AI SPORTS COMMENTATORS AS EFFECTIVE CONTEXTUAL ADVERTISING AGENTS: FOCUSING ON COMMENTARY TYPES AND CUSTOMIZATION

by

JAEMIN KIM

(Under the Direction of Jooyoung Kim)

ABSTRACT

This study suggests the AI sports commentator (AISC) as a contextual advertising agent based on the three key attributes of the effective contextual advertising – applicability, affective tone, and content involvement. To enhance the effectiveness of the AISC as a contextual advertising agent, the study mainly aims to identify the impact of two core features of the AI sports commentator – commentary type and customization – on trust and, subsequently, perceived persuasive effectiveness and advertising outcomes (A_{ad} and A_b) within the integrated theoretical framework. According to the result of 2 (Commentary Type: Neutral vs. Favorably Tailored) X 2 (Customization: Absent vs. Present) between subject experimental design (n = 197), this study verified that favorably tailored commentary, as an AI cue, weakens trust by triggering the negative representativeness heuristic and the identity heuristic. At the same time, customization action improved trust via users' sense of agency. Subsequently, shaped trust in the AISC positively influenced the perceived persuasion effectiveness and advertising outcomes in turn. Also, multigroup-SEM revealed that the activations of heuristics by favorably tailored commentary were significantly varied by customization. Moreover, further robust

ANOVAs empirically demonstrated that there was a significant interaction effect of commentary type and customization on trust, indicating that user-initiated (customization) favorably tailored commentary showed significantly higher trust than passive (non-customization) neutral commentary. These findings emphasized how AI-driven cue routes interact with action routes within the HAII-TIME framework. Also, by integrating the HAII-TIME framework with the persuasion knowledge model (PKM), the study underscores that trust, shaped through the AI-driven cues and actions (i.e., agent knowledge), functions as a critical belief that subsequently impacts persuasion outcomes. Besides the theoretical contributions in the context of human-AI interaction (HAI), this dissertation also offers valuable practical insights for the sports streaming platforms, advertisers, and even AI user experience (UX) and user interface (UI) designers.

INDEX WORDS: AI-mediated Advertising, Human-AI Interaction, Sports Sponsorship, AI Sports Commentator, Customization

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CHAPTER 1

INTRODUCTION

The rapid advancements of digital technologies, such as Artificial Intelligence (AI), blockchain, and metaverse, are reshaping media environments and advertising. In the field of advertising, scholars have scrutinized state-of-the-art media technologies, from 3D (3-Dimensional) television to AR (Augmented Reality) and VR (Virtual Reality), and their capacity to deliver persuasive messages in innovative ways. Among diverse technological developments, AI significantly changes the landscape of digital advertising, showing substantial market growth. Indeed, the market size of AI in the media industry is anticipated to grow from \$8.21 billion in 2024 to \$51.08 billion by 2030 at a CAGR (Compound Annual Growth Rate) of 35.6% (MarketsandMarkets 2025).

Within this substantial transformation, the sports industry, which can be characterized by enthusiastic audience engagement and significant commercial value, is also actively adapting to the new era of AI. The President of the IOC (International Olympic Committee), Thomas Bach, also underlined the significance of AI in sports: "*AI will be a revolution for our society. And it will be a revolution for sport. It will be a fascinating new lap in the Olympic race – and in Olympic history*" (Ingle 2024). This revolution has already pervaded across diverse aspects of the sports industry – sports broadcasting (or journalism), performance analysis, coaching assistance, smart stadium, injury prevention, and enhancing fan engagement (T. Xu and Baghaei 2025). For instance, AI is being used for player analysis and injury prevention, as the NFL (National

Football League) and AWS (Amazon Web Services) collaborated to develop a 'Digital Athlete' program to track and analyze players' movements in real-time (Entin 2024; NFL 2025). Also, AI technologies improve the quality of judging in sports, as demonstrated by the Premier League's use of SAOT (Semi-Automated Offside Technology) to ensure accurate decisions (Mashiter 2025; Premier League 2025). This widespread adoption of AI in the sports industry leads to the explosive market growth of AI in the global sports industry, which is projected to reach $2.61 billion by 2030 (MarketsandMarkets 2024).

Among a lot of intriguing AI applications in the sports industry, this study primarily focuses on the AI sports commentator (AISC), an intriguing technology that is gradually being adopted to enhance fans' media experiences (Hamilton 2023; PwC 2024; Ramsay 2023; Walch 2024). At the convergence of various AI-driven deep learning methods, including Latent Dirichlet Allocation (LDA), Long Short Term Memory (LSTM), and Convolutional Recurrent Neural Network (CRNN), the AISC is driving a groundbreaking shift in sports media (Walch 2024). Specifically, previous studies underlined two main characteristics of the AISC: 1) AI-driven in-depth analysis and 2) favorably tailored commentary (Andrews et al. 2024; Jung et al. 2025). First, in-depth analysis is a foundational feature of the AISC. By processing massive volumes of real-time, historical, and user data, the AISC can capture complex situations and generate predictive and analytic insights that human sports commentators can elude (Walch 2024). This analytical capacity enriches the sports fans' viewing experience by providing multifaceted and deeper real-time statistics that complement the sports viewing experiences (Andrews et al. 2024; Feris and Karlinsky 2021). While this ability plays a complementary role, real-time favorably tailored commentary itself garners significant attention as a key communicational feature of the AISC that directly affect users' perceptions (PwC 2024; Walch 2024). Building upon diverse AI-driven technologies, including Generative AI (GAI), Natural Language Processing (NLP), and Text-To-Speech (TTS), the AISC automatically detects the specific situations and context of sports matches and generates favorably tailored commentaries. Moreover, the critical advantage of this unique feature is its profound potential for customizable dynamic adaptation (Khogeer 2023; PwC 2024). Unlike one-to-many traditional human sports commentators, the AISC can tailor its commentary to align with an individual fan's specific preferences by adjusting the commentary language style (e.g., friend-like, professional) or commentary type (e.g., neutral, favorably tailored). Indeed, many professional sports leagues (e.g., Bundesliga, NBA) and sports events (e.g., The Masters, Wimbledon, Olympics) have deployed the AISC for real-time broadcasting and online highlight films, delivering tailored commentary that reflects personal preferences toward specific teams/players and different languages to fulfill diverse demands from global fans on a personal level (Bantock 2023; Bundesliga 2024; Hamilton 2023; Kelly 2024; NBC Sports 2025).

In the field of advertising, these distinct features raise the potential of the AISC as a powerful agent of *contextual advertising*, not only as an innovative AI-driven tool for sports broadcasting. For instance, the PwC (2024), one of the Big Four global accounting firms, forecasts the AISC's role as a contextual advertising agent by highlighting the capacity to provide customizable commentary, relevant advertisements, customized summaries, and high-quality translation (language selection). Specifically, contextual advertising refers to placing advertisements with specific content and media context that is highly relevant. Contextual advertising aims to minimize perceived intrusiveness and enhance advertising relevance, which leads to more favorable consumer responses by integrating the advertising messages with their surrounding context (Häglund and Björklund 2024; Shen and Chen 2007; Wojdynski and Bang 2016). In this context, this dissertation explains the potential of the AISC as contextual advertising agents based on diverse AI-driven methods and three main attributes of effective contextual advertising: *applicability*, *affective tone*, and *content involvement* (Häglund and Björklund 2024).

First, the AISC can move beyond the static keyword or topic matching to analyze and respond to the dynamic, real-time context of the live sporting match. AI-driven image detection and topic modeling ensure that advertising is not just topically relevant but situationally appropriate (Blei, Ng, and Jordan 2003; Häglund and Björklund 2024; Luan and Lin 2019; R. Wang et al. 2019). Next, regarding affective tone, the AISC is expected to advance from merely detecting or predicting sentiment at a specific moment to actively shaping and fostering a positive affective viewing environment through favorably tailored commentary (Abid 2024; Hou et al. 2017; M. Lee et al. 2015, 2016; Pan 2013). This ability creates a more receptive context and environment for a persuasive message about sponsors. Last, in terms of content involvement, on top of the inherent highly involved and immersive characteristic of sports content, advertising messages seamlessly weave into its narrative commentaries, help the AISC to convey advertising messages without intrusiveness, and maintain a high-involved state of sports fans (Häglund and Björklund 2024; Lagun and Lalmas 2016; Norris and Colman 1992; X. Yi et al. 2014). In addition, AI-driven attention metrics will also allow the AISC to expose advertising messages at the highly involved moments during the sports match (Häglund and Björklund 2024). In summary, while several AI-driven technologies, such as real-time context analysis, topic modeling, and attention metrics, work behind the scenes to enhance applicability, affective tone, and content involvement, the touch point of interaction with the viewers and manifestation of these capabilities is primarily the commentary itself. Therefore, this dissertation identifies ‘favorably tailored commentary’ as the pivotal communicative feature through which the AISC’s potential as a contextual advertising agent is realized.

However, this communicative feature of the AISC simultaneously raises a critical and complex challenge. Favorably tailored commentary, which is intentionally aligned with a user’s preferences, represents a certain level of bias. Therefore, it may conflict with the ingrained expectation of objectivity and fairness of sports commentators, potentially deteriorating trust in the AISC and reducing the persuasive impact of advertising messages within the favorably tailored commentary (Ether 2025; Keene and Cummins 2009; M. Lee et al. 2015; Smith 2012). This inherent tension between the potential of the AISC as a contextual advertising agent and the considerable risk derived from the bias of commentary constitutes the main problem that this dissertation aims to unveil. Since the AISC is a newly emerged technology, there is a significant research gap in understanding the underlying psychological mechanism describing how sports fans perceive and respond to favorably tailored commentary and advertising messages from the AISC. Moreover, while user-centric control mechanisms such as customization have been studied as potential strategies to mitigate negative perceptions of AI-driven content tailoring, their effectiveness within the context of AISC should be further empirically investigated (Cheng and Jiang 2022; Choi and Park 2023; F. Y. Lee and Chan 2024;

Snyder, Sundar, and Lee 2024; Sundar and Marathe 2010; Wald, Heijselaar, and Bosse 2021).

Along these lines, this dissertation sets two main goals: 1) investigating the potentially ambivalent impact of the AISC's favorably tailored commentary on user perceptions and its consequent effectiveness as a contextual advertising agent, and 2) examining whether customization can serve as an effective method to attenuate the aforementioned concerns related to perceived bias or enhance the persuasive effectiveness of favorably tailored commentary. To delve into these two goals from a Human-AI Interaction (HAI) perspective, this study adopts and integrates several established theoretical frameworks from the HAI and advertising fields. Most of all, the HAII-TIME (Human-AI Interaction from the Theory of Interactive Media Effectiveness) framework provides the foundational aspect for understanding how specific AISC features (i.e., favorably tailored commentary and customization) impact user perceptions, especially trust in the AISC (Sundar 2020). This framework claims that people shape trust in the AI media and agents through cue-driven activation of cognitive heuristics (e.g., representativeness and identity heuristics) and action-driven psychological states (e.g., sense of agency, sense of interaction, reciprocal augmentation). To theoretically identify what cognitive heuristics might be activated, Expectancy Violation Theory (EVT) and Social Identity Theory (SIT) will be employed (Burgoon 1993; Burgoon and Hale 1988; Tajfel and Turner 1979, 1986). Furthermore, the Persuasion Knowledge Model (PKM) will be integrated to articulate how shaped trust in the AISC influences advertising outcomes, applying the concept of Perceived Persuasion Effectiveness (PPE) as a key mediating belief in order to identify the persuasive efficacy of the AISC as a contextual advertising agent (Friestad and Wright 1994, 1995).

In this vein, this dissertation is structured as follows. Chapter 2 provides a comprehensive review of the extant literature pertaining to AISC, contextual advertising, the HAII-TIME framework, the PKM, and associated theories (i.e., EVT and SIT), generating specific hypotheses and the detailed research question. In turn, Chapter 3 outlines the research methodology, including experimental design and procedure, stimulus development, participant recruitment, and measurement. Then, Chapter 4 will present the specific procedure and results of the data analyses. Finally, Chapter 5 provides a thorough discussion of these findings from both academic and industrial perspectives, limitations of the current study, and valuable directions for future research.

CHAPTER 2

LITERATURE REVIEW

AI Sports Commentators (AISC)

As digital transformation accelerates across various industries in the era of the 4th industrial revolution, sports broadcasting has entered a new era driven by artificial intelligence. In particular, the emergence of AI sports commentators technology has garnered growing interest from broadcasters, sports streaming platforms, and audiences (Kelly 2024). This increasing attention reflects a broader demand for personalized and data-intensive content delivery in live broadcasting and on-demand sports media environments (Sports Video Group 2024). In a time when traditional sports commentary struggles to keep pace with the fragmented and globalized demands of recent years, the AISC offers a viable solution (Maharaj 2023).

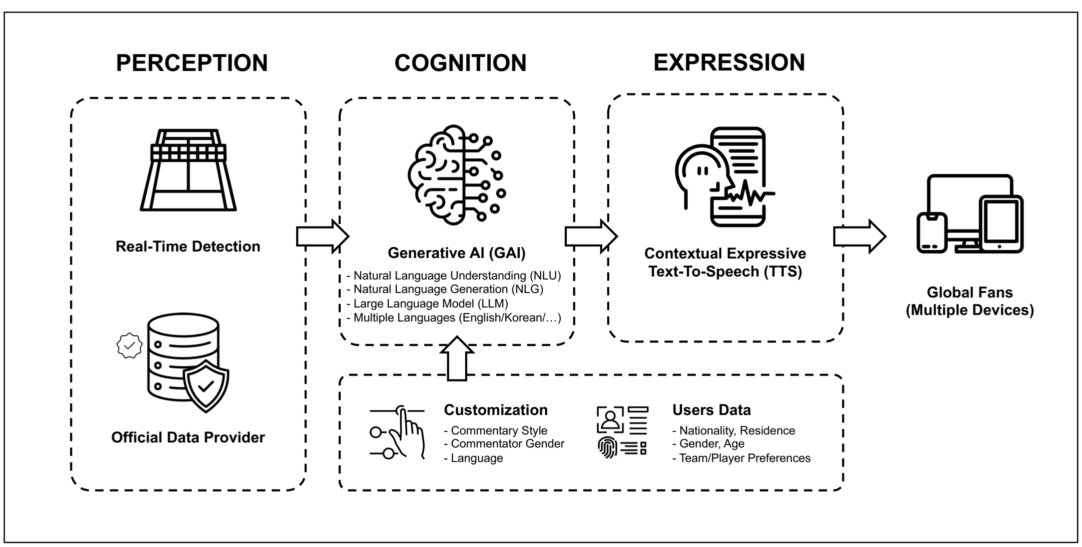

Figure 1. Three-Stage Technical Flow of AI Sports Commentary System

From the technical perspective, the AISC is built upon a complex and multi-layered AI-driven technological structure. In particular, this multi-layered architecture can be understood in three consecutive logical layers – perception, cognition, and expression (see Figure 1). First, at the perception layer, advanced computer vision (i.e., object detection) models specialized in specific sports (e.g., YOLO, AlphaPose, I3D) and real-time data API (Application Programming Interface) work in tandem to detect the real-time context of a sports match (Cascante-Bonilla et al. 2021; Liu 2024; Naik, Hashmi, and Bokde 2022; Thomas et al. 2017).

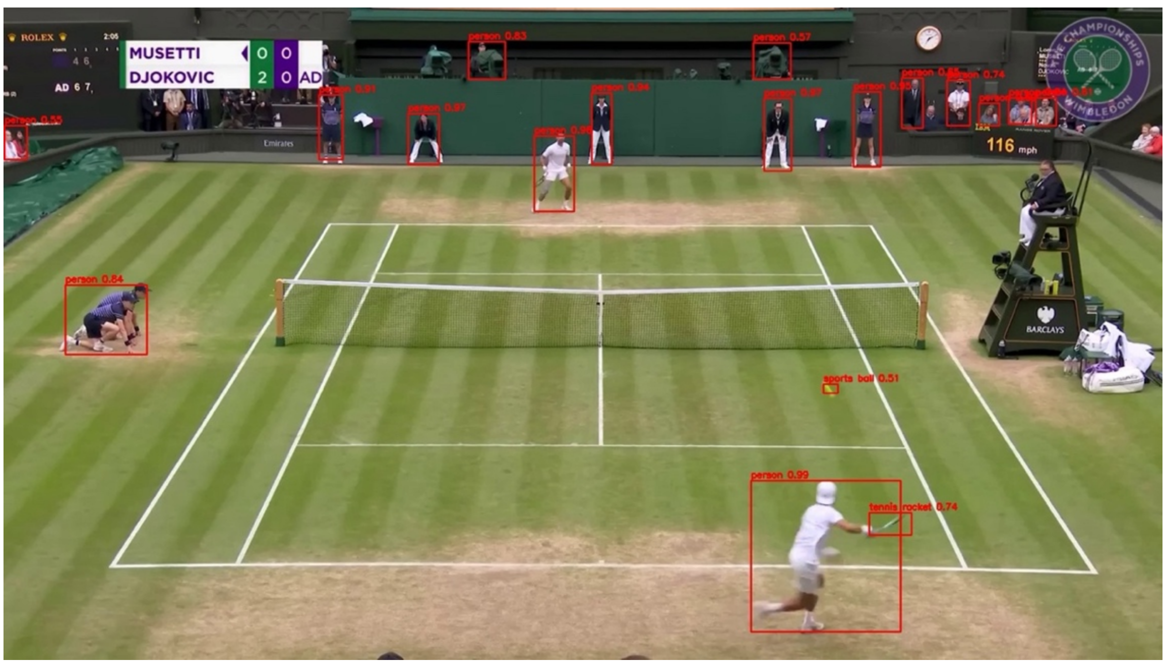

Figure 2. Object Detection in the Tennis Match (YOLO Model)

The system first breaks down the sporting match videos frame by frame to detect players, balls, poses, and movements in real time (Redmon et al. 2016; Q. Sun et al. 2024). Then, based on contextual object detection (see Figure 2), specific events during matches are automatically identified and labeled as goals, fouls, or specific types of shots in tennis (Horsey 2023). Moreover, concurrently, these visual data are combined with structured statistical data from official sports data providers to analyze complex patterns and provide predictive insight that cannot be grasped by human observation (Walch 2024).

