A Study on the Multi-stage Influence Mechanism of Artificial Intelligence Guidance on Consumer Long-term Goal Pursuit

Authors: Shu Lifang, Wang Kui, Wu Yueyan, Chen Siyun, Wu Yueyan

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Abstract

The artificial intelligence industry has experienced explosive growth in education, health, and other domains, witnessing the emergence of novel service forms such as AI teachers and AI coaches. However, whether AI guidance (abbreviated as AI-coach) can more effectively help consumers accomplish long-term goals such as learning and fitness compared to human guidance remains unclear. This paper, based on a dynamic perspective of goal management and integrating the characteristics of AI-coach in terms of operability, feedback, and emotionality, conducts an in-depth investigation and discussion of the impact of AI-coach on consumers' long-term goal pursuit and its underlying mechanisms. The research examines three stages of consumer goal pursuit: First, at the coach selection stage, it investigates how goal setting (proximal goals vs. distal goals) influences consumers' choice between AI-coach and human coach. Second, at the goal advancement stage, it examines the differential effects of AI-coach versus human coach on ability improvement for consumers with different skill levels (low vs. high) and the underlying mechanisms. Third, at the performance evaluation stage, it explores the asymmetric effects of consumers' word-of-mouth evaluations of AI-coach versus human coach and the underlying mechanisms. This paper will make theoretical and practical contributions to optimizing AI-coach design, promoting consumers' long-term goal pursuit, and realizing AI-enabled consumer well-being.

Full Text

A Multi-stage Investigation into the Mechanisms of AI Coaching's Impact on Consumers' Long-term Goal Pursuit

SHU Lifang[1], WANG Kui[2], WU Yueyan[3], CHEN Siyun[4]
[1] Department of Management, Shenzhen Polytechnic University, Shenzhen

518055, China
[2] Research Institute on Brand Innovation and Development of Guangzhou, School of Management, Jinan University, Guangzhou 510632, China
[3] School of Economics and Management, Fuzhou University, Fuzhou 350108, China
[4] School of Journalism and Communication, Jinan University, Guangzhou 510632, China

Abstract
The artificial intelligence industry has experienced explosive growth in education, health, and other domains, giving rise to novel service forms such as AI teachers and AI coaches. However, it remains unclear whether AI coaching (AI-coach) can more effectively help consumers achieve long-term goals like learning and fitness compared to human coaching. Drawing on a dynamic perspective of goal management and incorporating AI-coach's distinctive features in operational capacity, feedback mechanisms, and emotional attributes, this study investigates the multi-stage impact of AI-coach on consumers' long-term goal pursuit and its underlying mechanisms. The research examines three phases of consumer goal pursuit: First, during the coach selection phase, we explore how goal setting (proximal vs. distal goals) influences consumers' choice between AI-coach and human coaches. Second, during the goal advancement phase, we investigate the differential performance improvement effects of AI-coach versus human coaches on consumers with varying skill levels (low vs. high) and the mechanisms behind these differences. Third, during the performance evaluation phase, we examine the asymmetric effects in consumers' word-of-mouth evaluations of AI-coach versus human coaches and their underlying mechanisms. This research provides theoretical and practical contributions for optimizing AI-coach design, facilitating consumers' long-term goal pursuit, and enhancing AI-enabled consumer well-being.

Keywords: Service Technology, Artificial Intelligence, Coach, Consumer Behavior, Goal Regulation
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1. Problem Statement

Science and technology constitute primary productive forces. As a representative of cutting-edge technology, artificial intelligence (AI) is hailed as humanity's fourth industrial revolution, profoundly transforming how people learn and live. China's "New Generation Artificial Intelligence Development Plan" emphasizes seizing the significant opportunities in AI development to accelerate innovative AI applications in education, health, medical care, and other urgent areas of public welfare. According to the "2021 White Paper on Artificial Intelligence Development" released by the Shenzhen Artificial Intelligence Industry Association, by the end of 2020, China's core AI industry reached 325.1 billion yuan, with a year-on-year growth rate of 16.7%, and new service models such as AI coaching (AI-coach) have emerged. AI-coach represents a machine-assisted systematic process that analyzes customer goals and individual characteristics using deep learning algorithms and cognitive semantic analysis methods to construct solutions that effectively help customers achieve their objectives (see Graßmann & Schermuly, 2021; Luo et al., 2021). Based on data from users' learning, daily life, and exercise activities, AI-coach provides guidance in education, health, and medical care, manifesting as AI teachers, AI fitness coaches, AI health managers, and similar forms. For instance, iFlytek's AI teacher can deliver personalized and interactive tutoring, intelligently assess students' knowledge mastery, and recommend priority learning topics. FITURE's AI fitness coach can digitize users' exercise processes, provide real-time feedback on movement standards, and develop tailored training plans, enabling precise health guidance. Compared to human coaching, AI-coach can effectively reduce teaching costs, provide real-time feedback on goal progress, and track goal advancement digitally, representing an emerging trend.

However, despite rapid development in smart education, intelligent fitness, and smart healthcare, consumers remain significantly hesitant about adopting AI-coach. As a novel service form, consumers still harbor doubts about AI-coach's actual effectiveness compared to human coaches, with frequent accusations of it being an "intelligence tax." Meanwhile, enterprises urgently seek to understand what factors drive consumers to choose AI-coach and how to enhance consumers' reputation and word-of-mouth promotion of AI-coach. Scientific answers to these managerial questions will help consumers leverage AI-coach to achieve long-term goals in learning and fitness, enable AI companies to achieve both technological implementation and commercial success, and promote China's deep deployment and rapid development in smart education, intelligent fitness, and health medical care, seizing the opportunities in the new generation of AI development.

