>Items</b>	<b>Scale and Source</b>
<b>Amotivation</b>	<ul style="list-style-type: none"> <li>▪ Ich hatte früher gute Gründe, Sport zu treiben, aber inzwischen frage ich mich, ob ich weitermachen soll.</li> <li>▪ Ich weiß nicht mehr weiter, ich habe das Gefühl, dass ich in diesem Sport nicht erfolgreich sein kann.</li> </ul>	7-point Likert-Scale: Adapted version of the Sport Motivation Scale II by Pelletier et al. (2013)
<b>External Regulation</b>	<ul style="list-style-type: none"> <li>▪ Menschen, die mir wichtig sind, wären enttäuscht, wenn ich keinen Sport machen würde.</li> <li>▪ Andere loben oder belohnen mich, wenn ich Sport mache.</li> </ul>	
<b>Introjected Regulation</b>	<ul style="list-style-type: none"> <li>▪ Ich würde mich schlecht fühlen, wenn ich mir für Sport keine Zeit nehme.</li> <li>▪ Ich würde mich wertlos fühlen, wenn ich keinen Sport machen würde.</li> </ul>	
<b>Identified Regulation</b>	<ul style="list-style-type: none"> <li>▪ Ich habe festgestellt, dass ich durch Sport Seiten an mir entwickeln kann, die mir wichtig sind.</li> <li>▪ Ich habe diesen Sport gewählt, um mich persönlich weiterzuentwickeln.</li> </ul>	
<b>Integrated Regulation</b>	<ul style="list-style-type: none"> <li>▪ Sport zu treiben gehört einfach zu mir dazu.</li> <li>▪ Durch den Sport lebe ich nach meinen wichtigsten Überzeugungen.</li> </ul>	
<b>Intrinsic Motivation</b>	<ul style="list-style-type: none"> <li>▪ Es interessiert mich sehr, wie ich mich verbessern kann.</li> <li>▪ Es macht mir Spaß, neue Wege zu entdecken, wie ich meine Leistung verbessern kann.</li> </ul>	
<b>Autonomy</b>	<ul style="list-style-type: none"> <li>▪ Ich kann mitentscheiden, was ich beim Sport mache.</li> <li>▪ Ich fühle mich gezwungen, Übungen in meinem Sport zu machen, auch wenn ich sie eigentlich nicht machen will.</li> <li>▪ Ich kann beim Sport die Dinge tun, die ich selbst machen möchte.</li> </ul>	7-point Likert-Scale: Adapted from Hollembeak and Amorose (2005)
<b>Competence</b>	<ul style="list-style-type: none"> <li>▪ Ich finde, dass ich in meinem Sport gut bin.</li> <li>▪ Ich habe das Gefühl, über viele sportliche Fähigkeiten zu verfügen.</li> <li>▪ Ich halte mich für qualifiziert für meinen Sport.</li> </ul>	7-point Likert-Scale: Adapted from Amorose (2003)
<b>Relatedness</b>	<ul style="list-style-type: none"> <li>▪ Ich fühle mich von meinem Team unterstützt.</li> <li>▪ Ich habe das Gefühl, dass ich mit meinem Team eng verbunden bin.</li> <li>▪ Ich fühle mich von meinem Team verstanden.</li> </ul>	7-point Likert-Scale: Sport-oriented version of the Feelings of Relatedness Scale from Hollembeak & Amorose (2005) and Richer & Vallerand (1998)
<b>Autonomy-Supportive Coaching Behavior</b>	<ul style="list-style-type: none"> <li>▪ Ich habe das Gefühl, dass mir Coach Alex Wahlmöglichkeiten und Optionen gibt.</li> <li>▪ Ich habe das Gefühl, dass mich Coach Alex versteht.</li> <li>▪ Coach Alex hört zu, wie ich die Dinge gerne machen möchte.</li> </ul>	7-point Likert-Scale: Adapted short version of the Sport Climate Questionnaire from Amorose & Anderson-Butcher (2007)

<b>Construct</b>	<b>Items</b>	<b>Scale and Source</b>
<b>Commitment</b>	<ul style="list-style-type: none"> <li>▪ Ich fühle mich von Coach Alex unterstützt.</li> <li>▪ Ich fühle mich mit Coach Alex verbunden.</li> <li>▪ Ich habe das Gefühl, dass meine sportliche Entwicklung mit Coach Alex vielversprechend ist.</li> </ul>	7-point Likert-Scale: Adapted version of the Coach-Athlete Relationship Questionnaire (CART-Q) from Jowett and Ntoumanis (2004)
<b>Closeness</b>	<ul style="list-style-type: none"> <li>▪ Ich mag Coach Alex.</li> <li>▪ Ich vertraue Coach Alex.</li> <li>▪ Ich respektiere Coach Alex.</li> </ul>	
<b>Complementarity</b>	<ul style="list-style-type: none"> <li>▪ Wenn ich mit Coach Alex arbeite, fühle ich mich wohl.</li> <li>▪ Wenn ich von Coach Alex angeleitet werde, gehe ich auf seine Bemühungen ein.</li> <li>▪ Wenn ich von Coach Alex betreut werde, bin ich bereit, mein Bestes zu geben.</li> </ul>	
<b>Social Presence</b>	<ul style="list-style-type: none"> <li>▪ Bei den Interaktionen mit Coach Alex habe ich das Gefühl mit einem Menschen zu interagieren.</li> <li>▪ Die Kommunikation mit Coach Alex empfinde ich als persönlich.</li> <li>▪ Die Interaktion mit Coach Alex fühlt sich sozial an.</li> </ul>	

**Table 7: Operationalization of Constructs**

## Appendix B: Declaration on the Use of GenAI Tools

In the preparation of this paper, I have used following tools based on generative artificial intelligence (GenAI):

1. ChatGPT
2. DeepL Write
3. DeepL Translate

I further declare that

- I have labeled the content taken from the GenAI tools listed above with my details in the table below,
- I have verified that the content generated by the above-mentioned GenAI tools and adapted by me is factually correct,
- I am aware that, as the author of this work, I am responsible for the information and the statements made in it, and
- I am aware that violating the disclosure of the use of generative AI in my work is a deception and leads to an evaluation with an insufficient grade.

I have used the above-mentioned AI systems as indicated below.

<b>Areas of contribution</b>	<b>AI tool(s) used</b>	<b>Description of the manner of use and compliance with good scientific practice (if applicable, please indicate the section of the thesis)</b>
Development and conception of the research project	None	
Identification of literature	None	
Synthesizing of literature	1	Concise summary of the selected articles to get a first overview (key findings & results)
Structuring the text	None	
Formulation of text	1, 3	Support with the re-formulation of the text (improvements for sentence structure, grammar, academic style)
Revision of text	1, 2	Content review, correct citations, sentence structure, orthography
Creation of visualizations	None	
Further contributions	1	Coding, Data Analysis