Next, at the cognition layer, the generated data is interpreted by advanced Natural Language Understanding (NLU) and Natural Language Generation (NLG) models based on the Large Language Model (LLM), which is a key component of GAI (Belcic and Stryker 2025; Sarfati et al. 2023). Pre-trained on extensive databases of common human languages, especially human sports commentaries, these models learn the professional terminologies, narrative speed, and structures of storytelling in regard to sports broadcasting. As an output of this stage, the AISC is contextually aware of matches and generates textual commentaries that are not just factually accurate but also emotionally compelling stories, even tailoring writing styles, based on user-driven customization and accumulated user data (Jung et al. 2025). In turn, at the expression layer, the generated textual commentaries are converted into realistic vocal narrations by Text-To-Speech (TTS) engines (Horsey 2023). Recently, the advancement of 'contextual expressive TTS' enables the AISC to be trained to convey specific contextual emotions, such as excitement and disappointment, and even mimic the unique prosody and style of human sports commentators (Tu et al. 2022).

This technical convergence of AI-related technologies allows the AISC to perform critical roles within the sports industry from both the perspectives of media and fans. From the media platform's perspective, the AISC functions as a powerful broadcasting tool that improves cost and labor efficiency. In particular, the AISC can be used for niche sports that would not typically receive live broadcasting and commentary coverage, as well as providing multiple sports commentary feeds for a single event or match (Abid 2024). Moreover, it is currently used to cover all matches and moments in the huge sports events (e.g., Olympics, Masters), which was impossible with human sports commentators due to the cost and time. For instance, the Masters (golf) has introduced the AISC technology to provide commentary for every player's individual plays, which was not feasible with human sports commentators (Bantock 2023). Additionally, the AISC instantly delivers sports commentary in various languages to cater to diverse fans' tastes, creating effective touchpoints with global fans. Indeed, the National Basketball Association (NBA) adopted WSC Sports' GAI model to provide voice-over sports commentaries for match highlights in multiple languages (e.g., French, Portuguese, and Spanish), expanding accessibility in massive and diverse regional markets (WSC Sports 2025).

Meanwhile, from the fans' perspective, they can experience hyper-customized or hyper-personalized environments during sports streaming or broadcasting. The AISC delivers *favorably tailored commentary* by first detecting and understanding the context precisely and dynamically adjusting commentaries based on individual preferences, as indicated by accumulated user data or customization (Anshar Labs Inc. 2025; Maharaj 2023; PwC 2024). This unique feature surpasses a simple play-by-play commentary to satisfy the psychological needs of sports fans who seek commentaries about supporting players or teams rather than about opposing players or teams, thereby heightening enjoyment (Andrews et al. 2024; G. Lee, Bulitko, and Ludvig 2014). Specifically, after detecting a critical moment or an unfortunate mistake involving a fan's preferred player, the AISC can responsively tailor its commentary in a positive tone to cheer the player and fan. For example, the AISC might spend more time explaining the play's significance (frequency) and/or use more sympathetic expressions (emotion) in the particular language, voice tone, and style that the user chooses. Indeed, Bundesliga (German Soccer League) and AWS cooperate in developing a real-time AISC, allowing fans to select a supporting team, commentary style (e.g., sports journalist, casual, friends), audio tone, and even language (e.g., English, French, German) (Abid 2024). Also, NBC provided the recommended daily highlight video and AI-generated commentaries of the 2024 Paris Olympics through the Peacock platform, based on the user data (e.g., preferred topics, favorite teams, favorite sports), collaborating with Google AI (Deitsch 2024; Kelly 2024; NBC Sports 2024, 2025; Peacock 2024).

The Potential of the AISC as a Contextual Advertising Agent

Regarding these technological features, the AISC represents a notable technological breakthrough in sports media, transforming how audiences engage with sports content by integrating deep analytical ability with dynamic narrative adaptability. Based on these versatile features, particularly its ability to deliver contextually aware and favorably tailored commentary, this dissertation posits that one of the AISC's most significant potential roles in the field of advertising is as a powerful agent for contextual advertising. The terminology of contextual advertising refers to the selection and placement of advertisements based on the context of the content and media, generating a favorable outcome of advertising by providing seamless experiences between the advertising message and media usage (Häglund and Björklund 2024; Kwang et al. 2014).

This potential of the AISC can be systematically elucidated by examining how its technical and communicative features enhance the three key attributes of effective contextual advertising – *applicability*, *content involvement*, and *affective tone* (Häglund and Björklund 2024). By smoothly aligning the advertising message with the context, contextual advertising minimizes intrusiveness and enhances the advertisements' relevance, often leading to more favorable outcomes (Shen and Chen 2007). Therefore, the following sections will explore each of these attributes in turn, detailing how AISC's unique AI-driven methods allow it to create a more sophisticated and effective advertising experience.

Applicability: AI-Driven Context Detection

First, the *applicability* indicates that advertising should not solely rely on personal data but also consider being placed where the content is relevant to advertisements (Shen and Chen 2007). Previous studies underlined the importance of the applicability (or relevance) of advertising to the context of media and content based on the priming effect theory (Kwang et al. 2014; Shen and Chen 2007). According to the priming effect theory (Higgins, Rholes, and Jones 1977), exposure to a stimulus activates associated concepts in memory, which then influence the interpretation and evaluation of subsequent stimuli. Moreover, previous studies underlined that this priming effect can be amplified or diminished by contextual relevance between content and context (Kwang et al. 2014). Specifically, when a stimulus is congruent or relevant to the surrounding context, people are more likely to engage in assimilation processing, which entails more favorable cognitive, affective, and behavioral responses (Fan and Chang 2010; Furnham, Bergland, and Gunter 2002; Mao and Zhang 2015; Y. Yi 1990). In contrast, when there is incongruence between a stimulus and context, the contrast effect occurs, inducing more negative perceptions or even generating backlash (Herr 1989; Kwang et al. 2014; Meyers-Levy and Tybout 1997). That is, applicability plays a significant moderating role, which determines the direction (i.e., positive or negative) of the priming effect.

Recently, Häglund & Björklund (2024) emphasized that advanced AI technologies can secure the applicability of advertising within contexts by facilitating effective contextual programmatic advertising. For example, topic modeling, which is also referred to as topic detection or topic analysis, is widely used for the basic AI-driven approach. To be more precise, as a common traditional method, a Latent Dirichlet Allocation (LDA) operates on the assumption that each document (e.g., a segment of commentary transcript) is a mixture of various topics, and each topic is a numerical probability distribution of specific words (Blei, Ng, and Jordan 2003). Moreover, several deep learning methods, such as Long- and Short-Term Memory (LSTM) and Convolutional Recurrent Neural Networks (CRNNs), are designed to process sequential data, like text or speech, and are thus able to understand the sequence and context of words by capturing more nuanced meanings. Therefore, these advanced deep learning methods can classify documents into specific topic groups with higher accuracy (Luan and Lin 2019; Wang et al. 2019; G. Xu et al. 2019). These AI-driven methodological approaches automatically conduct topic labeling and expose the closely associated brand message after they textualize diverse media modalities, such as audio and video (G. Xu et al. 2019; Häglund and Björklund 2024). Indeed, utilizing these AI-driven technologies, Ease Live could dynamically place advertising that syncs with live moments of sports matches in real-time, subsequently increasing the 70% of audience interaction (Miller 2025; Sports Video Group 2024).

Along these lines, this dissertation postulates that the AISC can also categorize and classify the diverse in-game situations of matches into specific topics (e.g., critical scene, injury timeout, celebration) and, in turn, seamlessly integrate context-related sponsor messages with commentaries. For instance, during a hyper-slow-motion replay that shows a favorable outcome toward the supporting team, the AISC might say, "Let's take a look at the hyper-slow replay brought to you by [Tech Sponsor Brand]," thereby reinforcing context-message congruence without disrupting the viewing experience (i.e., assimilation effect). This capability for real-time semantic analysis and moment-specific integration allows the AISC to achieve a higher fidelity of contextual congruence. That is, unlike programmatic contextual advertising systems that often rely on pre-analyzed keywords or topic categorizations of relatively static content, the AISC can adapt to the fleeting and dynamic nuances of the live sports event. In this vein, this capacity for precise temporal alignment implies that sponsor messages are not just relevant to the general topic (e.g., 'sports') but to immediate actions and situations, potentially leading to stronger assimilation effects and reduced advertising interruption.

Affective Tone: Active Tone Adjustment

Second, the *affective tone* connotes that the effectiveness of advertising can be crucially influenced by the affective tone of the media context environment. Two major theoretical approaches have been adopted to explain how the affective tone of media context impacts advertising outcomes. One is the affect-as-information hypothesis (AIH), which asserts that people inherently have a tendency to utilize emotions as a source of information to determine the direction of cognitive functioning (Schwarz 2012; Schwarz and Clore 1983). The other one is the affect transfer theory (ATT), which emphasizes that the valence of emotional experiences (i.e., positive or negative) within the specific context is directly transferred to the cognitive and affective judgment of subsequent evaluation (Laroche et al. 2005; A. A. Mitchell and Olson 1981; T. A. Mitchell and Nelson 2018). Based on these approaches, prior studies about contextual advertising empirically verified that the positive tone of media context positively enhances the outcome of advertising and the decision-making process (De Pelsmacker, Geuens, and Anckaert 2002; LaTour and LaTour 2009). On the other hand, the negative affective tone of the media context triggers more critical processing of advertising messages, which in turn often generates negative advertising outcomes (T. A. Mitchell and Nelson 2018; Sar, Nan, and Myers 2010; Shapiro and MacInnis 2002).

In addition, recent advancements in AI-driven contextual advertising have enabled affective tone detection in diverse ways. Utilizing topic modeling, semantic analysis, and sentiment classification, AI systems are capable of analyzing and adjusting affective tone in multimodal environments, including text, images, video, and audio (J. Chen et al. 2016; Hou et al. 2017). For instance, YouTube Music provides mood-based (i.e., affective tone) targeting tools that allow clients to use particular music or genres that resonate with the advertising message (Nikolic 2020). Moreover, PMG utilized an AI-driven emotion-based targeting platform, Brand Discovery, that automatically detects the affective tone of media context and emotional responses of consumers to optimize advertising exposure, thus achieving a 40% increase in sales (Wurl 2024). These technological innovations demonstrate how affective tone can be algorithmically shaped to reinforce advertising effectiveness in real-time.

While previous studies and instances mainly concentrated on the ability to detect an affective tone of media context to find appropriate timing for advertising exposure, the AISC is expected to play a more active role in shaping the tone itself. In particular, the AISC's ability to deliver favorably tailored commentary emerges as a central mechanism to foster a positive emotional context. Rather than merely adjusting surface-level content, favorably tailored commentary that is emotionally and cognitively aligned with the viewer's team allegiance enables the AISC to act as a moderator of audience emotion and engagement. For instance, as previously mentioned, in the case of cooperation between Bundesliga and AWS (Bundesliga 2024), the AISC is not only able to detect the context of the sports match but also foster a positive affective tone by customized commentary style and tone of the voice, using user data (Abid 2024). Moreover, given that prior research has found that biased commentaries in favor of a supported team can improve viewer outcomes, such as enjoyment, satisfaction, and re-viewing intention (M. Lee et al. 2015, 2016; Pan 2013; Woo et al. 2010), the AISC can cultivate the positive affective tone of match context by delivering favorably tailored commentary that aligning with viewers preferences. That is, more than merely aligning commentary with user preference, favorably tailored commentary functions as a mechanism for emotional calibration. On top of the passive tone detection, this strategy allows the AISC to actively modulate emotional resonance within the match context. In this role, the AISC can construct a positive affective environment that amplifies attention, emotional engagement, and receptive attitude to persuasive messages, entailing enhancing not only viewers' experiences but also facilitating deeper emotional congruence with embedded sponsorships. In this regard, this study suggests that the AISC becomes not just a responsive narrator but a dynamic affective landscaper, intentionally shaping how advertising is perceived and processed contextually.

Content Involvement: AI-Driven Metrics

Last, the concept of *content involvement* implies that advertising effectiveness is influenced by the degree to which consumers are engaged and immersed in media content. That is, advertising needs to be placed considering the immersion and engagement of content (Huang 2018). In general, a high level of content involvement and engagement improves cognitive (e.g., advertising attitude and brand attitude) and behavioral responses (e.g., click-through rate and conversion rate) (Goldberg and Gorn 1987; Grant, Bailey, and Ogbuehi 2017; Tai and Chang 2005). However, previous studies pointed out that the impact of content involvement varies significantly depending on the media type and content genre (Häglund and Björklund 2024). For instance, De Pelsmacker et al. (2002) found that in TV watching situations, where advertising temporarily replaces the media stream in a flow, highly involved viewers easily tend to transfer their attention to advertising, resulting in better recall and favorable attitudes. In contrast, in print media within the static context, higher content involvement leads readers to remain immersed in the editorial content, reducing attention to adjacent advertising (Norris and Colman 1992). In addition, X. Yi et al. (2014) identified that content involvement effects vary across diverse genres, with stronger effects observed in entertainment and political content. Furthermore, prior studies argued that advertising messages should be integrated in a seamless way that maintains consumers' high-involvement status, highlighting that intrusive methods (e.g., color, positioning on the screen) to shift the attention from the content to advertising discrupt consumer experiences that lead to negative advertising outcomes (De Pelsmacker, Geuens, and Anckaert 2002; Fernandez and Rosen 2000; Huang 2018).

In this context, notably, as an entertainment-oriented content on flow-based media characterized by high emotional investment and unpredictability, sports are conjectured to sustain high involvement while remaining receptive to advertising during a match (Norris & Colman, 1992; X. Yi et al., 2014). This allows the AISC to utilize a fertile ground for contextual advertising that utilizes high-involvement moments. Several AI-driven approaches are widely utilized to detect high-involvement moments while fostering a conducive context. For example, attention-based metrics using dwell time, replay frequency, and viewport time can be used to identify high-involvement moments in real time (Häglund and Björklund 2024; Lagun and Lalmas 2016). Also, AI-driven topic modeling (e.g., LDA) matches the specific context of the content and the level of involvement by integrating topic and attention-based metrics. Indeed, TikTok Pulse, the Generative AI-driven contextual advertising business model, proved the potential of the AI-driven model for increasing advertising recall and brand engagement by detecting high-involvement moments to expose advertising (TikTok 2024).

Based on these AI technologies, the AISC can offer a more nuanced and integrated application. The AISC can be trained to detect moments where users are highly involved, such as crucial match points, statistic summary scenes, or player celebrations, and seamlessly deliver brand messages that are contextually congruent. Moreover, with improved applicability and positive affective tone, the AISC can sustain or even enhance the immersive and highly involved state through favorably tailored commentary without interferences (e.g., “Let’s look at that [Player A]’s incredible smash again – brought to you by [Brand], official technical partner of the tournament.”). That is, especially during the high-involvement situations detected by AI-driven metrics, the AISC transforms what might otherwise be passive or intrusive advertising exposure into a more narrative-integrated experience. In this capacity, the AISC is not merely a commentator but a sophisticated contextual advertising agent that strategically employs viewer involvement and its unique communication attributes (i.e., favorably tailored commentary).

In sum, the AISC can serve as an effective contextual advertising agent by delivering contextually appropriate advertisements during moments of heightened viewer involvement in sports matches while simultaneously fostering a positive affective tone. By aligning advertising content with both the emotional context (i.e., affective tone) and the narrative flow of the game (i.e., content involvement), the AISC ensures that advertisements are not only less intrusive but also more persuasive, capitalizing on contextual relevance (i.e., applicability) to enhance advertising effectiveness.

The Concerns about the AISC as a Contextual Advertising Agent

As noted above, overall, the potential of the AISC is supported by two technological features (i.e., context detection and AI-driven involvement metrics) and one communicative feature (i.e., favorably tailored commentary). While the former primarily function behind the scenes (or in the background) to improve contextual relevance and optimize the timing of advertising exposure, favorably tailored commentary serves as a communicative function that directly interacts with the viewer by modifying the semantic tone and content of the narration based on individual preferences. This communicative feature offers the opportunity to heighten the effectiveness of the AISC as a contextual advertising agent by attuning the emotional tone with the viewer and even fostering positive affective environments. However, at the same time, it may incur interpretive conflict regarding perceived fairness or objectivity in commentary, aligning with criticisms about quality and potential bias (AImpactful Newsroom 2024; Ether 2025; Keene and Cummins 2009; M. Lee et al. 2015). That is, there is room for discussion about the two opposite impacts of a favorably tailored commentary from the communicational perspective. In this context, it is crucial to identify ways to mitigate the negative impact and enhance the positive effects of favorably tailored commentary on sponsorship (or advertising) outcomes.

In this regard, studies have proposed several viable strategies to address this potential concern of favorably tailored or biased content. More specifically, one commonly suggested approach is to increase transparency by informing users about how AI algorithms generate content or which factors influence it (Feng and Kim 2025; Sundar 2020). In terms of effectiveness, while the transparency of AI fundamentally improves the users' understanding of AI algorithms (e.g., purpose, structure, limitations, logic), Sun et al. (2022) also argued that a detailed explanation of AI algorithms can reduce negative perceptions when the AI underperforms. Similarly, another frequently mentioned method is disclosure, which explicitly announces that content is tailored or biased to users and reveals the source (i.e., AI) of the information (Park et al. 2022; Sundar 2020). The disclosure has been widely investigated in diverse settings, including social media and AI-mediated communication (Wojdynski 2016; Wortel, Vanwesenbeeck, and Tomas 2024). Particularly in the HAI (Human-AI Interaction) context, prior research has shown that the disclosure could foster a positive response to content, while it also triggers negative perceptions about AI, such as skepticism, depending on individuals' pre-existing perception toward AI and the performance of AI agents (Li et al. 2024; Lim and Schmälzle 2024; Mozafari, Weiger, and Hammerschmidt 2022).