AI-consumer service interactions have attracted extensive scholarly interest with diverse theoretical perspectives. Nevertheless, existing research suffers from three limitations: First, most studies focus on one-time service encounters rather than long-term collaborative services. Current research predominantly examines one-time, non-collaborative AI-consumer relationships, such as AI customer service (Crolic et al., 2022; Wang et al., 2021), AI sales (Luo et al., 2019), and AI reception (Yam et al., 2020), with insufficient exploration of long-term collaboration domains. Second, most research examines scenarios where consumers passively receive AI services, rarely addressing situations where consumers actively learn skills from AI (Garvey and Duhachek, 2023; Srinivasan and Sarial-Abi, 2021). Third, most studies focus on AI's negative effects (Luo et al., 2023), paying limited attention to AI's well-being effects. Research predominantly centers on consumers' preset biases, negative impacts, and service failure scenarios (Mende et al., 2019). A few frontier studies on AI-coach focus on service providers while neglecting end consumers (Luo et al., 2019). Since AI-coach can become direct competitors to service providers, providers develop AI aversion or replacement anxiety. Currently, academic discussion is insufficient on how to leverage AI-coach to help consumers actively pursue long-term goals.

This study aims to overcome previous AI research limitations that predominantly focus on one-time encounters, passive acceptance, and negative effects, extending AI service research to the coaching domain where end consumers actively pursue long-term goals. In domains like fitness and learning, coach selection, goal achievement, and feedback evaluation are involved. The dynamic perspective of goal management precisely addresses theoretical research on how consumers set, select, manage, and evaluate goals. Therefore, this study investigates the multi-stage impact and mechanisms of AI-coach on consumers' long-term goal pursuit from a dynamic goal management perspective.

Goal management research suggests that in the initial stage of goal pursuit, consumers weigh the attractiveness of various achievement methods. For instance, when consumers are uncertain about goal attainment at the outset, diversified (vs. specialized) achievement methods increase the likelihood of success, leading initial-stage consumers to prefer diversified approaches (Huang & Zhang, 2013). During the goal persistence stage, consumers decide whether to persist or abandon based on a "commitment-progress" framework. For example, under a weight loss goal, if consumers view their exercise behavior as commitment to (vs. progress toward) the goal, their likelihood of subsequently choosing low-fat meals increases (Fishbach & Dhar, 2005). In the goal evaluation stage, consumers assess achieved goals. For instance, when consumers view past goals as a completed journey (vs. reaching a destination), it enhances their perception of personal growth, thereby strengthening subsequent goal pursuit behavior (Huang & Aaker, 2019). This study integrates AI-coach's (vs. human coaching) unique characteristics and examines three questions sequentially based on the three stages of goal selection, persistence, and evaluation:

(1) In the coach selection stage, how does goal setting (distal vs. proximal goals) affect consumers' decision to choose AI-coach (vs. human coaching)?

(2) In the goal advancement stage, what are the differences in performance improvement effects of AI-coach (vs. human coach) on consumers with different skill levels (low vs. high), and what are the underlying mechanisms?

(3) In the performance evaluation stage, when AI-coach successfully (vs. unsuccessfully) completes goal coaching, how do consumers' word-of-mouth evaluations differ compared to human coaching?

This study will systematically and deeply reveal the mechanistic processes and boundary conditions through which AI-coach assists consumers in achieving long-term goal performance, providing theoretical insights and practical implications for consumers' long-term goal decision-making and achievement, as well as for enterprise AI product improvement.

2.1 Conceptual Definition of AI Coaching

Based on prior research and this project's content, this study defines the concept of AI-coach. In previous research, Luo et al. (2021) defined AI-coach as "a computer software program that uses deep learning algorithms and cognitive semantic analysis methods to analyze conversations between sales representatives and customers and provide training feedback to improve sales representatives' job skills." Graßmann and Schermuly (2021), from a human resources perspective, proposed that AI-coach can help customers achieve goals and defined it as "a machine-assisted system that helps customers set professional goals and construct solutions to effectively achieve customer objectives."

Although Luo et al. (2021) provided a clear definition, they focused on how AI-coach instructs employees to serve customers, where the AI-coach's service object is the service provider—guiding employees on how to better serve customers. In the context of AI-coach guiding employees, employees do not have explicit performance goals, and the article does not clarify whether employees have the willingness to actively learn AI-coach skills or are "forced" to improve skills. The article also notes that in AI-coach scenarios, employees experience supervision (Luo et al., 2021, p.6) and threat (Luo et al., 2021, p.3), which differs significantly from this study's focus on "AI-coach serving students who have clear goals and active willingness to learn skills." Graßmann and Schermuly (2021) examined AI-coach's process of helping customers set and achieve goals from a human resources perspective, which is more similar to this study's context, but their focus on AI-coach helping customers set goals differs from this study's context of "consumers actively setting goals."

Based on this, this study provides a definition of AI coaching that aligns with the research context, incorporating features including AI-coach's interaction object being end consumers, consumers actively setting goals, and having active willingness to learn skills:

AI coaching (AI-coach) is a machine-assisted systematic process that analyzes customer goals and individual characteristics based on deep learning algorithms and cognitive semantic analysis methods, constructs solutions, and effectively helps customers achieve their objectives.

Similarly, consistent with Graßmann and Schermuly (2021), the AI-coach context in this study involves an equal dyadic relationship between customer and coach. AI-coach can learn from training processes based on big data, learn from previous coaching sessions to subsequent ones, self-adjust, iteratively update, and select optimal tools for training or questioning when working with the same customer, thereby more effectively helping customers achieve goals.

2.2 Analysis of Human-AI Relationship Characteristics in AI Coaching

Currently, a few frontier articles in management have examined AI-coach, such as Luo et al. (2021) investigating AI-coach's impact on improving sales representatives' customer service performance and its mechanisms, and Graßmann and Schermuly (2021) proposing AI-coach as an effective tool for human resource development while elaborating on its implementation processes and steps. However, overall, AI-coach research remains in its infancy with limited quantity, and understanding of human-AI relationships in AI-coach contexts is still limited. Therefore, this section analyzes, compares, and summarizes the characteristics of human-AI relationships in AI-coach based on existing AI and AI-coach research.