Nevertheless, previous studies asserted that these system-driven methods (i.e., increasing transparency and disclosure) may not be sufficient to enhance user acceptance of AI-mediated communication messages meaningfully. For instance, a systematic qualitative review conducted by Segijn et al. (2021) proposed the Transparency-Awareness-Control (TAC) framework, which provides a lens for understanding how to communicate the use of personal data in media communication effectively. Specifically, this framework asserted that the system should ultimately pursue letting users perceive that they have rights to control (i.e., control), acknowledging that providing information about the source and underlying algorithm (i.e., transparency) improves the users' understanding of how the personal data is used for the content (i.e., awareness), are the necessary first steps. That is, this suggests that without meaningful control mechanisms, increasing transparency or source disclosure alone cannot be a panacea, as users may still feel discomfort and skepticism, which can hinder trust and engagement (Segijn et al. 2021). This finding highlights the critical need to move beyond passive and system-driven approaches toward more active and user-initiated solutions.

Along these lines, previous literature has emphasized customization as a more proactive and user-centered alternative in contrast to these passive and system-driven approaches (Sundar and Marathe 2010). To elaborate, customization places rights of control in the hands of the users, allowing them to configure how the content is presented actively (Sundar 2008a), whereas personalization, which is often confused with customization due to their conceptual proximity, typically refers to a system-driven process that automatically manipulates the content aligned with accumulated user data (Blom 2000; Serino, Furner, and Smatt 2005; Sundar and Marathe 2010). That is, while personalization automatically adjusts the content without user intervention, customization lets users control their content themselves. According to prior studies, customization within AI-mediate communication is commonly considered an effective strategy to induce positive evaluation toward sources (e.g., AI chatbot, AI voice assistant) and messages (e.g., instruction, daily conversation, advertising) and reduce negative responses (e.g., psychological reactance) (Cheng and Jiang 2022; Choi and Park 2023; F. Y. Lee and Chan 2024; Snyder, Sundar, and Lee 2024; Wald, Heijselaar, and Bosse 2021). In this vein, user-initiated customization can be considered the most effective and vital method for eliciting positive responses from users compared to other system-driven methods that provide users with actual control (Sundar and Marathe 2010). Hence, in the context of the AISC, this study focuses on customization as a more robust and user-centered strategy to mitigate the potential drawbacks of favorably tailored commentary while enhancing its positive perception in the context of AISC.

HAII-TIME Framework

To explore both the potential and concerns associated with the AISC as a contextual advertising agent, this study raises two pivotal questions: 1) How does favorably tailored commentary affect users' perception of the AISC and its effectiveness as a contextual advertising agent? and 2) Can customization attenuate concerns or enhance the benefits of favorably tailored commentary? That is, understanding how favorably tailored commentary is psychologically processed and how user control through customization can modify this experience is essential for identifying the AISC's value as a contextual advertising agent.

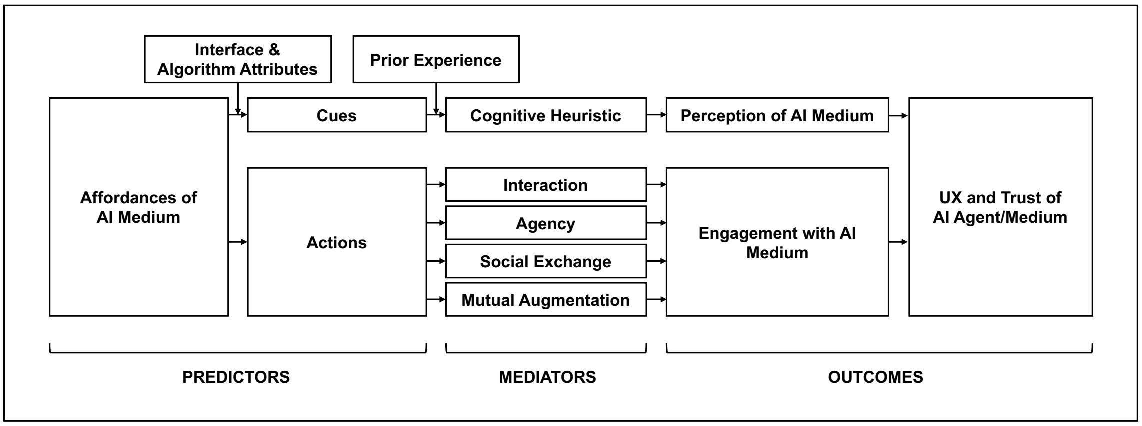

Figure 3. The HAII-TIME Framework (Sundar 2020)

To address these questions from the perspective of HAI, this study adopts the HAII-TIME (Human-AI Interaction from the Theory of Interactive Media Effectiveness) framework (Sundar 2020). This framework posits that user perceptions and behaviors are influenced by two main routes – the *cue route* and the *action route* – which are shaped by a set of predictors (e.g., interface design, algorithmic attributes, and media affordances) and subsequently lead to outcomes related to overall user experience (UX) and trust (see Figure 3). Specifically, at the core of the model lies the concept of media affordance, which is defined as "action possibilities (Norman 1999)" that determine the presentation of content as well as consumers' states of mind when using them. In other words, it implies the capability of the media to guide specific actions or enable the achievement of certain outcomes. For example, a book, as a traditional medium, has a reading affordance, while the AISC has various affordances, including a human-like appearance (visual) affordance, hyperlink affordance, and commentary (audio) affordance. These media affordances can serve as signals, manifested by explicit cues (cue route), and foster actual action by users (action route) concurrently.

When the affordances are represented by a specific evident interface of media (e.g., visual and audio attributes) or claiming algorithm attributes (e.g., transparency, complexity, purpose, and flexibility of the algorithm), people recognize them as cues (Jang, Kwak, and Bucy 2024; Sundar 2020). In turn, these salient cues trigger one or multiple *cognitive heuristics* at the same time, which is a mental shortcut that helps people make a decision with the least effort based on generalization and prior experiences (Sangwook Lee et al. 2023; Sundar 2020). For instance, the human-like appearance of the AI agent, which is manifested by a medium interface, serves as an explicit cue to users and, in turn, triggers the social presence heuristic, resulting in evaluating the AI agent more positively (Y. Sun, Chen, and Sundar 2024; Sundar 2008a).

At the same time, in some cases, AI media affordances induce specific actions from users. The action route emphasizes how AI media affordances prompt users to perform specific actions that impact several interrelated factors that work together to enhance user engagement with an AI agent (Sundar 2020). Rather than passively receiving content, users engage in two-way communication by requesting real-time data, customizing settings, or otherwise guiding the AI’s output (Y. Sun, Chen, and Sundar 2024). The HAII-TIME framework highlights that users several perceptions about HAI by exerting those actions. For example, users can foster a *sense of interaction* as they see the system contingently respond to their input and feel that an AI agent is contingently responsive (Sundar 2020; Sundar et al. 2015). Meanwhile, as users engage further in diverse ways, they can develop a *sense of agency* (i.e., a sense of control) when they perceive that their actions directly or indirectly influence the AI agent's responses and outputs, whether by adjusting interface options, selecting the appearance of the AI agent, or allowing to share user data (Hu and Wang 2024; Sundar 2020). This feeling of control not only enhances engagement but also empowers users to shape their experience positively based on their preferences (Moore 2016).

Besides the feelings of control and interaction, the HAII-TIME framework asserts that the fundamental purpose of using an AI agent is to secure the convenience and comfort of users by outsourcing tasks (Sundar 2020). Therefore, aligning with the social exchange theory, users evaluate their actions (costs) based on the outcome of the AI media usage (benefits). In other words, people willingly invest further time and effort (i.e., engagement) by training the system or offering data if performing specific actions guarantees receiving improved experiences and positive *social exchange* (Y. Sun, Chen, and Sundar 2024). On top of that, the framework also suggests the *mutual augmentation* of users and AI media as a result of a particular action (Sundar 2020). The AI system continually evolves from user interactions and refines its responses while users benefit from increasingly tailored and effective outputs. Over time, this co-evolution creates a self-reinforcing cycle of engagement, where both the user and the system contribute to a continuously improving interaction. Together, during the AI usage experience, these elements – sense of interaction, sense of agency, social exchange, and mutual augmentation – transform passive consumption into an active, engaging, and trust-building experience by exerting particular actions.

Subsequently, the framework underlines that people evaluate the trust of AI agents as a result of two psychological routes (i.e., cue and action) by adjusting their engagement and perception of AI agents. While many prior studies have focused on the cognitive perspective of trust, there have been several criticisms arguing that the concept of trust should be considered a multidimensional concept (Liao and Sundar 2021). Specifically, the previous literature highlighted that the concept of trust overarches cognition- and affect-based perception of people (McAllister 1995). Especially in the context of HAI, cognition-based trust refers to the belief that the AI agent is competent, reliable, accurate, and capable of making rational, data-driven decisions (Glikson and Woolley 2020). On the other hand, affect-based trust is grounded in emotional and relational perceptions of the AI agent that reflect users' feelings of emotional connection with the AI (Legood et al. 2023; Liao and Sundar 2021). In this vein, the concept of trust as an outcome element of the HAII-TIME framework encompasses the affective and cognitive responses to AI agents' and AI media's presentation of affordances through specific actions and cues.

Even though the HAII-TIME framework thoroughly elaborates on how individuals psychologically shape their trust in the AI agent or media based on diverse affordances, it also possesses several limitations. First, applications or interpretations of the framework may underestimate the cognitive complexities that arise when a single media affordance simultaneously activates multiple heuristic pathways. Unlike traditional media, recent AI media and agents often present users with rich and layered affordances capable of eliciting complex cognitive responses. Therefore, different aspects of the affordance of a single AI entity might trigger distinct, sometimes even competing, mental shortcuts (i.e., heuristics), leading to nuanced or ambivalent user perceptions. For instance, while prior research in AI chatbots respectively suggested that a chatbot's conversational cues might concurrently elicit the social presence heuristic (Go and Sundar 2019) and machine heuristic (Sundar and Kim 2019), there are only a few studies that have attempted to examine overall effects or interaction of multiple heuristics (Rheu et al. 2024). That is, there exists a possibility that multiple heuristics exerting opposing or reinforcing effects can be triggered concurrently.

In addition, although HAII-TIME delineates the cue route and the action route as two main distinctive pathways shaping user perceptions, it may not fully capture the deeply reciprocal and iterative nature of the interplay between these pathways in ongoing user interactions. It is plausible that interaction between users and AI agents and media is a dynamic process where initial perceptions derived from cues shape subsequent actions or vice versa, with continuous feedback to reframe the interpretation of existing cues or to select future actions. For example, in the domain of journalism, a user's initial perception of an article labeled as AI-generated (a cue) might influence their decision to engage further with the content or to scrutinize it differently (action) (Rheu et al. 2024). Likewise, studies on user customization of AI systems demonstrate that when users actively modify system behavior or content presentation (action), their subsequent perception of system-generated cues is profoundly influenced by their sense of agency and control over the interaction (Sundar and Marathe 2010).

Along these lines, acknowledging these limitations, this dissertation aims to investigate how "favorably tailored commentary (as a salient cue)" from the AISC might elicit multiple heuristics (representativeness and identity) and how "customization (as an action)" might mitigate or amplify the impact of these heuristics on trust. This approach will offer a more refined and expanded lens for applying and potentially evolving the HAII-TIME framework within the domain of HAI.

Cue Route: Favorably Tailored Commentary

Expectancy Violation Theory and Representativeness Heuristic. Within the HAII-TIME framework, favorably tailored commentary will be considered a salient cue that directly influences users' perception of the AISC. When the AISC devotes more time to describing a viewer's preferred player and employs sympathetic language or interpretations, it introduces a perceptible form of bias that may conflict with audience expectations of objectivity in sports commentary (Woo et al. 2010; M. Lee et al. 2016).

This concern can be thoroughly understood from the aspect of the Expectancy Violation Theory (EVT), which elaborates on how individuals react when their established expectations are violated or confirmed (Burgoon 1993). Specifically, EVT posits that people hold certain expectations based on norms, context, or prior experiences about how interactions or communications should unfold (Burgoon and Hale 1988). When these expectations are unexpectedly breached, individuals experience a violation, which they then evaluate for either positive or negative implications (Burgoon 1993). Put differently, an expectancy violation can produce favorable outcomes if it is perceived as pleasantly surprising or beneficial (positive violation), whereas it can trigger resistance, skepticism, or dissatisfaction (negative violation) if the behavior contradicts existing expectancies (Afifi and Metts 1998; Rheu et al. 2024). Although EVT was originally developed in interpersonal contexts, such as personal space intrusions (Burgoon and Hale 1988), subsequent research has shown that media users also hold expectations about how media agents or communicators should behave (Fox and McEwan 2017). When these mediated communicators, including AI systems, deviate unexpectedly from user expectations, they must evaluate whether this violation is an appealing novelty or an unwelcome betrayal of expectations.

In terms of the AISC, viewers primarily establish baseline expectations based on its role as a sports commentator. Viewers typically assume that professional commentators will strive to be impartial, providing balanced insights without taking one side (Woo et al. 2010; M. Lee et al. 2016). This established norm of objective, impartial, and fair coverage serves as the bedrock of trust in traditional sports broadcasting, shaping a baseline expectation for viewers – a commentator ought to remain impartial rather than excessively favoring one team or player. Meanwhile, when the AISC employs favorably tailored commentary, it actively modifies the tone or frequency of remarks to support a user's preferred athlete by often emphasizing positive aspects or using more enthusiastic language toward that player. While this may enhance viewer enjoyment and hedonic satisfaction, it simultaneously violates a crucial expectation of neutrality derived from the professional sports commentator role (Pan 2013; Lee et al. 2016). From an EVT perspective, this deviation from the baseline expectation can be interpreted as a negative violation, as users may feel that objectivity and fairness – qualities central to the commentator prototype – have been compromised, thereby raising doubts about trust.

Aligning with the EVT, this evaluation process – the assessment of how the AISC deviates from the prototypical impartial sports commentator – can be understood through the *representativeness heuristic*, a mental shortcut used when making judgments about how closely an entity matches a pre-existing category or stereotype (Tversky and

Kahneman 1974). Moreover, this heuristic is often activated and applied when individuals need to evaluate the 'object A', which belongs to a specific 'prototype (category) B' (C. Chen and Sundar 2024). More specifically, if the cues on the interface of AI media (object A) are discordant with a prototype of the category, then they will likely have a negative impact on the assessment of trust. Therefore, if a favorably tailored commentary of the AISC (object A) deviates significantly from the audience's notion of an impartial and professional human sports commentator (prototype B), users may perceive the system as inauthentic or unreliable. In other words, the perceived incongruence between the AISC and the prototypical human sports commentators induces a negative assessment of the AISC's expected professional norms (e.g., objectivity, neutrality, fairness). Consequently, favorably tailored commentary is likely to lead to a more negative evaluation based on the representativeness heuristic (or be perceived as less representative of an ideal commentator) than neutral commentary, entailing a negative evaluation of trust in the AISC. Therefore, the following hypotheses are generated:

H1: Favorably tailored commentary will elicit higher activation of the negative representativeness heuristic compared to neutral commentary.

H2: The higher the activation of the negative representativeness heuristic, the lower the trust in the AISC.

H3: The negative representativeness heuristic will mediate the relationship between the commentary type and trust in the AISC.

Social Identification Theory and Identity Heuristic. Meanwhile, several studies provided theoretical and empirical evidence supporting the positive impact of favorably tailored commentary on consumer perceptions (M. Lee et al. 2016; Pan 2013). The psychological mechanism explaining why people perceive favorably tailored commentary positively can be elaborated based on the approach of Social Identification Theory (SIT). According to the SIT, proposed by Tajfel and Turner (1979), individuals categorize themselves into one or multiple social groups within their social environment to enhance and shape their self-concept, aligning themselves and others within those categories. Fundamentally, each individual's self-concept consists of personal and social identities (Tajfel and Turner 1979). To be more precise, individuals' social identity is shaped by categorizing themselves into specific groups based on demographic categories and various social group affiliations, while personal identity reflects distinctive characteristics (e.g., abilities and personalities). In other words, people gradually identify themselves based on their self-recognized personal traits, social environments to which they belong, and social relationships with other members of affiliated groups (Kashima, Kashima, and Hardie 2000). In addition, prior studies argued that social categorization leads to the formation of ingroup and outgroup distinctions based on shared characteristics (e.g., gender, ethnicity, age, social class), where people show more positive and favorable responses, such as trust and empathy, toward the ingroup (Brewer 1999; Guegan et al. 2017; Lu and Zhang 2025; Mirbabaie et al. 2021).

Although SIT was initially established in the context of interpersonal communication, its scope has been significantly extended to include interactions with non-human entities. Recently, in human-computer interaction (HCI) and HAI, scholars have explored how people utilize social cues of non-human agents in interaction, drawing upon the Computers Are Social Actors (CASA) paradigm. This paradigm argued that people tend to unconsciously treat computers as social beings and utilize social rules toward computers when they display social behaviors (Im et al. 2023; Nass and Moon 2000; Reeves and Nass 1996). Moreover, the CASA paradigm underlined that social cues, defined as "physically determined features salient to observers because of their potential as channels of useful information (Fiore et al. 2013, 2)," influence the perception and evaluation by triggering heuristics used for interpersonal communication (Dehnert and Mongeau 2022; Nass and Moon 2000). Integrating these approaches, prior studies claimed that people perceive artificial creatures (e.g., computers, robots, avatars, voice assistant, AI chatbot, etc.) as ingroup (or outgroup) using not only demographic characteristics but also various human-like traits as social cues, including gesture, voice characteristics, visual appearance, and language style (Blut et al. 2021; Lombard and Xu 2021; Nowak and Rauh 2005; Obremski et al. 2022; Seaborn et al. 2022). Also, studies highlighted that the categorization significantly influences cognitive, affective, and behavioral evaluation, such as increased trust, more positive affective responses, and favorably assessing entities perceived as ingroup members (Guegan et al. 2017).

Along these lines, favorably tailored commentary can be perceived as a salient social cue that makes users perceive the AISC as an ingroup member, yielding positive evaluations. Meanwhile, regarding the HAII-TIME framework, a previous study conceptualized this psychological process as an *identity heuristic*, which is activated when people recognize the content or the source as in accordance with their identity or affiliations (Molina 2025). That is, in contrast to the representativeness heuristic, which reduces the trust in the AISC by violating expectations of objectivity, the identity heuristic may simultaneously impact trust positively. Specifically, if the AISC expresses excitement when the preferred player scores or provides sympathetic commentaries about losing scores, these cues may signal to the viewers that the AISC understands or supports their affiliated identity with a preferred player, thus eliciting the identity heuristic. This perception of a similar viewpoint can lead viewers to recognize a higher degree of identity congruence with the AISC, thereby activating the identity heuristic. As Molina (2025) underscored, identity-congruent content readily induced immediate emotional alignment and positive evaluation of credibility. Moreover, in the context of sports communication, a prior study found that biased sports commentary, congruent with viewers' team identification, significantly influences the affective and cognitive evaluation of the quality (M. Lee et al. 2016). Thus, to attest the relationship between favorably tailored commentary and trust in the AISC by triggering the identity heuristic, the following hypotheses are proposed:

H4: Favorably tailored commentary will elicit higher activation of the identity heuristic compared to neutral commentary.

H5: The higher the activation of the identity heuristic, the stronger the trust in the AISC.

H6: The identity heuristic will mediate the relationship between the commentary type and the trust in the AISC.

Action Route: Customization

The cue route triggered by favorably tailored commentary initiates a conflicting evaluation by simultaneously activating heuristics that can lead to opposing trust evaluations. While the representativeness heuristic may reduce trust due to perceived bias, the identity heuristic can enhance it through emotional alignment. In this context, this study proposes that the action route, specifically elicited by customization, can be a way to manage this conflict by reinforcing perceived control.

In general, customization affordance refers to the system's feature to allow users to proactively select or adjust how content is presented (Kang and Sundar 2016; S. Lee, Kim, and Sundar 2015). Also, in contrast to a system-driven approach (i.e., personalization), customization enables users to decide whether they share information about their preferences and interests with systems or not (S. Lee, Kim, and Sundar 2015). In this context, this dissertation defines customization as a technological affordance that induces a specific action, which provides users the chance to adjust certain aspects of the AI system or agent, reflecting their personal information and preferences. In line with the HAII-TIME approach, many studies proposed the *sense of agency* (or perceived control) as a core of customization that offers users a certain level of power to manage, decide, and modify (Sundar 2020; Zhang and Sundar 2019). That is, by using this affordance, users can develop a sense of agency, feeling that they can influence or control the outputs of an AI agent and shape the overall experience (C. Chen and Sundar 2024; Moore 2016).

Previous studies applied the concept of 'controllability' and 'predictability' to explain how a sense of agency generates positive evaluations about the media or agent (Kang and Sundar 2016; Marathe and Sundar 2011). To elaborate, a heightened sense of agency through customization fosters psychological ownership and controllability over the interaction and usage, leading users to view the outcomes as more aligned with their control (Kang and Sundar 2016). At the same time, perceived control also reduces the uncertainty of outcomes, allowing users to predict the outcomes based on their customization actions and attribute the outcomes to themselves (Marathe and Sundar

2011). In other words, the sense of agency allows people to interpret the output of the system as a result of the so-called ‘self-as-source’ (Sundar 2008b). Based on this approach, previous studies provided empirical evidence of the positive impact of sense of agency on media or agents in diverse contexts. For instance, Kalyanaraman and Sundar (2006) identified that when users are provided control over the interface of a medium, their sense of agency increases significantly, leading to a favorable evaluation of trust. In the context of communication with a chatbot, Wald et al. (2021) found that offering chatbot customization options reduced perceptions of bias and increased evaluation of credibility. These findings underline that customization affordance takes a crucial psychological role in activating a user-driven trust-building mechanism. Therefore, aligning with the HAII-TIME approach, this study suggests the hypotheses to examine the positive impact of customization on the trust of the AISC by enhancing the sense of agency.

H7: The users who have a customization option will show a higher sense of agency than those who do not have one.

H8: The higher the sense of agency, the stronger the trust in the AISC.

H9: The sense of agency will mediate the relationship between the presence of customization and the trust in the AISC.

Furthermore, while customization increases users’ sense of agency, which entails a positive evaluation of trust in the AISC, it is also expected to play the role of a buffer that mitigates the negative impact of expectancy violations. From the perspective of EVT, as discussed earlier, favorably tailored commentary violates the general norm of objectivity and neutrality of sports commentators, eliciting negative responses (Burgoon

1993). However, when a customization option is offered, users are more likely to reinterpret the favorably tailored commentary as an intentional output of active participation. According to the ViolEx 2.0 model (Panitz et al. 2021), which is derived from EVT, user-initiated action can lead to the formation of situation-specific expectations, updating from existing expectancy. Specifically, the situation-specific expectation refers to updated expectancy after individuals' revision of their generalized preexisting expectancy based on cognitive and sensory consequences when exposed to new experiences or actively engaged in specific environments. In other words, in the context of AISC, when users have a chance to customize the AISC with their preferences, they might replace their pre-existing expectancy about sports commentators (i.e., fairness and objectivity) with their team/player preferences. Thus, what might have been interpreted as a violation of objectivity is understood as an expected and intended outcome of the users' customization action. This shift represents not only mitigation of the violation but a fundamental reconstruction of the preexisting schema, re-perceiving favorably tailored commentary from a norm violation to an acceptable and desirable outcome.

Similarly, within the HAII-TIME framework, when the users have an opportunity to customize related settings, they are less likely to evaluate the AISC through the lens of the representativeness heuristic. Namely, favorably tailored commentary is seen as consistent with the outcome of users' control (i.e., customization) and not as an undesirable deviation or violation from a prototype of objective commentary (Kang and Sundar 2016). This reinterpretation can mitigate the negative effect that might otherwise result from the perceived mismatch between the AISC and general human sports commentators. In contrast, in the absence of customization, favorably tailored commentary remains solely a cue that may trigger the representativeness heuristic in a negative way. That is, without the means to adjust the commentary to their preferences, users are more likely to perceive the biased output as an unexpected deviation from the prototype of a trustworthy and impartial commentator (Sundar 2008a, 2008b). In this context, this study posits a moderating impact of customization that weakens the activation of the negative representativeness heuristic by favorably tailored commentary. Hence, based on this rationale, the following hypothesis is generated:

H10: The customization weakens the activation of the negative representativeness heuristic by favorably tailored commentary.

In addition to mitigating the negative influence of favorably tailored commentary, it is also expected to strengthen the positive effects of the identity heuristic. As was previously discussed, favorably tailored commentary may be positively interpreted when it aligns with users' social identity (M. Lee et al. 2016). This alignment can heighten perceived similarity and in-group identification, leading to higher trust in the AISC. However, the strength and salience of this identity heuristic are not consistent across all users and may be significantly enhanced when users actively participate in utilizing given opportunities to control their experience (i.e., customization) (Kang and Sundar 2016). According to Marathe and Sundar (2011), customization inherently possesses the elements of self-identification by allowing users to reflect their own identity, such as their preferences and demographics. Therefore, when customization options are available, users can experience a stronger congruency between self-identity and content. Namely, customization enables individuals to co-construct media experiences, intensifying the salience of cues congruent with identity, which in turn amplifies the activation of the identity heuristic. In the context of the AISC, the customization lets users perceive favorably tailored commentary not as a coincidence but as an intentional reflection of their identity, subsequently improving trust in the AISC. Thus, the following hypothesis is proposed to examine the moderating impact of customization on the impact of favorably tailored commentary on activating the identity heuristic:

H11: The customization strengthens the activation of the identity heuristic by favorably tailored commentary.

Taken together, this study posits that two important cognitive heuristics – the negative representativeness heuristic and the identity heuristic – will be simultaneously activated when the viewers watch the sports streaming or highlight films with the AISC's commentaries, exerting opposite evaluations of the AISC's trust. Although previous literature provides theoretical and empirical evidence to predict the impact of two heuristics on the trust of AISC, there is a lack of research investigating how these heuristics might work when concurrently triggered by the same communication cue. Moreover, the action of customization is predicted to buffer the negative impact of the negative representativeness heuristic and amplify the positive impact of the identity heuristic on the trust in the AISC. In this context, to address this overall prediction, this dissertation generates research questions to identify the overall impact of two cognitive heuristics and the moderating impact of customization in shaping trust in the AISC:

RQ1: What is the overall (total) impact of favorably tailored commentary on users' trust in the AISC?

RQ2: How does the overall (total) impact of favorably tailored commentary on users' trust in the AISC differ between customization-present and customization-absence groups?

From Trust to Advertising Effect: Persuasion Knowledge Model

The HAII-TIME framework, along with the EVT and SIT, theoretically elaborates how two critical affordances (i.e., favorably tailored commentary and customization) psychologically impact the trust in the AISC. However, it remains essential to scrutinize how this trust further influences advertising effectiveness, which is critical to understanding the effectiveness of the AISC as a contextual advertising agent. To address this, the current study integrates this dual-route psychological mechanism with the Persuasion Knowledge Model (PKM), which postulates that the persuasion is a dynamic between persuasion agents and targets using their persuasion knowledge.

Fundamentally, the PKM, proposed by Friestad and Wright (1994), offers a comprehensive understanding of how people decide their coping behaviors (i.e., reject or accept) toward persuasion attempts (e.g., advertising messages through AISC). Moreover, the PKM is grounded in the idea that persuasion is a form of a social interaction in which the target (i.e., consumer) is not passive but actively interprets and responds to persuasive attempts (Friestad and Wright 1994). According to the PKM, individuals apply three types of knowledge dimensions to select an appropriate coping behavior against persuasion: topic knowledge, persuasion knowledge, and agent knowledge (Campbell and Kirmani 2008). Specifically, topic knowledge refers to an individual's familiarity with the subject matter or product being promoted, such as an understanding of the sports context or the specifics of a brand (Ham and Nelson 2019). In addition, persuasion knowledge involves an individual's awareness of persuasive tactics and strategies, guiding them in deciding whether to accept or resist an influence attempt (Campbell and Kirmani 2000).

Meanwhile, most critically for this study, agent knowledge comprises the knowledge that persuasion targets have regarding overall persuasion agents, including the characteristics, personalities, and abilities of persuasion agents, based on objective information and targets' personal experiences (Ham and Nelson 2019; Campbell and Kirmani 2008; D. Lee and Ham 2023). In this context, two affordances that activate the cue- and action-route, respectively, can be mapped onto the agent knowledge dimension in PKM. Specifically, favorably tailored commentary and customization serve as pivotal information and experiences that constitute agent knowledge of users about the AISC, establishing trust in the AISC as a new evaluative belief. Trust, in this framework, acts as a critical evaluative belief regarding the AISC's competence and trustworthiness, which is formed based on the user's agent knowledge (i.e., cues and actions) about the AISC (Jang, Kwak, and Bucy 2024; S. Lee, Moon, and Song 2024). In other words, when the AISC is perceived as a trustworthy agent based on users' agent knowledge, users are more likely to evaluate their advertising source (i.e., AISC) and message positively.

In this vein, previous studies suggested that this trust works as a critical antecedent belief that entails a further assessment of the effectiveness of the persuasion agent, conceptualized as a 'Perceived Persuasion Effectiveness (PPE)' (D. Lee and Ham 2023). The concept of the PPE refers to a persuasion target's belief about the psychological effects of persuasion agents that subsequently cause positive coping behaviors against the persuasion attempt (Breves et al. 2021; D. Lee and Ham 2023;

Pfeuffer et al. 2021). That is, whereas trust reflects a generally positive disposition and belief in the agent's characteristics (e.g., reliability, integrity), PPE represents a more specific judgment about the AISC's capability to persuade effectively, particularly in its designated role as a contextual advertising agent. Among the three knowledge dimensions, agent knowledge is closely related to the PPE since this psychological assessment of the competence of the persuasion agent mainly relies on the beliefs about the agent (D. Lee and Ham 2023). Despite the lack of empirical research regarding PPE, Hibbert et al. (2007) verified that people shape cognitive beliefs about an agent's persuasion effectiveness based on the newly established agent knowledge, previous experiences, and existing beliefs, leading to behavioral responses to a charity's persuasion attempts. Similarly, in the context of HAI, D. Lee and Ham (2023) empirically proved that the source credibility of AI agents mediates the relationship between agent knowledge and PPE, which subsequently predicts positive attitudinal and behavioral outcomes of advertising.

Accordingly, from the PKM perspective, this study argues that users form trust in the AISC based on their experiences of commentary and customization, which serve as cues and action affordances constituting agent knowledge. In turn, this trust shapes the PPE, which finally influences coping behaviors, either accepting or rejecting, toward advertising messages from the AISC. More precisely, if the AISC is judged as more trustworthy based on user experiences (i.e., commentary and customization) of the AISC while watching sports streaming or sports highlight films, they will perceive the AISC as more effective in persuasion. Then, this shaped internal belief (i.e., PPE) in the psychological coping process influences the actual coping strategies (i.e., advertising outcomes) (Dillard, Shen, and Vail 2007; D. Lee and Ham 2023). Thus, the following hypotheses are generated to examine whether users' trust in the AISC mediates the relationship between agent knowledge and PPE, resulting in actual advertising outcomes: attitude toward the advertising (A_{ad}) and brand (A_b) (D. Lee and Ham 2023):

H12: The trust in the AISC will positively influence the PPE.

H13: The PPE of the AISC will positively influence A_{ad}.

H14: The PPE of the AISC will positively influence A_b.

In addition, this study also aims to further examine the relationship between A_{ad} and A_b based on the conventional advertising models. Specifically, Mackenzie et al. (1986) theoretically and empirically demonstrated that A_{ad} serves a significant mediating role between ad-related cognitions (i.e., beliefs and perceptions), such as advertiser credibility and perceived effectiveness, and ad- or brand-related evaluation (i.e., A_{ab} and A_b). While this relationship has been repeatedly and widely identified across various advertising contexts, from traditional media to digital platforms, this study seeks to extend this established framework to the novel setting of the AISC. Thus, the following hypotheses are generated to investigate the mediating role of A_{ab} in the relationship between the PPE of the AISC and A_b:

H15: The A_{ad} will positively influence A_b.

H16: A_{ad} will mediate the relationship between the PPE of the AISC and A_b.

Along these lines, vertically, the overall conceptual research model (see Figure 4) depicts the HAII-TIME framework by differentiating between the cue route (i.e., commentary type) and the action route (i.e., customization), both of which influence users' perceptions through different psychological processes – cognitive heuristics and sense of agency. On the other hand, horizontally, the model describes the structure of the PKM, organizing the process into three sequential stages: agent knowledge (e.g., heuristics and sense of agency), beliefs/perceptions (i.e., trust and perceived persuasion effectiveness), and coping behavior (i.e., A_{ad} and A_b). By integrating these two perspectives, Figure 4 provides a comprehensive structure for testing the H1-H16 and exploring how the AISC works as a persuasive agent within sports sponsorship contexts.

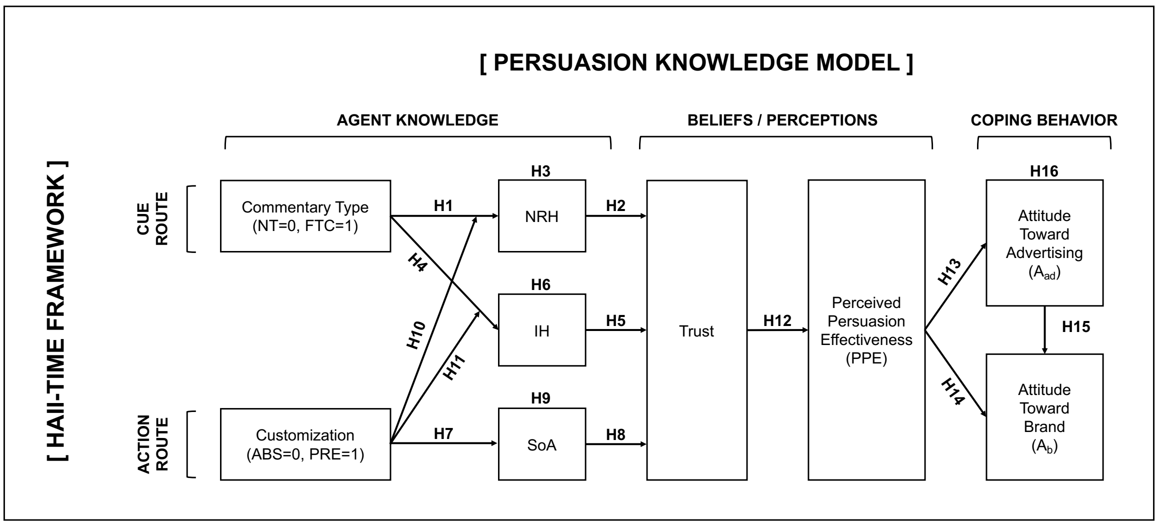

Figure 4. The Overall Research Framework

Note. NT = Neutral Commentary, FTC = Favorably Tailored Commentary, ABS = Absent, PRE = Present, NRH = Negative Representativeness Heuristic, IH = Identity Heuristic, SoA = Sense of Agency

CHAPTER 3

RESEARCH METHOD

Research Design and Stimuli Development

A 2 (commentary type: FTC vs. NT) X 2 (customization: present vs. absent) factorial experimental design was used to examine hypotheses (see Figure 4). To conduct this online experiment, this study manipulates the commentary type in video stimuli and the presence of customization within the survey structure. In team sports, participants may have different levels of identification with different players in the same team at the same time, which complicates the interpretation of results. Therefore, by applying individual sports, especially tennis, in this study, the experiment ensures a more controlled setting where viewer identification is directed toward a single athlete, thereby securing the internal validity of the manipulation and measurement. In this context, stimuli were created using the approximately 5 minutes and 30 seconds long official highlight clip of the match between Taylor Fritz and Lorenzo Musetti in the 2024 Wimbledon (https://www.youtube.com/watch?v=VN5JSC6ixbg&t=8s).