First, AI-coach involves long-term collaborative service rather than short-term one-time encounters. For example, AI-coach sends teachers weekly updates on student homework progress and error analysis based on each assignment, helping teachers adjust instruction more targeted (Kim et al., 2022). Compared to human coaches' scheduled guidance, AI-coach provides 24/7 uninterrupted service and supports students' interactive coaching for up to 10 months (Terblanche et al., 2022). However, existing AI research primarily focuses on one-time service encounters, with limited exploration of long-term collaborative AI contexts. Most current AI research roles involve AI messengers, AI product recommenders, AI sales representatives, etc., with experimental scenarios mostly involving one-time consumer-AI interactions, such as informing interview results, product recommendations (Garvey and Duhachek, 2023; Srinivasan and Sarial-Abi, 2021; Longoni et al., 2023; Kim and Duhachek, 2020; Adam et al., 2022). Consumer-AI contact is one-time and brief, where consumers' naive beliefs about AI play important roles in AI product selection decisions (Molden & Dweck, 2006; Mai et al., 2019). Numerous studies have found that consumers' naive beliefs—such as AI being more capable in utilitarian domains (Longoni and Cian, 2022), AI having lower recognition of consumer uniqueness (Longoni et al., 2019), and AI being less empathetic (Luo et al., 2019)—influence consumer decisions regarding AI products. However, which naive beliefs about AI-coach may influence consumer decisions during long-term collaborative interactions, and which AI-coach characteristics will exert effects in subsequent learning interactions and evaluation stages, remain underexplored.

Second, AI-coach's learning attribute involves consumers actively seeking to learn from AI rather than passively receiving AI services. For example, students actively seeking AI-coach training suggestions (Terblanche et al., 2022), teachers actively using AI-coach recommendations to adjust teaching methods (Kim et al., 2022), and salespeople learning communication improvement methods from AI-coach (Luo et al., 2021) all represent consumers actively using and accepting AI-coach guidance to achieve goals. However, previous AI research has primarily focused on scenarios where consumers passively receive AI services, such as being assigned AI service during after-sales support, being greeted by AI at hotel checkin, or being served by AI when ordering at restaurants (Wang et al., 2021; Yam et al., 2020; Castelo et al., 2023; Luo et al., 2019; Garvey and Duhachek, 2023). Passive AI service reception easily leads to consumer resistance. Research shows that once consumers identify the caller as an AI salesperson, the probability of immediately hanging up jumps to 79.7% (Luo et al., 2019). Even when AI and humans provide identical services, consumers still perceive that companies sacrifice customer interests (e.g., service quality) to enhance corporate benefits (e.g., cost reduction), thereby lowering evaluations of AI services (Castelo et al., 2023). Previous research has rarely explored scenarios where consumers actively seek AI services, particularly situations where consumers actively learn specific skills from AI, such as AI fitness coaching, AI English tutoring, or AI vocal coaching, and even fewer studies have examined how AI-coach helps consumers improve skill levels.

Third, existing AI-coach research primarily focuses on service providers rather than end customers. Current research finds that AI-coach has dual mechanisms of empowerment and depletion, where provider characteristics (e.g., work tenure) and environmental features (e.g., technology overload) moderate AI-coach's effects. For example, although AI-coach can more targeted and effectively improve telephone sales personnel's performance, salespeople distrust AI-coach recommendations and fear AI replacing their jobs, resulting in AI-coach's empowerment effect improving employee performance by 12.9%, but disclosing AI-coach identity reduces performance by 5.4% (Tong et al., 2021). Moreover, AI-coach's improvement effect is not linear but inverted U-shaped: AI-coach improves performance most for mid-ranked employees, while improving less for bottom- and top-ranked employees (Luo et al., 2021). Similarly, Kim et al. (2022) found that some teachers struggle to benefit from AI-coach, with highly educated and experienced teachers being more reluctant to use AI assistants, while teachers with heavy teaching loads and complex tasks who actively used AI assistants did not achieve expected student performance improvements. AI aversion or technology overload moderates AI-coach's effects.

Fourth, AI-coach's service valence is positive, whereas existing research mostly focuses on AI services' negative effects. A few frontier studies show that AI-coach can effectively improve student academic performance (Terblanche et al., 2022), help teachers improve student outcomes (Kim et al., 2022), and help telephone salespeople improve sales performance (Luo et al., 2021). However, previous AI research predominantly focuses on AI's negative impacts, arguing that AI services produce numerous adverse effects on consumers. For example, when receiving restaurant AI service, consumers experience uncanny valley effects toward AI waiters (Mende et al., 2019; Xu et al., 2022a). When encountering AI customer service during online donations, consumers increase their utilitarian (vs. deontological) moral perspective and reduce donation amounts (Zhou et al., 2022). When facing traffic accidents with AI autonomous driving, consumers engage in more self-preservation rather than life-saving behaviors (Gill, 2020). Researchers have also concentrated on attribution mechanisms and boundary conditions for consumer evaluations of AI (vs. human) services in AI service failure scenarios (Srinivasan & Sarial-Abi, 2021; Wang et al., 2021; Crolic et al., 2022; Garvey et al., 2023; Song & He, 2021). In the few studies on AI's positive effects, scholars have discussed how algorithmic models' precise identification capabilities help merchants better identify consumer brand decision preferences (Qian & Xu, 2019). However, AI's positive impacts on human life, particularly AI-coach, have rarely been addressed.

Evidently, service providers experience strong AI resistance and aversion when receiving AI-coach feedback, which is one reason for AI-coach's double-edged sword effect. However, in the consumer goal pursuit domain that this study focuses on, AI-coach does not compete with consumers for the same job positions, and consumers actively seek AI-coach guidance, which weakens recipients' resistance and makes AI-coach's positive effects more likely to dominate. Nevertheless, research on AI-coach's impact on consumers is still emerging, and the academic community currently lacks understanding of when consumers are more willing to choose AI-coach, which consumers are more likely to benefit from AI-coach's skill guidance, and consumers' post-service word-of-mouth evaluations of AI-coach, all of which require urgent discussion.