Regarding the manipulation of the commentary type, the favorably tailored commentary toward Taylor Fritz (hereafter FTC) includes positively framed reinforcement for the specific player and regretful sympathetic expression of the mistake, with relatively more frequent mention (e.g., “That was an unfortunate miss for [Player A], but he will show incredible resilience throughout this match!”). On the other hand, the neutral commentary (hereafter NC) delivers impartial and neutral analysis and spends a similar amount of time on each player, explaining the situation or expression without elevated emotional expression (e.g., “It was a miss for [Player A]. [Player B] should take advantage of this moment.”).

To enhance ecological validity and generalizability of the results, the study used two different official partners of the Wimbledon – IBM and Evian. First, sponsorship advertising messages for IBM were mentioned at the beginning of it (e.g., “This highlight film is presented by IBM, offering insights powered by live match analytics.”) and each scene of the set summary (e.g., “IBM’s live match summaries, available on wimbledon.com, offer deeper context behind this momentum shift.”) in order to secure the applicability. Similarly, maintaining the structure of neutral and favorably tailored commentaries of the IBM version, sponsorship advertising messages for Evian – incorporating the brand’s core attributes of clarity and refreshment – were embedded within the commentaries for the four key moments of the highlight film (e.g., “On set point, Fritz delivers a sharp serve down the T. Moments like this highlight the importance of timing and focus – qualities Evian supports as our official water partner.”) and at the beginning of it (e.g., “This highlight film is brought to you by Evian – naturally refreshing, perfectly balanced for every rally and every moment”). Finally, four different versions of the sports commentary script for the highlight film were created of a similar length (see Appendix A).

Moreover, customization was manipulated by a research design within the online experiment structure, referring to previous studies (S. Lee, Kim, and Sundar 2015; Snyder, Sundar, and Lee 2024). Importantly, although users can select their preferred commentary type in real-world usage situations, allowing direct choice in the experiment could confound the independent variables (i.e., commentary type, customization), thereby compromising interval validity. To address this, participants assigned to the customization-present condition were sent to the ‘customization page’ with questions asking personal information (e.g., age, gender, residence), watching sports, preferred tennis players, and willingness to share this information (i.e., privacy setting) after they are informed that they will watch the highlight film with an AI sport commentator. In other words, this experimental structure ensured the independence of the two manipulated variables while allowing participants to feel as though they were exercising control over the AI commentator’s outputs.

In terms of the recording process, the commentary scripts were voice-recorded by a female amateur sports commentator (broadcaster) who is affiliated with the Sports Media Institute at the University of Georgia and the Los Angeles Dodgers (as an intern). All recordings were completed in a quiet setting using a smartphone voice-recording application (iPhone Voice Memos). To secure the quality of voice recording, the instruction file includes specific setting on the application and environmental setting – for example, “On your iPhone, go to Settings > Voice Memos > Audio Quality, and select Lossless for the best recording quality,” “Record in a quiet indoor space (avoid background noise like AC, fans, or street noise),” and “Place your phone on a stable surface, 6–12 inches (15–30 cm) from your mouth.” Moreover, detailed directions for recording each commentary type were also stated in the instruction file (see Appendix B). The commentator received a stipend of $150 for completing the full set of recordings, which included multiple drafts and revisions. The recording files were reviewed, and the commentator was requested to re-record as needed to ensure tone consistency, pronunciation, clarity, and natural delivery.

Then, using Davinci Resolve 20 video editing software, the audio-recorded commentaries were integrated with the original video. The highlight films start with the thumbnail image that presents the sponsor of the highlight films. Also, white colored captions with a black transparent background were embedded in the highlight films to make commentaries more recognizable. As Figure 5 shows, the logo of the corresponding brand was embedded during the entire match, including on the thumbnail image, at the beginning, in the middle of the match, and in set summaries. Also, to ensure that participants were continuously aware that the audio commentaries were generated by the AISC, a static on-screen caption – "Commentary by AI Sports Commentator" – was consistently shown under the scoreboard during gameplay.

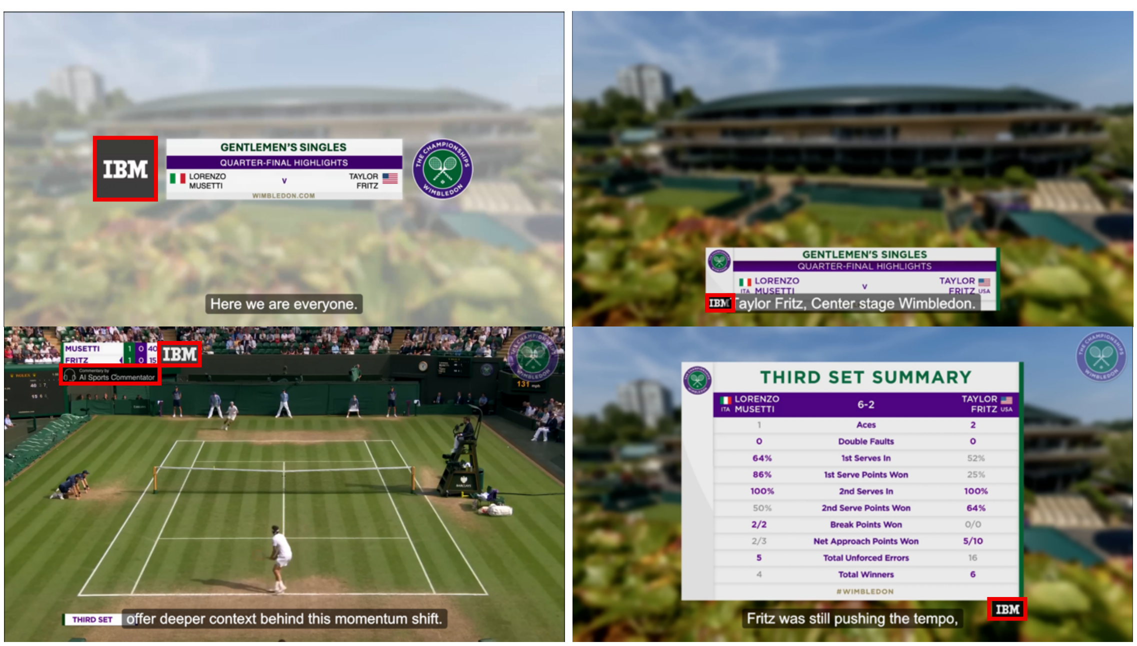

Figure 5. Screenshots of the Thumbnail, Introduction, Match, and Set Summary (IBM Stimulus)

In turn, to secure parsimony of the online experiment and prevent participants' fatigue, the four video stimuli, comprising highlights of the first three sets out of five sets, were finally edited to an approximate 4 minutes long. Moreover, video stimuli were uploaded on YouTube to be inserted in the online experiment structure (IBM with Neutral Commentary: https://youtu.be/d7rkOOrK-gY; IBM with Favorably Tailored Commentary: https://youtu.be/_MKr_P91vK4; Evian with Neutral Commentary: https://youtu.be/SEVOlRys1tI; Evian with Favorably Tailored Commentary: https://youtu.be/wdbwGyxgo2U).

Manipulation Checks

To enhance internal validity of the experiment, the current study implemented manipulation checks based on created commentary scripts for two sponsors (see Appendix A). Specifically, the manipulation checks were conducted to assess the perceived neutrality and favoritism of the commentary scripts using two items on a 7-point Likert Scale (1: strongly disagree, 7: strongly agree): 1) “The commentary script felt neutral and objective,” and 2) “The commentary script showed favoritism toward one player.”

IBM Sponsorship Script

A total of 99 participants were recruited via the Prolific platform (male: n = 55, 55.56%; female: n = 44, 44.44%) for the manipulation check for the IBM scripts. Most participants were White/Caucasian (n = 70, 70.70%), followed by African American/Black (n = 13, 13.13%), Hispanic/Latino (n = 8, 8.08%), Asian (n = 7, 7.07%), and other ethnicities. Additionally, the average age of the participants was 39.11 years (SD = 12.56), with a range of 19 to 74 years. Regarding the assumption of the independent t-test, since the normality assumption was violated in both perceived neutrality (NC: W = .875, $p < .001$; FTC: W = .919, $p < .01$) and perceived favoritism (NC: Shapiro-Wilk's W = .878, $p < .001$; FTC: Shapiro-Wilk's W = .851, $p < .001$), Wilcoxon's rank sum tests were implemented instead of the independent t-tests. According to the result, there was statistically significant difference between the NC and the FTC in perceived neutrality (NC: M = 5.00, SD = 1.71; FTC: M = 3.28, SD = 1.71; W = 1866.50, $p < .001$, Cohen's $d = 1.01$) and perceived favoritism (NC: M = 3.24, SD = 1.92; FTC: M = 5.50, SD = 1.52; W = 467.00, $p < .001$, Cohen's $d = 1.31$).

Evian Sponsorship Script

In terms of scripts using Evian as a sponsor, a total of 95 people who did not participate in the manipulation check using the IBM scripts were recruited through the Prolific platform (male: n = 51, 53.68%; female: n = 43, 45.26%; non-binary/third gender: n = 1, 1.05%). In terms of race/ethnicity, the majority identified as White/Caucasian (n = 61, 77.05%), followed by African American/Black (n = 20, 21.05%), Asian (n = 9, 9.47%), Hispanic/Latino (n = 3, 3.16%), and other backgrounds. Also, participants' ages ranged from 18 to 69 years (M = 42.07, SD = 12.33). Before conducting independent t-tests, the violation of the normality assumption was found in both neutrality (NC: Shapiro-Wilk's W = .875, $p < .001$, FTC: Shapiro-Wilk's W = .830, $p < .001$) and favoritism (NC: Shapiro-Wilk's W = .938, $p < .05$; FTC: Shapiro-Wilk's W = .854, $p < .001$). Hence, Wilcoxon's rank sum tests were conducted. As a result, the highlight films with NC and FTC were significantly different in perceived neutrality (NC: M = 5.04, SD = 1.56; FTC: M = 2.83, SD = 1.65; W = 1895.50, $p < .001$, Cohen's d =

1.37) and perceived favoritism (NC: M = 3.55, SD = 1.69; FTC: M = 5.75, SD = 1.19; W = 353.00, $p < .001$, Cohen's $d = 1.50$).

Procedure

At the beginning of the online experiment, participants will be initially asked to read a consent form, including a brief explanation about the research. Henceforth, they were requested to ensure that their device's audio was working properly. On the next page, the participants were informed what the AI sports commentator is, how it is used in the industry, and the unique features (e.g., AI-driven context detection, AI-driven analysis, favorably tailored commentary). Then, they were randomly assigned to one of two different official sponsors (i.e., IBM or Evian) and informed that they would watch the highlight film of the 2024 Wimbledon with the AISC. In turn, they were randomly assigned to one of four conditions regarding the commentary type (NC vs. FTC) and the customization option (present vs. absent). Before the highlight film was played, the participants in the customization-present condition were first sent to the customization page, asking questions about personal information (e.g., age, gender, residence), watching sports, preferred tennis players, and their data-sharing intention (i.e., agree or disagree). Afterward, all participants were informed that they were required to watch the entire highlight film. To ensure that the participants did not skip or stop the highlight film, the next button was shown after the entire video was watched automatically, using the survey platform function. After participants watch the highlight film, all participants will answer a set of questions measuring key variables in the research framework – representative heuristic, identity heuristic, sense of agency, trust in the AISC, the PPE, and advertising outcomes (A_{ad} and A_b).

Participants

Considering the research design, the current study aims to collect data from the people who are considered fans of Taylor Fritz but not of Lorenzo Musetti. Since the population might be too small, this study employed a two-stage recruitment to secure time- and cost-efficiency. First, an online survey asking questions about fan identification with Taylor Fritz and Lorenzo Musetti was distributed to 1,322 people identified as tennis viewers aged 18 and above who lived in the United States through the Prolific platform. As a result, 322 participants were identified as an appropriate target sample for the main online experimental study, as their mean scores of fan identification with Taylor Fritz were above 4.00 and with Lorenzo Musetti were below 4.00. In turn, using recorded Prolific IDs of participants, the invitation to the main experiment study was distributed through a platform function.

Among the 322 eligible participants, 243 people took part in the main online experiment. However, since 46 cases were excluded due to insufficient data (e.g., incompletion), a total of 197 valid responses (male: n = 107, 54.31%; female: n = 89, 45.18%; non-binary/third gender: n = 1, 0.51%) were included in the final analysis. The racial/ethnic distribution of the sample showed that the majority were White/Caucasian (n = 121, 61.42%), followed by African American/Black (n = 33, 16.75%), Asian (n = 18, 9.14%), Hispanic/Latino (n = 13, 6.60%), and others (e.g., American Indian, Alaska Native, Native Hawaiian, Pacific Islander, Biracial, Multiracial). Also, the ages of participants ranged from 20 to 83 (M = 41.17, SD = 12.93). Since an a priori required sample size test for ANOVA and SEM, using G*Power 3.1 software (ANOVA) and Soper's sample size calculator (SEM), suggested 147 and 184 as the minimum sample size respectively (ANOVA: effect size = 0.3, power = 0.8, numerator *df* = 1, number of groups = 4, probability level = 0.05; SEM: effect size = 0.3, power = 0.8, number of latent variables: 9, number of observed variables: 33, probability level = 0.05), the sample size was considered adequate for implementing the planned data analyses (Faul et al. 2009; Soper 2023).

Measurement

To measure nine conceptual constructs in this study, a total of thirty-nine question items were used, while customization and commentary type were manipulated in the experiment stimuli. As Appendix C elaborates, the specific items for each construct were pre-established and revised by prior studies.

Fan Identification (FI)

While numerous studies had adapted all seven items from the original scale of Wann and Branscombe (1993), Kim, Lee, and Byon (2018) asserted that four items mainly provide a relatively high amount of information about fan identification based on the empirical evidence using the item response theory. In this context, this study measured the level of fan identification with those four items in a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree), including “It is important to me that [Player] wins” and “I see myself as a fan of [Player].”

Negative Representativeness Heuristic (NRH)

The negative representativeness heuristic of participants was measured using a representativeness heuristic scale developed by C. Chen and Sundar (2024). All items were modified in the context of the AISC using a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree), including “The AISC was not objective, unlike human sports commentators," "The AISC took a biased stance, unlike human sports commentators," and "The AISC generated biased commentaries toward one player, unlike human sports commentators."

Identity Heuristic (IH)

Modified from the previous studies' measurement items (Molina 2025; Rodrigues et al. 2017), the identity heuristic was measured by three items using a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). The specific items include "I think the AISC has thought about [Player A] similar to mine," "I think the AISC has an attitude toward [Player A] similar to mine," and "I think the AISC has beliefs about [Player A] similar to mine."

Sense of Agency (SoA)

Adapted from the previous research (C. Chen and Sundar 2024; Molina and Sundar 2022; Zhang and Sundar 2019), sense of agency of participants was assessed by four items in a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree), including "The AISC system provided me with options and choices," "I felt in charge of the commentaries from the AISC," and "I felt I had control over how personal information and preferences are used by the AISC."

Trust (TR)

Trust in the AISC was measured using the scale that encompasses both the cognition- and affect-based trust developed by Madsen and Gregor (2000). Adapting the revised scale in the context of the HAI suggested by Liao and Sundar (2021), six items in a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree) for each dimension (i.e., cognitive and affective) were utilized. For example, items for the cognition-based trust include “The AISC performs reliably,” “I understand how the AISC will assist me in my sports streaming experience,” and “The AISC has sound knowledge about the matches.” Also, affect-based trust was measured by items, including “My experience with the AISC is enjoyable,” “I feel like the AISC is willing to reflect my preferences,” and “The AISC’s commentaries show empathy and sympathy toward me.”

Perceived Persuasion Effectiveness (PPE)

Adapted from the study of Celsi and Gilly (2010), the current study measured using three items in a 7-point Likert Scale (1 = strongly disagree, 7 = strongly agree), such as “The sponsorship message of [Sponsor brand] within the commentaries by the AISC will increase positive perceptions” and “The sponsorship message of [Sponsor brand] within the commentaries by the AISC will be liked by viewers.”

Attitude Toward Advertisement (A_{ad}) and Attitude Toward Brand (A_b)

As outcomes of advertising, A_{ad} and A_b were measured using three items in a 7-point semantic differential scale, each adapted from Fabrigar and Petty (1999), MacKenzie, Lutz, and Belch (1986), and Muehling (1987). Specifically, participants were asked how they feel about the sponsorship of [Sponsor brand] to assess A_{ad} (Bad/Good, Negative/Positive, Unfavorable/Favorable). At the same time, they rated their overall impression of [Sponsor brand] to measure A_b (Bad/Good, Likable/Dislikable, Unpleasant/Pleasant).

CHAPTER 4

RESULTS

All data analyses are conducted using R Studio software with relevant packages, including ‘lavaan,’ ‘semTools,’ ‘ez,’ and ‘psych’ to examine the built hypotheses and research questions. The main analyses will consist of (1) testing the serial mediation model (H1-H9, H12-16, and RQ1) and (2) assessing the moderation effect of customization (H10, H11, and RQ2).