2.3 Relevant Research on the Dynamic Perspective of Goal Management

This study investigates the multi-stage impact mechanisms of AI-coach on consumers' long-term goal pursuit based on the dynamic perspective of goal management, sequentially examining the pre-goal-pursuit selection stage, the in-progress pursuit stage, and the post-completion evaluation stage. In the pre-goal-pursuit selection stage, previous research has discussed how consumers adopt appropriate methods to achieve goals, focusing on how factors such as the number, similarity, flexibility of means, and goal distance affect goal achievement (Huang & Zhang, 2013; Zhang et al., 2007b; Etkin & Ratner, 2012, 2013), and how different means need to match consumers' different pursuit stages (Shaddy et al., 2021). In the in-progress pursuit stage, existing research has primarily focused on when consumers view achieved sub-goals as goal commitment versus goal progress, and how sub-goal categorization affects overall goal pursuit (Fishbach & Dhar, 2005; Zhang et al., 2007a; Sharif & Woolley, 2020). In the post-completion evaluation stage, research has mainly examined how viewing past goals affects consumers' subsequent goal selection (Xu et al., 2019; Huang & Aaker, 2019). In short, research from the dynamic perspective of goal management includes content on selecting goal achievement methods, persistently pursuing goals, and evaluating goal completion (Sharif & Woolley, 2020; Huang et al., 2019).

Goal management research finds that the more diverse the means adopted in the early stage of goal progress, the higher the likelihood of goal achievement, while more singular means in the late stage facilitate rapid goal attainment (Huang &

Zhang, 2013). Goal management research has also explored the effects of different feedback and evaluation mechanisms during goal pursuit. For example, for low-skilled individuals, positive feedback should be provided during goal pursuit to enhance goal commitment and motivation, whereas for high-skilled individuals, negative feedback should be provided to enhance perceived insufficient progress and boost motivation (Finkelstein & Fishbach, 2012).

However, previous goal management research has mostly discussed consumers' self-management of goals (Jin & Zhang, 2015) or the influence of others' feedback on consumer goal management (Huang et al., 2019), with scarce research on AI as a coach (vs. human coaching) affecting consumer goal pursuit. This gap creates a disconnect from the managerial practice of increasingly using AI-coach to guide consumers in achieving long-term learning and fitness goals, urgently requiring researchers to discuss AI-coach's impact effects and mechanisms.

2.4 Summary

Although previous research has examined AI-consumer interactions with some beneficial results, three issues warrant further in-depth investigation.

First, previous research has focused on one-time AI-consumer service encounters, with limited exploration of long-term collaborative interactions. Previous AI services such as intelligent recommendation AI, restaurant service AI, front desk customer service AI, and medical AI (Kim & Duhachek, 2020; Yam et al., 2020; Longoni et al., 2019) all involve one-time service contexts, such as recommending a stock, providing a dinner, inquiring about product needs, or diagnosing a condition, typically unrelated to consumers' long-term goal pursuit. However, existing research has found that AI can serve as a long-term coach, providing continuous supervision and error correction for employees, effectively improving telephone sales performance (Luo et al., 2019). Numerous industry examples also demonstrate that AI can already assume long-term coaching roles like teachers and coaches (Miao et al., 2022). Yet scarce research has explored how AI-coach affects consumers in the long-term goal pursuit domain. Compared to previous AI applications, AI-coach's service context features long-term interactive characteristics, requiring consumers and AI to engage in long-term collaborative interactions to accomplish specific consumer goals. Investigating AI-coach's impact on consumer goals can break through the constraint of previous research focusing mostly on one-time AI services and extend frontier AI-coach research in the consumer goal pursuit domain.

Second, previous research has focused on scenarios where consumers passively receive AI services, with limited exploration of consumers actively learning skills from AI. In previous contexts like AI recommendation, AI customer service, and even some medical AI scenarios (e.g., examination, condition analysis, surgery), consumers mostly play a simple service recipient role without active learning motivations regarding AI's skills. For example, in AI telephone sales scenarios, consumers neither need nor desire to master the conversational techniques of AI sales agents, and consumers' own communication skill levels do not affect their interaction effectiveness with AI. However, in AI-coach contexts, the consumer role changes: consumers actively learn and acquire professional skills possessed by AI, such as actively learning parallel parking from an AI driving instructor, English pronunciation from an AI teacher, or correct fitness postures from an AI coach—these are all situations where consumers hope to master AI's skills and engage in active learning. Compared to previous AI services, consumer-AI-coach interactions require greater mobilization of consumers' cognitive resources. Consumers' own skill levels may substantially influence their learning effectiveness when interacting with AI-coach (vs. human coaches). Current limited AI-coach research mostly examines AI-coach interactions with service providers (Tong et al., 2021; Luo et al., 2021). Future research urgently needs to focus on consumers' subjective agency, extending AI research into the domain of consumer active learning.

Third, previous research has primarily investigated AI services' negative effects, with limited exploration of AI's positive effects in positive events. Previous research has emphasized consumers' pre-existing biases toward AI services, such as believing AI is only suitable for objective tasks (Castelo et al., 2019), cannot recognize unique conditions (Longoni et al., 2019), and threatens human identity expression (Leung et al., 2018). Numerous studies have found negative consumer behaviors after receiving AI services, such as lower donation intentions (Zhou et al., 2022; Giroux et al., 2022), more self-preservation behaviors (Gill, 2020), and poorer service evaluations (Wang et al., 2021). AI's positive effects only appear in service failure contexts, such as AI errors reducing consumer dissatisfaction compared to human errors (Srinivasan & Sarial-Abi, 2021), and algorithmic errors (vs. human errors) eliciting less moral punishment intention in discrimination scenarios (Xu et al., 2022b). Although these studies effectively reveal AI's negative or mixed impacts, for consumers, how to use AI to better achieve positive pursuit of long-term goals (e.g., fitness, learning), embrace AI's beneficial life changes, and harvest goal achievement and happiness represents a more urgent practical need.

The dynamic perspective of goal management provides a systematic, whole-process theoretical framework for interpreting AI-coach's impact on consumers' long-term goal pursuit—covering the pre-pursuit selection stage, in-progress pursuit stage, and post-completion evaluation stage. This study integrates AI-coach's characteristics and examines three angles: the "means-goal" construal level matching in the pre-pursuit stage, the "means-goal" feedback needs in the in-progress stage, and the "means-evaluation" social cognition in the post-completion stage, comprehensively revealing AI-coach's (vs. human coaching) mechanisms in assisting consumers' long-term goal pursuit. Specific content is shown in Table 1 .

Table 1 Analysis of This Study's Content Integration with Goal Management Perspective

Goal Management Stage	Foundational Literature	Integrated AI Characteristics	Main Research Content
Study 1: Pre-pursuit Selection Stage	Huang & Zhang (2013), Zhang et al. (2007b), Etkin & Ratner (2012, 2013), etc.	Strong method operability, rich methods	How consumers select appropriate coaches (AI-coach vs. human coach) to achieve goals
Study 2: In-progress Pursuit Stage	Fishbach & Dhar (2005), Zhang et al. (2007a), Sharif & Woolley (2020), etc.	Fast feedback speed, insufficient feedback granularity	How to encourage consumers to persist in long-term goal pursuit under AI-coach guidance
Study 3: Post-completion Evaluation Stage	Xu et al. (2019), Huang & Aaker (2019), etc.	High tool attributes, low emotional attributes	How consumers evaluate AI-coach performance when goals are achieved or failed

In summary, this study will extend AI research in the domain of consumers' long-term goal pursuit by breaking through previous research limitations focusing mostly on one-time, passive, and negative AI services, based on the dynamic perspective of goal management, thereby strengthening AI-coach's positive effects on consumer well-being.

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3. Research Framework on AI Coaching

Based on the dynamic perspective of goal management, this study explores the multi-stage impact mechanisms of AI-coach on consumers' long-term goal pursuit across three phases of consumer-AI-coach interaction: First, in the AI-coach selection stage, drawing on AI-coach's characteristics of rich, highly operable methods, we examine how goal setting (proximal vs. distal goals) influences consumers' choice of AI-coach (vs. human coaching). Second, in the goal advancement stage under AI-coach guidance, based on AI-coach's characteristics of fast but insufficiently granular feedback, we investigate AI-coach's (vs. human coach) performance improvement effects on consumers with different skill levels (low vs. high). Third, in the AI-coach performance evaluation stage, based on AI-coach's characteristics of strong tool attributes but weak emotional capacity, we examine consumers' word-of-mouth evaluations of AI-coach (vs. human coaching) under different coaching outcomes (successful vs. unsuccessful).

This study will unfold closely around the "AI-coach and consumer goal pursuit" framework, progressing layer by layer to form an organic whole. The research framework is shown in Figure 1 [Figure 1: see original paper].

Figure 1 Overall Research Logic Framework

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Study 2: Goal Advancement Stage Under AI-coach Guidance
Consumer Skill Level (Low vs. High)
AI Anthropomorphism Level (High vs. Low)
Feedback Characteristics:
- Positive feedback timeliness
- Negative feedback granularity
Consumer Goal Skill Incremental Performance Improvement

Study 1: AI-coach Selection Stage
Goal Setting (Proximal vs. Distal)
Consumer Choice (AI-coach vs. Human Coaching)

Study 3: AI-coach Word-of-mouth Evaluation Stage
Coaching Outcome (Achieved vs. Not Achieved)
Consumer Word-of-mouth Evaluation
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3.1 Study 1: The Effect of Goal Setting on Consumer Choice of AI Coaching

Consumers often set temporal parameters for goals, such as setting goal completion for the near-term next month (proximal goal) or the distant next year (distal goal). This study proposes that during the coach (AI-coach vs. human coaching) selection stage, when goals are set as proximal (vs. distal), consumers are more likely to choose AI (vs. human) coaching. Previous research indicates that when goals are set as proximal, consumers operate in a low-construal level, concrete thinking mode, such as specifically considering what methods to implement and how much time to spend; when goals are set as distal, consumers operate in a high-construal level, abstract thinking mode, such as considering the goal's attractiveness and whether they should pursue it (Trope & Liberman, 2010). Based on construal level theory, this study speculates that in abstract thinking mode, consumers may think more about the goal's importance and necessity, whereas in concrete thinking mode, consumers focus more on the goal's implementability and operability. Compared to abstract thinking, concrete thinking more strongly motivates consumers to choose coaches with strong method operability.

Compared to human coaching, AI-coach better matches highly operable guidance content (Kim & Duhachek, 2020). Since AI-coach's goal judgment is simple and objective with a series of explicit rule settings, its input and output instructions are often step-by-step operations that more easily help consumers learn quickly (Yalcin et al., 2022). For example, AI-coach integrates extensive data display functions that can clearly show consumers the clear steps needed to achieve goals, such as completing 20 crunches within 5 minutes, where each crunch must involve touching above the knee and holding for 3 seconds to count as successful. AI-coach's clear, easy-to-understand goal achievement steps better match the low-construal level thinking mode activated when consumers pursue proximal goals. Previous research shows that consumers believe AI lacks autonomous consciousness and cannot engage in abstract thinking (Bigman & Gray, 2018), making its model suitable for matching low-construal level, operational information content, such as performing specific behaviors according to specific codes. Conversely, consumers believe humans possess high-construal level abstract thinking abilities, better matching high-construal level, abstract information content, and are suitable for explaining the reasons behind behaviors (Kim & Duhachek, 2020). Therefore, this study proposes that compared to distal goals, proximal goals will motivate consumers to choose highly operable guidance and be more likely to select AI-coach (vs. human coaching).