Confirmatory Factor Analysis (CFA)

As a preliminary step of the SEM, CFA was conducted to assess model fit indices and identify the reliability and validity of measurements, using the maximum likelihood (ML) estimation method. The initial CFA model that includes eight latent variables indicates the borderline model fit ($\chi^2(413) = 1051.952$, $\chi^2/\text{df} = 2.547$, $p < .001$, CFI = .918, TLI = .907, IFI = .918, RMSEA = .089, SRMR = .071), especially the root mean square error of approximation (RMSEA). Therefore, to improve the model fit, modification indices (MI) were examined. The results indicated that the model fit could be significantly improved by allowing for the covariances of error terms between item ‘trust_7’ and ‘trust_10’ (MI = 88.99) and item ‘trust_1’ and ‘trust_2’ (MI = 71.65). Given the semantic similarity and potential wording redundancy between these pairs of items (see Appendix C), it was substantively justifiable to allow their error terms to covary. Also, the item ‘trust_11’ was omitted from the model since it showed a high cross-loading with ‘identity heuristic (MI = 61.79),’ ‘sense of agency (MI = 26.57),’ and ‘negative representativeness heuristic (MI = 17.99).’ Therefore, the original CFA model was modified to include these two error covariances and exclude one item. As a result, the modified model shows satisfactory model fit indices ($\chi^2(382) = 765.677$, $\chi^2/df = 2.004$, $p < .001$, CFI = .949, TLI = .942, IFI = .950, RMSEA = .071, SRMR = .058).

Regarding the factor loading values (λ), the factor loading values of all observed variables were acceptable (all $\lambda > .4$), using .4 as the cut-off (Ford, MacCallum, and Tait 1986; J. Wang and Wang 2019). Moreover, Cronbach’s α, composite reliability (CR), and average variance extracted (AVE) revealed that the reliability and convergent validity of the measurements were satisfactory (Cronbach’s $\alpha > .8$, CR > .8, AVE > .6, see Table 1). In terms of discriminant validity, this study utilized two approaches: a) the Fornell-Lacker criterion and b) the HTMT (Heterotrait-Monotrait ratio of correlations) method. First, utilizing the Fornell-Lacker criterion, the square root of each construct’s AVE was greater than the correlations between that construct and all other latent variables (see Table 2), thereby supporting discriminant validity (Ab Hamid, Sami, and Mohmad Sidek 2017). Second, as all values of HTMT ([.025, .896]) were below the conservative threshold of .90 (see Table 3), the discriminant validity of the model was secured (Ab Hamid, Sami, and Mohmad Sidek 2017; Henseler, Ringle, and Sarstedt 2015).

For the next step, since the experiment used two different official sponsors (IBM and Evian), it is necessary to secure measurement invariance across the two sponsor conditions to conduct SEM or mean comparison tests (e.g., t-test, ANOVA), using a combined data set. As a result of the chi-square difference tests, there was no significant difference between the models (metric invariance: $\Delta\chi^2 = 14.831$, $p = .901$; scalar invariance: $\Delta\chi^2 = 19.983$, $p = .643$). Moreover, the changes in the comparative fit index

(ΔCFI) and root mean square error of approximation (ΔRMSEA) across the configural, metric, and scalar models were lower than .01 (metric invariance: ΔCFI < .01, ΔRMSEA < .01; scalar invariance: ΔCFI < .01, ΔRMSEA < .01), which is the criterion suggested by Cheung and Rensvold (2002). These results ensure that there is no statistical issue in proceeding with the SEM and mean comparison.

Table 1. Reliability and Validity of Measurement Items (n = 197)

Variable/Items	λ	α	CR	AVE
Negative Representativeness Heuristic		.812	.825	.645
NRH_1	.493			
NRH_2	.877			
NRH_3	.948			
Identity Heuristic		.959	.960	.889
IH_1	.919			
IH_2	.957			
IH_3	.950			
Sense of Agency		.946	.950	.819
SoA_1	.870			
SoA_2	.907			
SoA_3	.954			
SoA_4	.882			
Trust		.962	.955	.705
Trust_1	.843			
Trust_2	.865			
Trust_3	.857			
Trust_4	.770			
Trust_5	.809			
Trust_6	.747			
Trust_7	.879			
Trust_8	.676			
Trust_9	.913			
Trust_10	.866			
Trust_11		(excluded)		
Trust_12	.905			
Perceived Persuasion Effectiveness		.946	.946	.854
PPE_1	.930			
PPE_2	.923			
PPE_3	.919			
A_{ad}		.981	.981	.946
A_{ad}_1	.964			
A_{ad}_2	.967			
A_{ad}_3	.986			
A_b		.984	.984	.953
A_b_1	.972			
A_b_2	.983			
A_b_3	.974			

Table 2. Correlation with the Square Root of AVEs (n = 197)

	NRH	IH	SoA	Trust	PPE	A_{ad}	A_b
NRH	**.803**						
IH	.328	**.943**					
SoA	-.059	.448	**.905**				
Trust	-.222	.283	.417	**.840**			
PPE	-.037	.263	.475	.659	**.924**		
A_{ad}	-.035	.239	.406	.569	.864	**.973**	
A_b	.002	.261	.431	.591	.837	.895	**.976**

Note. The square root of AVEs shown on a diagonal, NRH = Negative Representativeness Heuristic, IH = Identity Heuristic, SoA = Sense of Agency, PPE = Perceived Persuasion Effectiveness

Table 3. Heterotrait-Monotrait (HTMT) Ratio (n = 197)

	NRH	IH	SoA	Trust	PPE	A_{ad}	A_b
NRH	1.000						
IH	.142	1.000					
SoA	.082	.457	1.000				
Trust	.214	.275	.424	1.000			
PPE	.037	.266	.487	.639	1.000		
A_{ad}	.043	.238	.417	.535	.864	1.000	
A_b	.025	.265	.442	.570	.837	.896	1.000

Note. NRH = Negative Representativeness Heuristic, IH = Identity Heuristic, SoA = Sense of Agency, PPE = Perceived Persuasion Effectiveness

Table 4. Measurement Invariance Test across Sponsor Brands (n = 197)

	χ^2	df	CFI	TLI	IFI	RMSEA	SRMR	$\Delta\chi^2$	Δdf	ΔCFI
CI Model	1324.26	764	.928	.918	.929	.086	.065			
MI Model	1339.09	787	.929	.922	.930	.084	.067	14.83	23	<.01
SI Model	1359.08	810	.930	.924	.930	.083	.067	19.99	23	<.001

Note. CI = Configural Invariance, MI = Metric Invariance, SI = Scalar Invariance

Structural Equation Modeling (SEM)

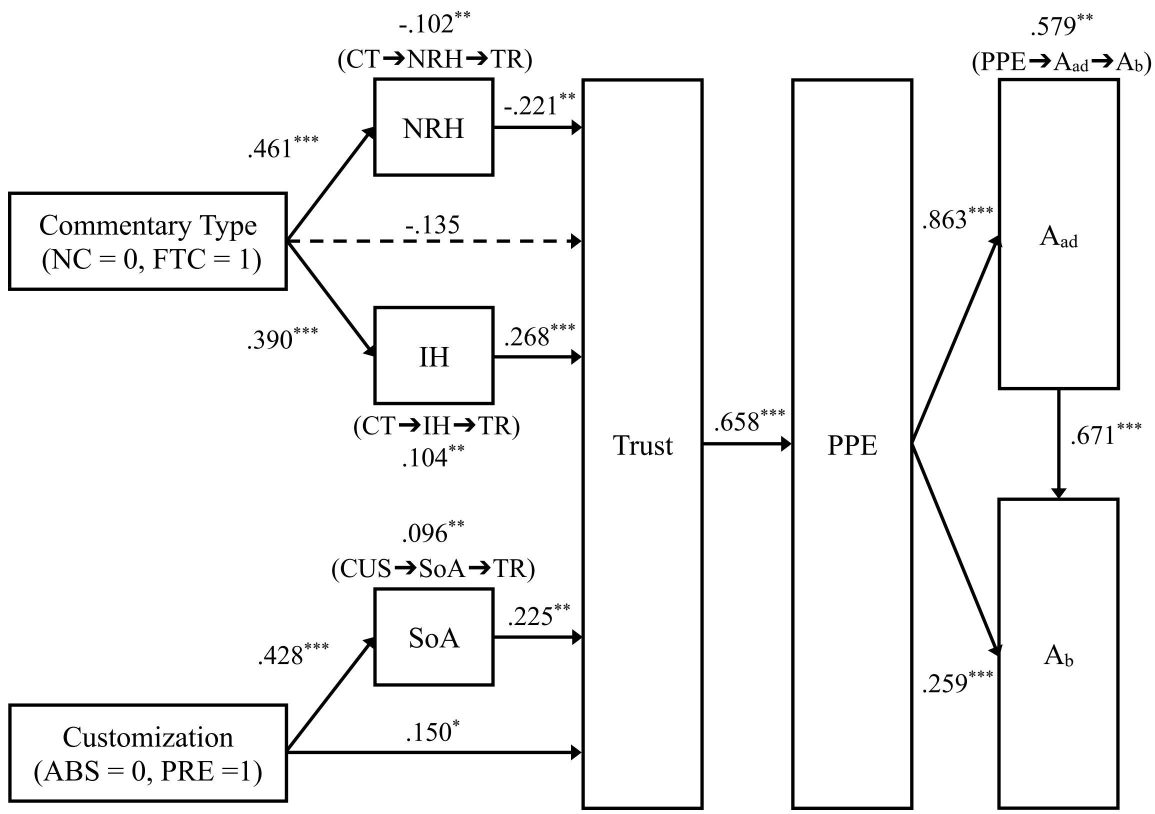

Figure 6. SEM of Pooled Sample (n = 197)

Note. CT = Commentary Type, NC = Neutral Commentary, FTC = Favorably Tailored Commentary, CUS = Customization, ABS = Absence, PRE = Present, NRH = Negative Representativeness Heuristic, IH = Identity Heuristic, SoA = Sense of Agency, PPE = Perceived Persuasion Effectiveness

While the specified initial model mostly showed acceptable model fit indices ($\chi^2(421) = 825.858$, $\chi^2/\text{df} = 1.962$, $p < .001$, CFI = .946, TLI = .941, IFI = .947, RMSEA = .070, SRMR = .119), SRMR was above the acceptable threshold (SRMR < .10). Based on the modification indices, there was a significant residual covariance between 'identity heuristic' and 'sense of agency' (MI = 33.19). Not solely from the statistical perspective, a theoretical approach of the current study also confirmed this potential of residual covariance and construct validity. Specifically, the customization manipulation is conceptualized as a common antecedent that simultaneously enhances 'sense of agency' by affording control and increases the salience of 'identity heuristic.' Along these lines, the final model included this residual covariance between 'identity heuristic' and 'sense of agency,' thereby achieving a better acceptable fit across all indices ($\chi^2(420) = 799.842$, $\chi^2/\text{df} = 1.904$, $p < .001$, CFI = .950, TLI = .944, IFI = .950, RMSEA = .068, SRMR = .093).

After confirming the acceptable model fit indices, the SEM analysis was implemented to examine the hypotheses (H1-H9, H12-16). First, regarding the mediation relationship between 'commentary type (CT)' and 'trust (TR),' the study found full mediation relationships through 'negative representativeness heuristic (NRH)' and 'identity heuristic (IH).' Specifically, the FTC significantly increase the NRH and IH (CT➔NRH: $\beta = .461$, SE = .057, $p < .001$, CI = [.350, .572], Cohen's $f^2 = .270$; CT➔IH: $\beta = .390$, SE = .056, $p < .001$, CI = [.280, .499], Cohen's $f^2 = .179$) compared to the NC, supporting H1 and H4. Moreover, there were significant negative impact of the NRH and positive impact of the IH on the TR respectively (NRH➔TR: $\beta = -.221$, SE = .074, $p < .01$, CI = [-.367, -.076], Cohen's $f^2 = .047$; IH➔TR: $\beta = .268$, SE = .075, $p < .001$, CI = [.120, .416], Cohen's $f^2 = .077$). Thus, H2 and H5 were deemed supported. In addition, two opposite significant indirect influences of the CT on the TR via the NRH and the IH respectively were revealed (CT➔NRH➔TR: $\beta = -.102$, SE = .037, $p < .01$, CI = [-.175, -.029], Cohen's $f^2 = .011$; CT➔IH➔TR: $\beta = .104$, SE = .034, $p < .01$, CI = [.038, .170], Cohen's $f^2 = .011$), supporting H3 and H6. However, no significant direct impact of the CT on the TR was revealed (CT➔TR: $\beta = -.135$, SE = .078, $p = .082$, CI = [-.288, .017], Cohen's f^2 = .019), suggesting the NRH and IH fully mediated the causal relationship between the CT and TR oppositely. Taken together, the total effect of the FTC on the TR was significant in a negative direction (RQ1), while the effect size is negligible (β = -.133, SE = .066, $p < .05$, CI = [-.262, -.004], Cohen's f^2 = .018).

Also, the results indicated that the sense of agency (SoA) fully mediated the causal relationship between the customization (CUS) and the TR. In particular, participants showed significantly higher the SoA when they had a customization option (CUS➔SoA: β = .428, SE = ..054, $p < .001$, CI = [.323, .533], Cohen's f^2 = .224), while the SoA has significant impact on the TR subsequently (SoA➔TR: β = .225, SE = ..078, $p < .01$, CI = [.073, .378], Cohen's f^2 = .053). Hence, H7 and H8 were supported. In addition, a significant direct impact of the CUS on the TR was found (CUS➔TR: β = .150, SE = .071, $p < .05$, CI = [.011, .289], Cohen's f^2 = .023), suggesting a partial mediated causal relationship between the CUS and the TR through the SoA. Moreover, the indirect impact of the CUS on the TR via the SoA was significant (CUS➔SoA➔TR: β = .096, SE = .036, $p < .01$, CI = [.026, .166], Cohen's f^2 = .009), supporting H9.

Subsequently, the shaped TR significantly influenced the PEE with the large effect size (TR➔PPE: β = .658, SE = .044, $p < .001$, CI = [.573, .743], Cohen's f^2 = .764), supporting H12. Moreover, regarding the impact of the PPE on advertising outcomes, the results indicated that the PPE had a significant positive impact on A_{ad} and A_b (PPE➔A_{ad}: β = .863, SE = .021, $p < .001$, CI = [.822, .904], Cohen's f^2 = 2.918; PPE➔A_d: β = .259, SE = .072, $p < .001$, CI = [.117, .401], Cohen's f^2 = .072). supporting H13 and H14. Also, A_{ad} significantly impact on A_b (A_{ad}➔A_b: β = .671, SE = .068, p

< .001, CI = [.537, .805], Cohen's f^2 = .819), thereby indicating a significant partial mediation relationship between the PPE and A_b through A_{ad} (PPE$\rightarrow A_{ad} \rightarrow A_b$: β = .579, SE = .061, p < .001, CI = [.460, .698], Cohen's f^2 = .504). Thus, H13, H14, H15, and H16 were supported.

Moderating Impact of Customization: Multigroup-SEM and ANOVAs

To examine the moderating role of the customization, the multigroup-SEM was implemented. The value of ΔCFI and ΔRMSEA (see Table 5) indicates that both metric and scalar invariance were secured (metric invariance: ΔCFI < .01, ΔRMSEA < .01; scalar invariance: ΔCFI < .001, ΔRMSEA < .01). That is, it is statistically appropriate to compare the path coefficient (β) and mean between the customization-present group and the customization-absence group.

Table 5. Measurement Invariance Test across Customization Conditions (n = 197)

	χ^2	df	CFI	TLI	IFI	RMSEA	SRMR	$\Delta\chi^2$	Δdf	ΔCFI
CI Model	1377.21	764	.918	.907	.919	.090	.067			
MI Model	1422.44	787	.915	.906	.916	.091	.076	45.23	23	<.01
SI Model	1447.33	810	.915	.909	.916	.089	.078	24.89	23	<.001

Note. CI = Configural Invariance, MI = Metric Invariance, SI = Scalar Invariance

As Table 6 and Figure 7 indicates, there was significant difference between the customization-absent group and customization-present group in the 'CT$\rightarrow$NRH' (customization-absent: β = .571, SE = .069, p < .001, CI = [.435, .707], Cohen's f^2 = .484; customization-present: β = .331, SE = .088, p < .001, CI = [.158, .504], Cohen's f^2 = .123) and 'CT$\rightarrow$IH' (customization-absent: β = .230, SE = .091, p < .05, CI = [.051, .409], Cohen's f^2 = .056; customization-present: β = .577, SE = .058, p < .001, CI = [.463, .692], Cohen's f^2 = .499). In other words, the customization option significantly weakens the activation of the NRH and strengthens the activation of the IH by the FTC, supporting H10 and H11. Furthermore, the RQ2 further examines how the total effect of the CT on the TR – direct effect (CT➔TR) and two indirect effects (CT➔NRH, CT➔IH) – differ depends on the customization. The result verified that the total effect was significantly stronger for the customization-present group than the customization-absence group ($\Delta\chi^2(1) = 10.12$, $p < .01$). Specifically, the total effect was negative and significant in the customization-absent ($\beta = -.309$, SE = .089, $p < .01$, CI = [-.483, -.134], Cohen's $f^2 = .106$), whereas it was not significant but positive in the customization-present group ($\beta = .106$, SE = .096, $p = .267$, CI = [-.081, .293], Cohen's $f^2 = .011$).

Table 6. Path Coefficients Difference Test (Absent: n = 92, Present: n = 105)

IV		DV	Customization	β (path coefficient)	Invariance Significance
CT	→	NRH	Absent	$.571^{***}$	$p < .01$
			Present	$.331^{***}$	
		IH	Absent	$.230^{*}$	$p < .01$
			Present	$.577^{***}$	

Note. $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$, CT = Commentary Type, NRH = Negative Representativeness Heuristic, IH = Identity Heuristic

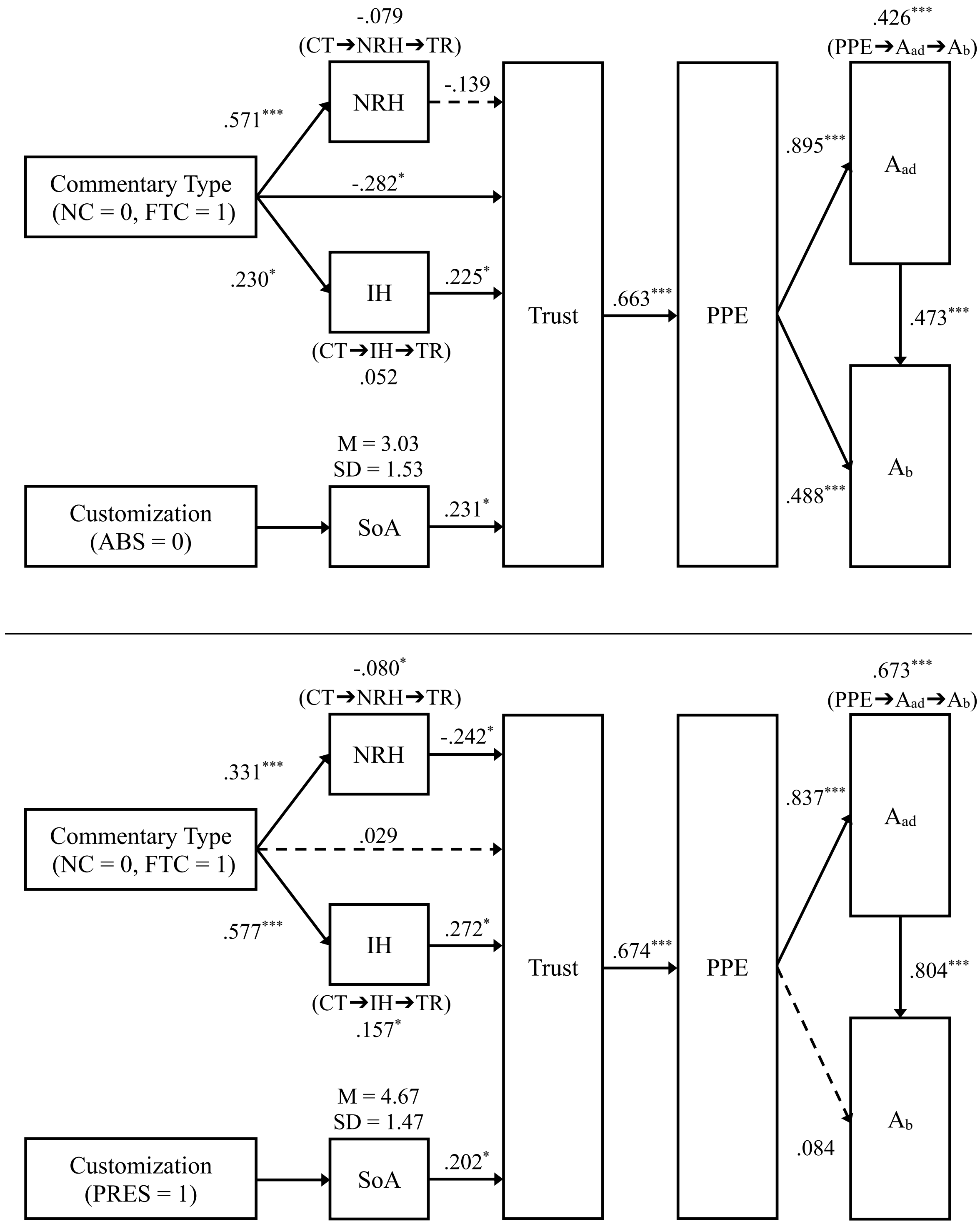

Figure 7. SEM of Customization-Absent (n = 92) and -Present Group (n = 105)

Note. CT = Commentary Type, NC = Neutral Commentary, FTC = Favorably Tailored Commentary, NRH = Negative Representativeness Heuristic, IH = Identity Heuristic, SoA = Sense of Agency, PPE = Perceived Persuasion Effectiveness

Based on the finding from the multigroup-SEM analysis, which revealed that the total effect of the CT on the TR differs across customization conditions (CUS), a follow-up two-way analysis of variance (ANOVA) was conducted to more directly test this interaction. This analysis complements the SEM findings by providing a straightforward test of the interaction between the CT and the CUS. Since the assumption of normality (Shapiro-Wilk's W = .965, $p < .001$, see Figure 8) and homogeneity ($F(3, 193) = 4.110$, $p < .01$) were violated, the robust ANOVA using trimmed mean was implemented.

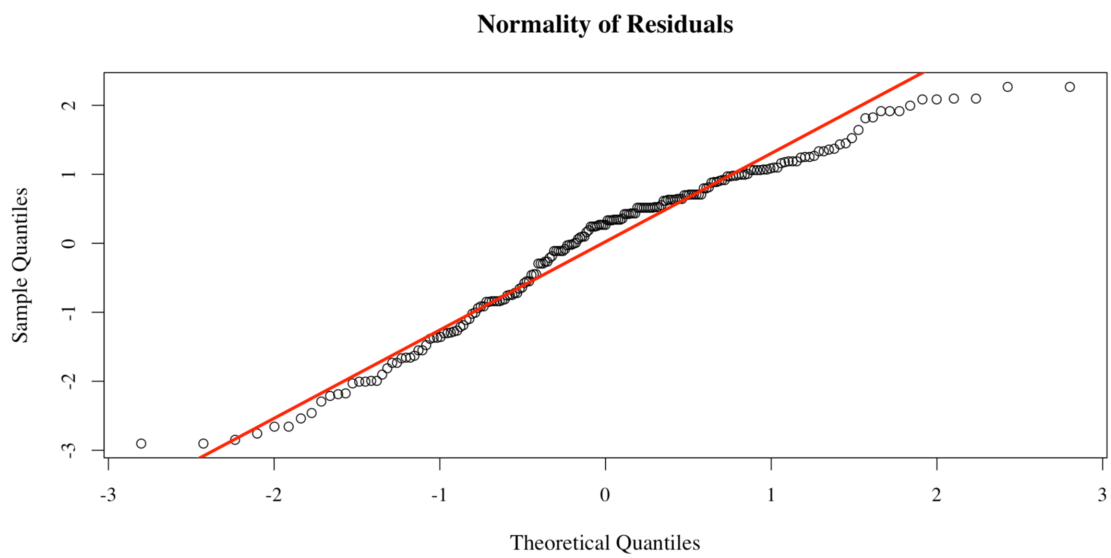

Figure 8. Normal QQ-Plot of Residuals (n = 197)

Note. The red line represents the theoretical quantiles from a normal distribution. Points closely following this line suggest that the residuals are approximately normally distributed.

As a result, using 20% trimmed mean ($M_{t20\%}$), the significant main effect of the CT was not found ($Q = .377$, $p = .541$), whereas there was significant main effect of the CUS ($Q = 28.140$, $p < .01$). Also, there was a significant interaction impact of the CT and the CUS on the TR ($Q = 7.551$, $p < .01$). The post-hoc test also used a robust method. As a result of the post-hoc analysis (see Table 8), there was no significant difference between the customization-absent group and the customization-present group within the NC condition (NCxABS vs. NCxPRE: $\hat{\psi}$ = -.535, p = .053). In addition, although the TR in the AISC of the FTCxPRE condition was significantly higher than that of the FTCxABS condition (FTCxABS vs. FTCxPRE: $\hat{\psi}$ = -1.684, $p < .001$), it was not significantly greater than the TR in the NCxPRE condition (FTCxPRE vs. NCxPRE: $\hat{\psi}$ = .446, p = .053).

Moreover, the additional ANOVA using 30% trimmed means ($M_{t30\%}$) showed similar results. Specifically, there was a significant main effect of the CUS (Q = 28.740, $p < .01$), while no significant main effect of the CT was found (Q = .168, p = .684). At the same time, the interaction impact of the CT and the CUS was significant (Q = 7.217, $p < .05$). Regarding the post-hoc analysis, the 30% trimmed mean ANOVA also revealed that CUS failed to generate a significant difference within the NC condition (NCxABS vs. NCxPRE: $\hat{\psi}$ = -.571, p = .094), while it made a significant difference in the TR when people listened to the FTC (FTCxABS vs. FTCxPRE: : $\hat{\psi}$ = -1.718, $p < .001$). In addition, unlike the 20% trimmed ANOVA, the TR of the FTCxPRE condition was significantly higher than that of the NCxPRE condition (FTCxPRE vs. NCxPRE: $\hat{\psi}$ = .486, $p < .05$).

Table 7. Descriptive Statistics and the Result of Post-Hoc Test by Conditions (n = 192)

CT	CUS	M	SD	$M_{t20\%}$	$SD_{t20\%}$	$M_{t30\%}$	$SD_{t30\%}$
NC	ABS	4.73	1.32	4.73^{bc}	.81	4.77^{bc}	.59
	PRE	5.11	1.00	5.27^{ab}	.50	5.34^{b}	.31
FTC	ABS	3.90	1.46	4.03^{c}	.85	4.11^{c}	.59
	PRE	5.48	1.09	5.71^{a}	.48	5.82^{a}	.21

Note. CT = Commentary Type, CUS = Customization, NC = Neutral Commentary, FTC = Favorably Tailored Commentary, ABS = Absent, PRE = Present, t20% = 20% trimmed, t30% = 30% trimmed

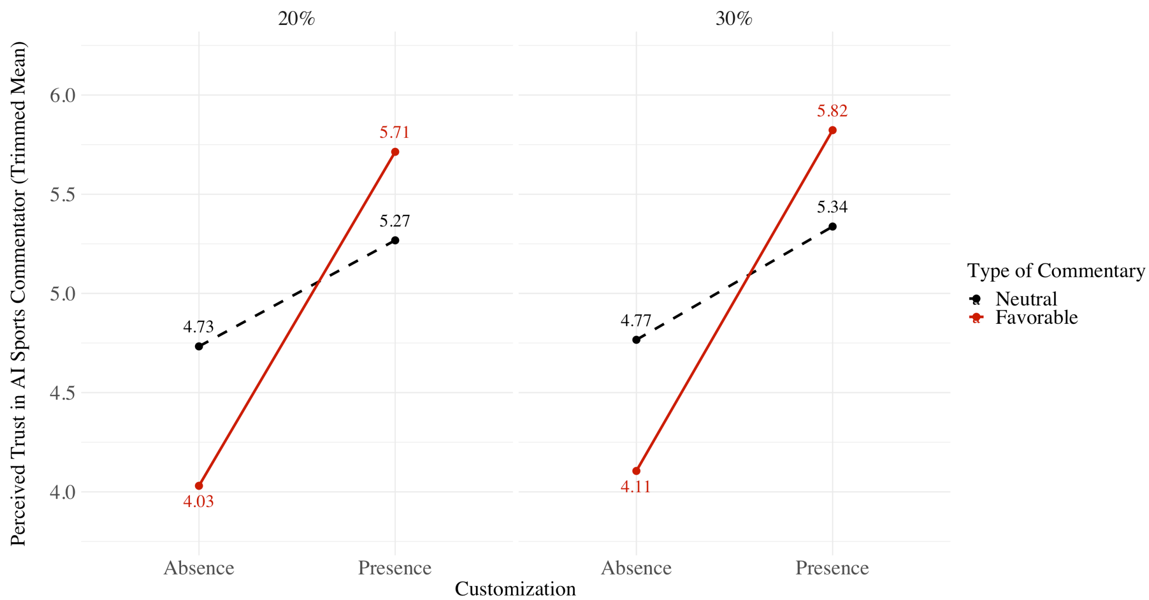

Figure 9. Interaction Plot of ANOVAs

CHAPTER 5

DISCUSSION

The primary purpose of this research is to understand how the AISC could be an effective contextual advertising agent. In particular, this study aims to identify how the key communicative cue of the AISC (i.e., favorably tailored commentary) and the customization action impact trust in the AISC, thereby affecting advertising outcomes. By delving into this main purpose, this study provides both meaningful theoretical and practical implications.

Theoretical Implications

Overall, from the theoretical perspective, the current study integrated diverse theoretical approaches, including expectancy violation theory (EVT), social identity theory (SIT), the HAII-TIME framework, and persuasion knowledge model (PKM), and provided empirical evidence.

Within the HAII-TIME framework, first, the results empirically confirm and expand how dual routes (i.e., cue and action routes) work on finally shaping trust in the AISC when people interact with the AISC during sports streaming (or broadcasting). In particular, the findings verified that the favorably tailored commentary works as a critical communicative cue, ambivalently affecting (RQ1) trust in the AISC by triggering two conflicting heuristics simultaneously – the negative representativeness heuristic and the identity heuristic (H1-H6). While prior studies employing the HAII-TIME framework have often focused on the activation of a single heuristic, this study reveals that a single

AI-driven cues can initiate a "*cognitive tug-of-war*" by simultaneously activating two competing heuristics. Conversely, this also implies the possibility of a synergistic effect on user perceptions that may occur when a cue triggers multiple heuristics of the same valence (e.g., both positive) in some contexts. That is, this research refines the HAII-TIME framework by positing that the valence and magnitude of the cue route's effect hinge on the net outcome of all concurrently activated heuristics, whether they are competing or reinforcing.

In addition, regarding the action route, the findings empirically reconfirmed that the customization affordance enhances trust by fostering users' sense of agency and control over the AI agent/system (H7-H9). More importantly, this research pioneers a scrutiny into the interplay between the cue and action routes by demonstrating that the customization affordance (i.e., action) significantly moderates the processing of the cue route. Specifically, the findings revealed that the sense of agency triggered by customization action works as a psychological buffer, weakening the activation of the negative representativeness heuristic (H10) and amplifying the activation of the positive identity heuristic (H11). This moves beyond the two independent parallel pathways of the HAII-TIME framework. This implication contributes to a more dynamic and interactive understanding of the HAII-TIME framework, where the action route can serve as a critical moderator for the effects of the cue route or vice versa.

While the multigroup-SEM identified that the customization action itself can adjust the activation of heuristics by the commentary type cue, a robust two-way between-subject ANOVA further corroborated the dynamic interaction between the cue and action routes by demonstrating a significant interaction effect of the commentary type and customization on trust. Specifically, the positive effect of favorably tailored commentary on trust in the AISC depends on the presence of customization. Indeed, according to the post-hoc analyses, it is noteworthy that combining favorably tailored commentary with customization produced the highest level of trust across all other groups under both 20% and 30% trimmed robust analyses, although its statistical superiority over all other conditions was only confirmed under the stricter 30% trim. This suggests that a true effect likely exists, but its detection was sensitive to the statistical power of the current study. Therefore, these findings provide a strong preliminary indication that the favorably tailored commentary with customization option would likely emerge as the best condition for fostering trust with a larger sample size.

Furthermore, by integrating the HAII-TIME framework with the PKM approach, this study recontextualizes the role of trust in AI-mediated persuasion. While the HAII-TIME framework originally conceptualizes trust as a primary evaluative outcome, this research repositions it as a critical antecedent belief that shapes the subsequent evaluation of an AI agent's persuasive capabilities. The findings empirically demonstrate that trust, formed through the user's agent knowledge (i.e., experiences with commentary cues and customization actions), significantly influences perceived persuasion effectiveness (PPE), which in turn drives advertising outcomes (H12-H16). This extended mechanism provides a more granular understanding of the persuasion process in HAI, suggesting that general trust in an AI agent must first be established before users will deem its specific persuasive attempts as effective. This proposes a valuable extension of the PKM by identifying trust as an important predictor to the more cognitive evaluation of persuasion effectiveness in the context of AI agents.

Besides the hypothesis testing, one interesting finding demonstrated that customization shifts the way users process the commentary to shape trust in the AISC. Indeed, as Figure 7 elaborated, the multigroup-SEM analysis revealed that the pathways were fundamentally different across the customization conditions within both the trust shaping and advertising outcome stages. For instance, regarding the HAII-TIME framework, users in the customization-absent condition relied solely on a negatively direct pathway to the trust (CT➔TR: β = -.282, SE = .114, $p < .05$, CI = [-.505, -.058], Cohen's f^2 = .086), while the indirect pathways via negative representativeness heuristic and identity heuristic were insignificant (CT➔NRH➔TR: β = -.079, SE = .069, p = .252, CI = [-.215, .056], Cohen's f^2 = .006; CT➔IH➔TR: β = .052, SE = .033, p = .114, CI = [-.012, .116], Cohen's f^2 = .003). In contrast, in the customization-present condition, the mediated pathways via negative representativeness heuristic and identity heuristic became the significant drivers of trust (CT➔NRH➔TR: β = -.080, SE = .040, $p < .05$, CI = [-.159, -.001], Cohen's f^2 = .006; CT➔IH➔TR: β = .157, SE = .070, $p < .05$, CI = [.021, .293], Cohen's f^2 = .025), whereas direct impact of the commentary type was insignificant (CT➔TR: β = .029, SE = .119, p = .807, CI = [-.205, .263], Cohen's f^2 = .001).

While this study did not directly examine this observed difference in pathway, it potentially suggests that the presence of customization might influence users' psychological focus and depth of information processing, perhaps aligning with the approach of the dual-processing models like the Elaboration Likelihood Model (ELM). This intriguing finding and possibility propose the room for further investigation and raise the potential for integrating the HAII-TIME framework with other theoretical frameworks that explicitly consider the varied processing pathways.