Additionally, research shows that when consumers are in concrete (vs. abstract) construal, they value method diversity more highly (Etkin & Ratner, 2013). Tong et al. (2021) found that AI-coach trained on large customer service conversation corpora can identify more telephone salespeople's conversation errors and provide multiple different solutions compared to human managers. AI-coach offers higher training course richness and method diversity than human coaching. For example, FITURE's AI fitness coach offers 15+ major course categories, including aerobic dance, yoga, strength training, and integrates numerous all-star coach training videos with over 200,000 cumulative teaching hours. Compared to human coaching, AI-coach learns from many excellent human coaching experiences, integrates multiple skills, and possesses more types of guidance methods and training approaches. Research shows that compared to single goal achievement means, diversified goal achievement means better motivate consumers in early (vs. late) stages to pursue goals more vigorously (Huang & Zhang, 2013). Therefore, compared to distal goal setting, proximal goal setting will motivate consumers to prefer more diversified goal achievement means, believing that AI-coach's multiple training methods can help them achieve goals more quickly.

Accordingly, this study proposes the following hypotheses:

H1: When goals are set as proximal (vs. distal), consumers are more likely to choose AI-coach (vs. human coaching).

H2: The effect of goal setting (proximal vs. distal) on consumer choice of AI-coach (vs. human coaching) is mediated by perceived (a) method operability and (b) method diversity of AI-coach (vs. human coaching).

Additionally, this study proposes that AI-coach's anthropomorphism level will moderate this effect. AI anthropomorphism reduces perceived differences between AI and humans. The higher the AI anthropomorphism level, the more consumers treat AI equally with humans. Anthropomorphism enhances consumers' cognition of AI's autonomous consciousness, increases AI's compatibility with high-construal level abstract thinking, while decreasing its compatibility with low-construal level concrete thinking, thereby reducing the effect of goal distance on coach selection differences. Previous research shows that when AI is anthropomorphized, consumers increase expectations of AI's autonomous agency (Crolic et al., 2022). Consumers believe anthropomorphized AI-coach will possess more human-like abstract thinking abilities (Kim & Duhachek, 2020), better adaptability in subjective (vs. objective) tasks (Castelo et al., 2019), and greater responsibility acceptance (Srinivasan & Sarial-Abi, 2021). Therefore, AI anthropomorphism will reduce consumers' tendency to differentially treat AI-coach and human coaching. Accordingly, this study proposes:

H3: When AI-coach's anthropomorphism level is high (vs. low), the differential effect of goal setting on consumers' preference for AI-coach (vs. human coaching) is weakened.

In summary, Study 1's framework is proposed (see Figure 2 [Figure 2: see original paper]).

Figure 2 Study 1: The Effect of Goal Setting on Consumer Choice of AI Coaching

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Goal Setting (Proximal vs. Distal)
    $\rightarrow$ Perceived Method Operability
    $\rightarrow$ Perceived Method Diversity
    $\rightarrow$ Consumer Choice (AI-coach vs. Human Coaching)
Moderator: AI-coach Anthropomorphism Level (High vs. Low)
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3.2 Study 2: The Effect of AI Coaching on Capability Improvement for Consumers with Different Skill Levels

In the goal advancement stage, the most common situation is that after some time, consumers cannot persist with existing goals. Previous research suggests that consumers primarily apply commitment and progress frameworks for sequential decision-making. Specifically, research indicates that if a previous behavior is viewed as commitment to the overall goal, it strengthens consumers' motivation to continue pursuing the goal, whereas if viewed as progress toward the overall goal, it weakens pursuit of that goal (Dhar & Simonson, 1999; Fishbach & Dhar, 2005). Research has also found matching effects between actor characteristics and goal progress stages: novices, having lower commitment to final goals and doubts about goal attainment, benefit more from positive (vs. negative) feedback to enhance goal motivation, whereas experts, being more confident about future goal attainment, benefit more from negative (vs. positive) feedback to enhance goal motivation (Finkelstein & Fishbach, 2012). This previous research informs Study 2's content on consumer classification and interaction effects with coaches.

This study proposes that in the goal advancement stage, AI-coach's (vs. human coaching) effect on consumer goal pursuit performance improvement is moderated by consumer skill level. Specifically, compared to high-skill consumers, AI-coach (vs. human coaching) improves low-skill consumers' goal performance more. The rationale is as follows:

When consumers have low prior knowledge and skill levels, they need more positive feedback to enhance goal confidence and commitment (Finkelstein & Fishbach, 2012). Compared to high-difficulty training requirements and content, low-difficulty training content better helps novice consumers build confidence, strengthen commitment to final goals, and thus persist in goal pursuit. Since AI possesses powerful computing capabilities and massive databases, AI makes judgments on highly structured information very quickly (Luo et al., 2019). Whether consumers meet standards during training, AI-coach can provide timely report feedback, meeting entry-level learners' core needs for quickly mastering simple techniques and obtaining timely positive feedback. For example, BodyPark's AI-coach for simple jumping jack training provides immediate evaluations of "good (basically meeting standards)/perfect (fully meeting standards)/not enough (not yet meeting standards)" for each jump. Most consumers receive a series of compliments during early training, and abundant positive feedback on simple movements can quickly enhance consumers' confidence and goal commitment. For human coaches, training for novices also starts with simple entry-level training to develop tailored tutorials that meet consumers' needs for simple, repetitive, achievable training, gradually building confidence and goal commitment to encourage continued exercise. Therefore, in training tasks for novices, both AI-coach and human coaching can exert good guidance effects, with no significant difference between the two.

However, when consumers have high prior knowledge and skill levels, they need more negative feedback to target improvements in their deficiencies and further enhance goal pursuit effectiveness. However, since AI-coach is algorithm-driven and lacks subjective judgment, and its development level has not yet achieved interconnectivity with hardware devices, AI-coach has lower specialization in recognizing consumer characteristics compared to human coaching (Tong et al., 2021), only reporting final results without deep analysis of the process to achieve results. For example, although BodyPark's AI-coach can quickly judge whether crunches meet standards (e.g., whether hands touch knees, whether they hold for 3 seconds), it cannot, like human coaches, provide detailed analysis of which muscles should be engaged and remind consumers not to compensate with other body parts—lacking detailed, personalized guidance. Although AI-coach offers diverse courses and recorded videos of human coaches, it still cannot meet high-skill consumers' needs for improvement in specific niche areas. When pursuing higher-level refined guidance, such as adjusting training programs according to consumers' physical characteristics, such detailed personalized guidance still requires human coaches, while AI-coach's guidance effectiveness is poorer. Accordingly, this study proposes:

H4: AI-coach's (vs. human coaching) improvement effect on consumer goal pursuit performance is moderated by consumer skill level. When consumer skill level is high, human coaching (vs. AI-coach) has a greater improvement effect on consumer goal pursuit performance, meaning consumers will be less likely to choose AI-coach; when consumer skill level is low, there is no significant difference in improvement effects between AI-coach (vs. human coaching).

H5: (a) When consumer skill level is high, because AI-coach's (vs. human coach) ability to provide granular negative feedback in advanced training is weaker, human coaches (vs. AI-coach) achieve higher goal improvement performance; (b) When consumer skill level is low, because both AI-coach and human coaching can provide timely positive feedback in simple entry-level training, there is no significant difference in their guidance effects.

Additionally, this study proposes that for high-skill consumers, if the quality of negative feedback provided by AI-coach is enhanced—such as providing more detailed feedback suggestions, strengthening AI-coach's connection with intelligent hardware, developing heart rate bracelets and patch-type intelligent hardware to coordinate with AI-coach's indicated muscle engagement—it will effectively improve AI-coach's goal performance for high-skill consumers. Alternatively, for high-skill consumers, directly increasing opportunities for face-to-face human coach guidance within AI-coach can meet their needs for refined guidance, thereby more targeted improvement of deficiencies and better goal performance enhancement.

In summary, Study 2's framework is proposed (see Figure 3 [Figure 3: see original paper]).

Figure 3 Study 2: The Effect of AI Coaching on Goal Skill Improvement Performance for Consumers with Different Skill Levels

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Consumer Skill Level (Low vs. High)
    $\rightarrow$ AI-coach (vs. Human Coaching)
    $\rightarrow$ Positive Feedback Timeliness
    $\rightarrow$ Negative Feedback Granularity
    $\rightarrow$ Consumer Goal Skill Incremental Performance Improvement
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3.3 Study 3: Consumer Word-of-mouth Evaluation of AI Coaching

In the post-goal-completion stage, the focus is on word-of-mouth and evaluation of completed goals. Research shows that people have different cognitive evaluations of past goals; for example, viewing past goals as a completed journey (vs. reaching a destination) enhances perception of personal growth gains, thereby increasing subsequent goal pursuit behavior (Huang & Aaker, 2019). Additionally, after consumers achieve focal goals, suppressed long-term goals resurface, leading to changes in reward needs (Xu et al., 2019). Study 3 primarily draws on goal evaluation and need change research, combined with AI's strong tool attributes but weak emotional attributes, discussing two types of coaching outcomes: successful and unsuccessful guidance.

This study proposes that when coaches successfully complete goal guidance, consumers will provide fewer positive word-of-mouth evaluations for AI-coach compared to human coaching. Previous research shows that consumers' positive evaluations and word-of-mouth recommendations are prosocial behaviors (Septianto & Chiew, 2018) that help consumers express goodwill and affirmation to recommendees (e.g., fitness coaches), promote emotional communication, and consumers expect such positive word-of-mouth to facilitate better future interpersonal interaction and exchange (Penner et al., 2005). However, compared to humans, AI itself lacks emotional perception ability (Wien et al., 2021; Han et al., 2022; Lin et al., 2021), and positive evaluations and recommendations cannot prompt AI-coach to favor consumers more in the future, so consumers have no expectations of emotional exchange or social resource exchange with AI-coach. Previous research also shows that even when AI algorithms have higher prediction accuracy than humans, consumers still adopt human predictions and treat AI performance more harshly (Dietvorst et al., 2015). Additionally, because consumers believe AI lacks subjective agency, they will not make positive attributions to AI even when service is successful (Jörling et al., 2019; Garvey et al., 2023). Therefore, after successfully completing coaching work, this study proposes that consumers will provide fewer positive word-of-mouth evaluations and recommendations for AI-coach compared to human coaching.

When coaches unsuccessfully complete training guidance, consumers will give lower word-of-mouth evaluations and exhibit more negative behaviors toward AI-coach compared to humans. Previous research shows that because negative behaviors (e.g., attacks and verbal abuse) threaten self-image perception, consumers often dehumanize targets before attacking by portraying them as insensate entities to reduce anticipated guilt and satisfy anger expression needs (Herak et al., 2020; Haslam & Loughnan, 2014). Compared to humans, consumers view AI more as a tool (Choi et al., 2021) and more as an outgroup (Longoni et al., 2023). Therefore, once AI-coach service fails, consumers' low sensitivity perception of AI will more greatly reduce their post-attack guilt. Previous research also shows that compared to humans, consumers use more profanity and negative emotional expressions when interacting with AI chatbots (Hill et al., 2015). After service failures, consumers give more negative evaluations to anthropomorphized AI customer service, reducing satisfaction and subsequent purchase intentions (Crolic et al., 2022). Therefore, when coaches unsuccessfully complete training guidance, consumers' negative emotions such as anger and dissatisfaction from unmet goal expectations will be more vented and expressed toward AI-coach (vs. human coach), manifesting as lower evaluation scores and more negative accusations. Accordingly, this study proposes:

H6: When training guidance is successfully completed, consumers will provide fewer performance evaluations and word-of-mouth recommendations for AI-coach compared to human coaching. This is because consumers have lower expected positive emotional returns from AI-coach compared to humans, making it less worthwhile to engage in word-of-mouth recommendation and other prosocial behaviors.

H7: When training guidance is unsuccessfully completed, consumers will provide lower performance evaluations and more negative accusations for AI-coach compared to human coaching. This is because AI-coach reduces consumers' anticipated guilt about their own negative behaviors compared to humans.

In summary, Study 3's framework is proposed (see Figure 4 [Figure 4: see original paper]).

Figure 4 Study 3: Consumer Word-of-mouth Evaluation of AI Coaching

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Coaching Outcome (Successful vs. Unsuccessful)
    $\rightarrow$ AI-coach (vs. Human Coaching)
    $\rightarrow$ Expected Positive Emotional Returns
    $\rightarrow$ Expected Negative Guilt
    $\rightarrow$ Consumer Word-of-mouth Evaluation
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4. Theoretical Framework of AI Coaching

With the rapid development of AI technology, AI coaching has been widely applied in smart education, intelligent fitness, and other domains, giving rise to new service forms such as AI teachers and AI coaches. However, how do consumers perceive AI-coach compared to human coaching? Can AI-coach truly effectively help consumers achieve long-term goals? How do consumers' word-of-mouth evaluations of AI-coach differ? Through literature review and consumer interviews, preliminary findings indicate that AI-coach has advantages in strong operability and high method diversity, features fast feedback and standardized feedback, while having disadvantages in low emotional perception ability and low social exchange expectations. Based on relevant goal management research, this study sequentially unfolds across three stages of consumers receiving AI-coach services (pre, during, post), with the following theoretical framework:

First, integrating AI-coach's operational characteristics, this study clarifies when consumers prefer AI-coach (vs. human coaching) in long-term goal pursuit contexts. This study breaks through previous limitations focusing on one-time AI service encounters, pioneering the exploration of AI's impact in long-term collaborative domains. Previous marketing AI research mostly personified AI as insurance salespeople (Luo et al., 2019), restaurant waiters (Leo & Huh, 2020), after-sales customer service (Giroux et al., 2022), and other roles, primarily providing one-time product sales and service experiences without shared long-term goals with consumers. Compared to human services, consumers generally exhibit avoidance and resistance to AI services. This study first positions AI as a coach helping consumers achieve long-term positive goals, focusing on AI-coach's coaching role, which helps extend AI service scenarios from simple contact services to active learning domains, from one-time encounter perspectives to long-term collaborative perspectives, and explores the effects of consumer goal setting and skill levels on AI-coach interaction effectiveness.

Drawing on construal level theory and goal pursuit research, this study proposes that when goals are set as proximal (vs. distal), consumers will more likely choose AI-coach (vs. human coaching), because proximal (vs. distal) goals activate more concrete (vs. abstract) thinking constructions, making consumers prefer AI-coach's characteristics of high method operability and high method diversity. Moreover, when AI-coach's anthropomorphism level is higher (vs. lower), the differential effect of goal distance on consumers' preference for AI-coach (vs. human coaching) will be weakened.

Second, integrating AI-coach's feedback characteristics, this study reveals AI-coach's mechanisms for improving consumer goal performance. Does AI-coach actually work? How useful is it? How much higher is its improvement effect compared to human coaching? These are core concerns for both enterprises and users. Focusing on consumer long-term goal pursuit task contexts and based on AI-coach's characteristics of fast feedback and standardized feedback, this study explores AI-coach's capability improvement mechanisms for consumers with different knowledge and technical skill levels.

This study proposes that AI-coach's (vs. human coaching) effect on consumer skill improvement is moderated by consumer skill level. Specifically, when consumer skill level is high, more negative feedback pointing out deficiencies is needed. Due to AI-coach's insufficient ability to provide granular negative feedback, high-skill consumers cannot receive beneficial guidance targeting their deficiencies, resulting in lower performance improvement effects for AI-coach (vs. human coaching). When consumer skill level is low, there is no significant difference in improvement effects between AI-coach (vs. human coaching), because when consumer skill level is low, more positive feedback is needed, and both AI-coach and human coaching can provide timely positive feedback information to encourage novice consumers to persist in goal pursuit.

Third, integrating AI-coach's emotional characteristics, this study clarifies consumers' word-of-mouth evaluation mechanisms of AI-coach. Previous research has two different views on whether consumers treat AI and humans equally: one affirmative view holds that humans treat robots as social actors, such as conforming to robots' wrong judgments due to social pressure after all robots make errors (Vollmer et al., 2018); the other negative view holds that humans treat robots as non-human tools, such as delivery robots and vacuum cleaning robots (Yam et al., 2020).

This study proposes that in AI-coach service contexts, people view robots as non-human and, based on this, examines consumers' word-of-mouth evaluations of AI (vs. human) coaches under successful (vs. unsuccessful) coaching scenarios. Specifically, this study proposes that when training goals are successfully completed, consumers will provide fewer positive word-of-mouth evaluations for AI-coach compared to human coaching. This is because consumers have lower expected positive emotional returns from AI-coach compared to humans, making word-of-mouth recommendations and other prosocial behaviors less worthwhile. When training goals are unsuccessfully completed, consumers will provide more negative word-of-mouth evaluations for AI-coach compared to human coaching. This is because consumers have lower anticipated guilt when making negative evaluations of AI-coach compared to humans.

Overall, this study breaks through three previous research bottlenecks in theoretical construction: First, it shifts from focusing on one-time AI service contexts to examining AI-coach impact in long-term collaborative contexts; second, it moves beyond simple passive consumer-AI contact to explore consumer learning contexts where consumers learn specific skills from AI-coach; and third, it distinguishes itself from existing AI-coach research focusing on service provider interactions by examining direct AI-coach and end consumer interactions. Moreover, different from previous research on AI's negative effects, this study focuses on AI-coach's positive effects on consumer well-being. Based on the dynamic perspective of goal management, this study explores AI's booster effects on consumers' long-term goal pursuit in long-term collaborative relationships, which will help enterprises achieve both technological implementation and commercial success, and effectively promote China's deep deployment and rapid development of new-generation AI in smart education, intelligent fitness, and health medical care.

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