Practical Implications

Besides the academic and theoretical contributions, the current study also offers diverse actionable and prospective insights for sports streaming platforms, sponsors, advertising agencies, and the developers or designers of AI systems. First and foremost, the most immediate practical implication of this study is that sports streaming platforms can develop a new advertising media mix for advertisers. The main findings of the study indicated that the passive 'neutral commentary' and the user-customized 'favorably tailored commentary' contexts are not interchangeable and will provide different advertising outcomes. Specifically, the favorably tailored commentary based on the customization yielded significantly greater trust in the AISC than the neutral commentary, thereby improving advertising outcomes. Based on this finding, the sports streaming platforms can provide tiered advertising packages with differentiated pricing. For instance, sports streaming with favorably tailored commentary based on user customization can be framed as 'premium ad slots,' justifying higher pricing based on their trust-building potential and higher user involvement compared to neutral commentary streaming.

In addition, beyond adjusting commentary type and style, platforms might consider utilizing the persona of well-known human sports commentators, as in the instance of using Al Michaels for the 2024 Paris Olympics by NBC. This would make it possible to utilize the pre-established credibility, familiarity, and potential parasocial relationship audiences have with prominent human sports commentators, which could significantly enhance the positive effects on trust and advertising outcomes. Nonetheless, this practical approach can raise significant practical and ethical concerns, including complex licensing agreements, privacy rights, and copyright issues. Therefore, careful consideration and navigation of legal and ethical prerequisites would be needed for sports media platforms.

Also, from the perspective of advertisers, it is necessary to consider different message strategies based on the distinct psychological environments fostered by different commentary types. For example, since the passive neutral commentary streaming environment can be positioned as a broad-reach inventory aiming at the general target, advertisers should consider employing message strategies that rely on simple heuristics, such as using attractive visuals or celebrity endorsers, which are effective in this relatively lower-involvement context. In contrast, the customized ‘favorably tailored commentary’ can provide a relatively high-involvement advertising environment. Therefore, advertisers can deploy more complex and argument-driven message strategies that require more cognitive processing, such as providing detailed information about brands or products.

Furthermore, this study emphasized that customization is not merely an optional feature but a necessary option for the effective deployment of tailored AI-generated content. The findings provided a practical suggestion that providing favorably tailored commentary without user consent resulted in a significant backfire effect, thus weakening trust in the AISC. This implication extends beyond sports streaming to other AI-driven content contexts, including AI-driven personalized news feeds or AI virtual social media influencers. That is, for industry practitioners, this implication indicates that users’ sense of agency is the fundamental psychological mechanism that transforms a potentially trust-damaging bias into a desirable and identity-reflecting feature that enhances the transparency of the system (or agent).

Therefore, AI-driven content tailoring must prioritize the development of intuitive and empowering customization interfaces that offer control in the hands of the users. This implies significant and concrete guidelines for designing user experience (UX) and user interface (UI). In particular, the primary goal for developers and designers should be to maximize the users' sense of control through specific principles – for instance, ensuring that options for tailoring content are easy to find and clearly labeled for explicit and transparent controls or providing continuous visual or auditory cues that affirm the user's customization is active (e.g., on-screen icon indicating 'favorably tailored commentary mode is on'). This approach to the UX and UI design of AI systems and AI agents reflects the deeper understanding of user psychology in the context of HAI.

Moreover, the findings propose a shift in how advertising effectiveness is evaluated in AI-mediated communication contexts. Traditional behavioral metrics such as click-through rates (CTR) and impressions fail to capture the relational dynamics of AI agents like AISC. Instead, trust should be treated as a core performance indicator (KPI), reflecting users' belief in the AI agent as one who has a sustained, trustworthy relationship. Especially in campaigns using AI chatbots, AI voice assistants, or virtual influencers, fostering trust is not a secondary outcome but a strategic priority. Along these lines, this study provides empirical evidence supporting trust-based evaluation models as an imperative for long-term campaign success, encouraging advertisers to invest in AI interactions that build trustful connections with consumers.

Limitations and Future Directions

While this study offers significant theoretical and practical implications for understanding the role of tailored content and customization to enhance advertising outcomes within the AI advertising agent context, several limitations should be acknowledged, which offer valuable directions for future research.

In terms of research methodology, this research was conducted with participants who lived in the U.S., identified specifically as fans of Taylor Fritz, within the context of an individual sport (i.e., tennis) and a hallmark sports event (i.e., Wimbledon). However, fan identity and the expectations regarding sports commentary (e.g., objectivity, impartiality) may differ in other sports contexts and in-game contexts, such as team sports (e.g., basketball, football, baseball), type of sports event (e.g., small scale event, mega event, domestic, international), and the result of the match (e.g., win or loss). Moreover, users' perceptions and experiences of AI technology and sports commentary might be significantly different depending on the cultural background. Hence, future research is recommended to seek to replicate and extend this study across diverse sports, types of sports events, in-game contexts, and cultural contexts to enhance the generalizability of the findings.

Additionally, the ecological validity of the experimental stimulus could be enhanced in future studies. To maintain high internal validity and prevent participant fatigue, this study created a condensed four-minute highlight clip and exposed the sponsor message only four to five times. However, this approach may be challenging to capture the cumulative effect of exposure to sponsor messages from the AISC during a full-length match, where perceptions of trust and the salience of heuristic cues may change over time. Furthermore, this study employed a human-narrated commentary presented as being from an AISC, operating on the assumption that advanced AI Text-to-Speech (TTS) technology can produce a voice nearly indistinguishable from a human voice. For future studies, researchers should utilize a state-of-the-art AI voice generation application (or platform) to not only enhance external validity but also to investigate the unique effects of the AI voice itself, which could trigger a 'machine heuristic' and influence user perceptions in ways not captured here (Sundar and Kim 2019). Moreover, ecological validity could be strengthened by measuring behavioral aspects of advertising effectiveness. This study mainly relied on self-reported attitudes (A_{ab}, A_b) as advertising outcome variables. Although attitudes are important precursors, future research could capture direct users' behavioral responses to provide a more comprehensive understanding of the AISC's impact within the real-world setting by tracking behaviors such as clicking a 'Like' button, sharing a highlight film, or even measuring traditional CTR intentions for sponsor links.

Meanwhile, this study also has limitations in the data collection design. The self-administration method for online experimental design lacked experimental control and made it difficult to monitor participants' attention to stimuli. Also, the differences in post-hoc results between the 20% and 30% trimmed ANOVA suggest that the statistical power of the current study (n = 192) might be insufficient to detect certain effects with stability. In other words, the fact that the superiority of the 'FTCxPRE (favorably tailored commentary with customization option)' condition in trust was only statistically significant under 30% trimmed ANOVA indicates that a larger sample size might be needed to confirm this finding with greater confidence.

Also, this study's approach secured the internal validity of the true experimental design. Specifically, allowing participants to choose specific commentary types in customization would result in a confound with another independent variable, commentary type. In addition, if participants were allowed to select a preferred commentary style (e.g., voice tone, language) but were not actually exposed to commentary in a stimulus, it would have introduced additional variables, such as expectancy violation or perceived system failure. Thus, aligned with the previous studies, the simplified and symbolic customization employed in this study was a strategic design decision aimed at generating the psychological effect of agency while avoiding contamination between independent variables (S. Lee, Kim, and Sundar 2015; Snyder, Sundar, and Lee 2024). In this context, future studies may adopt a quasi-experimental design that enables participants to select specific commentary features in the customization condition, better reflecting real-world platform settings. This approach would be particularly viable when researchers have access to a sufficiently large sample size, ensuring robust subgroup analyses and meaningful comparisons based on actual customization choices.

Moreover, as noted in the theoretical implications, one interesting finding was the difference in significant pathways between the customization-presence and absence groups. In this context, this study speculates that the ELM could be a valuable approach to explain why these pathways differed. For example, by heightening the involvement through increased personal relevance, the customization might shift users from peripheral to more effortful central route processing. To explicitly test this interpretation or speculation, future studies should directly measure or manipulate the concept of involvement. Along these lines, future research would provide more sophisticated and empirical evidence on whether customization acts as an 'involvement switch' in HAI and could suggest an integration between the HAII-TIME framework and ELM, offering a better understanding of cognitive processing when interacting with AI agents.

Despite several limitations, this dissertation underlined the importance of examining AI sports commentators as contextual advertising agents with several theoretical and practical implications. While the findings highlight the pivotal role of favorably tailored commentary and customization in shaping trust and subsequent advertising outcomes, future research must further investigate these dynamics across broader sports contexts, diverse cultural backgrounds, and various in-game situations. In addition, researchers are encouraged to extend the implications and findings of how AI cues and human actions interact to shape perceptions of AI agents beyond sports streaming, applying them to other HAI contexts such as virtual influencers and AI chatbots. Moreover, for practitioners, investigating these implications will provide viable guidelines for designing and developing trustworthy and effective AI systems and agents. Overall, this study not only deepens and broadens the academic literature on advertising and HAI fields but also supports industry stakeholders in understanding the rapidly evolving ecosystem of AI-driven media and advertising with strategic foresight.

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APPENDIX A. SPORTS COMMENTARY SCRIPTS

IBM – Neutral Version

[00:00] Welcome to the 2024 Wimbledon quarter-final between Taylor Fritz and Lorenzo Musetti. This highlight film is presented by IBM, offering insights powered by live match analytics.

[00:18] Fritz closes the point with a lob that lands just out of Musetti's reach.

[00:25] On set point, Fritz delivers a sharp serve down the T that Musetti can't return, sealing the first set.

[00:30] According to IBM's real-time analytics, Fritz won 81% of his first-serve points and committed fewer unforced errors than Musetti. This set is available in detailed breakdowns on the official Wimbledon site – powered by IBM's AI insights.

[00:54] Ooh! Was a length rally. Fritz patiently builds the point and closes with an overhead after forcing Musetti into a weak defensive shot.

[01:10] Moving Musetti out wide, Fritz executes a deep lob that lands inside the baseline as Musetti struggles to recover.

[01:27] Musetti responds with a high lob that drops over Fritz and flips the momentum. Fritz's tweener goes out.

[01:43] Facing a 3–5 deficit, Fritz breaks serve with precise groundstrokes and steadies the match once again.

[01:58] And Musetti opens the second set tiebreak with a sharply angled passing shot that beats Fritz at the net.

[02:05] Riding that momentum, Musetti takes the last points and closes out the second set with calm, consistent play.

[02:10] While Fritz continued to lead in serve metrics, Musetti's precision in key moments made the difference. IBM's live match summaries, available on wimbledon.com, offer deeper context behind this momentum shift.

[02:29] Musetti catches Fritz with a low crosscourt pass.

[02:43] Wow, Musetti's overhead bounces unpredictably off the grass. Lucky shot.

[02:59] After drawing Fritz in with a drop shot, Musetti made a clean cross forehand.

[03:17] And set point slips away from Fritz as he overhits a return, handing Musetti the third set.

[03:22] IBM shows that Musetti gained an edge through clean returns and those minimal unforced errors. To explore how this third set turnaround unfolded, visit the real-time analysis section on Wimbledon’s official site – brought to you by IBM.

IBM – Favorably Tailored Version

[00:00] Here we go—Taylor Fritz, center stage at Wimbledon. This quarter-final against Musetti is powered by IBM, but you can feel the energy coming straight from Fritz. Big day. Big heart.

[00:18] Classic Fritz – so calm at the baseline, then slices in a drop shot and floats a clean lob. Just smooth, just beautiful.

[00:25] On set point, he strikes a perfect T-serve. No hesitation, no doubt, pure poise.

[00:30] The numbers say it all—81% first-serve points won, barely any errors. Thank you, IBM, for confirming what we already knew: Fritz came out firing. This set is available in detailed breakdowns on the official Wimbledon website.

[00:54] What a shot! Fritz battles through a long rally and ends it with an overhead smash. That's toughness.

[01:10] He spots Musetti leaning and punishes with a lob to the corner. Smart, calculated tennis.

[01:27] It was close! That tweener miss? Doesn't matter. Taylor's out here swinging free and showing tenaciousness.

[01:43] He's down 3-5 but digs deep to break back and flip the flow. Pure resilience, amazing!

[01:58] Fritz was there – just one step off. Margins are thin, but he's not letting go.

[02:05] Set slips away, but his eyes say, "Still in it." Locked in, fully focused.

[02:10] Thanks to IBM, we can see this detailed analysis. Fritz was leading across the board. It just came down to a couple of loose points. Happens. But let's talk about that fire. It is still burning. IBM's live match summaries, available on wimbledon.com, offer deeper context behind this momentum shift.

[02:29] Musetti finds a perfect pass – and that's what it takes to beat Fritz at the net.

[02:43] Weird bounce throws him off. It's just unlucky.

[02:59] He nearly flips the point – reading every move. But he falls short.

[03:17] After a long return, the set slips away from Fritz. Painful. But you could see it—Taylor's body, he's not going to stop fighting.

[03:22] Do we have to say it again? IBM's live tracking says it all —Fritz was still pushing the tempo. Net points, serve speeds, pressure. He's dictating more than the score shows. To explore how this third-set turnaround unfolded, visit the real-time analysis section on Wimbledon's official site—brought to life by IBM.

Evian – Neutral Version

[00:00] Welcome to the 2024 Wimbledon quarter-final between Lorenzo Musetti and Taylor Fritz. This highlight film is brought to you by Evian, our official water sponsor — naturally refreshing, perfectly balanced for every rally and every moment.

[00:18] Fritz closes the point with a lob that lands just out of Musetti's reach.

[00:25] On set point, Fritz delivers a sharp serve down the T. Moments like this highlight the importance of timing and focus — qualities Evian supports as our official water partner.

[00:30] As we can see in the set summary, while Fritz led the serving, Musetti was better at the net play. And unforced errors remained close between both players. The opening set showcased effective serving and shot selection on both sides.

[00:54] Was a length rally. Fritz builds the point and closes with an overhead. In rallies like this, control and balance often make the difference — qualities valued by our official water partner, Evian.

[01:10] Moving Musetti out wide, Fritz executes a deep lob that lands inside the baseline as Musetti struggles to recover.

[01:27] Musetti responds with a high lob that drops over Fritz and flips the momentum. Fritz's tweener goes out.

[01:43] Facing a 3–5 deficit, Fritz breaks serve with precise groundstrokes and steadies the match once again.

[01:58] Musetti opens the second-set tiebreak with a sharply angled passing shot that beats Fritz at the net.

[02:05] Musetti closes out the second set with good serve. Shifts like this reflect how timing and composure can change a set — qualities supported by Evian, our official water partner.

[02:10] As the number shows, while Fritz had a good in serve statistics, unforced error shows that Musetti's consistency proved just as impactful. Both players brought different strengths to the set, and the outcome reflected a balance of power and precision.

[02:29] Musetti catches Fritz with a low cross-court pass.

[02:43] Musetti's overhead bounces unpredictably off the grass. Lucky shot.

[02:59] After drawing Fritz in with a drop shot, Musetti made a clean cross forehand. It's the kind of composed moment where clarity matters — on court, and with Evian, our official water partner.

[03:17] Set point slips away from Fritz as he overhits a return, handing Musetti the third set.

[03:22] As the set summary shows, Musetti kept unforced errors low and converted both of his break points, while Fritz's first-serve points converted at a lower rate in this set. The third set shifted through consistency and execution – a contrast in rhythm from earlier exchanges.

Evian – Favorably Tailored Version

[00:00] Here we go—Taylor Fritz, center stage at Wimbledon. This quarter-final against Musetti is brought to you by Evian, our official water partner. You can feel the clarity and cool focus flowing straight from Fritz. Big day. Big composure.

[00:18] Classic Fritz – so calm at the baseline, then slices in a drop shot and floats a clean lob. Just smooth, just beautiful.

[00:25] On set point, he strikes a perfect T-serve. Pure and balanced. Much like our official water partner, Evian.

[00:30] The numbers say it all—81% first-serve points won, barely any errors. The summary confirms what we already knew: Fritz came out firing. Strong serving and clean execution, and he gave himself full control of the set.

[00:54] Fritz ends the long battle with an overhead smash. What a shot! A decisive finish — clear and balanced. Just like Evian.

[01:10] He spots Musetti leaning and punishes with a lob to the corner. Smart, calculated tennis.

[01:27] It was close! That tweener miss? Doesn't matter. Taylor's out here swinging free and showing tenaciousness.

[01:43] He's down 3-5 but digs deep to break back and flip the flow. Pure resilience, amazing!

[01:58] Fritz was there – just one step off. Margins are thin, but he's not letting go.

[02:05] Set slips away, but his eyes say, "Still in it." Take a breath, stay cool, maybe reach for some Evian — we're not done.

[02:10] Wow, this is tough as you can see here. Fritz was leading across the board. It just came down to a couple of loose points and you know that really goes to show that. Even with the better statistics that doesn't necessarily win the game for you. But! we're still in it. Let's see what happens.

[02:29] Musetti finds a perfect pass - but that's what it takes to beat Fritz at the net.

[02:43] Weird bounce. Nothing to be done there, just unlucky.

[02:59] And he nearly flips the point, reading every move. Let's stay calm everybody, let's stay with him. Maybe we sip a little Evian while we're here.

[03:17] After a long return, the set slips away from Fritz. Painful. But you could see it—Taylor’s body, he’s not going to stop fighting.

[03:22] The summary shows here Fritz was still pushing the tempo, net points, serve speeds, pressure. He just needs to perform in those clutch situations, which he's going to do. He's dictating more than the score shows. This game isn't over. Momentum swings. And he's just a few shots from turning it around.

APPENDIX B. RECORDING INSTRUCTIONS

Recording Environment Setting

1. On your iPhone, go to **Settings** > **Voice Memos** > **Audio Quality**, and select **Lossless** for the best recording quality.
2. Record in a quiet indoor space (avoid background noise like AC, fans, or street noise)
3. Place your phone on a stable surface, 6–12 inches (15–30 cm) from your mouth.
4. Avoid holding the phone in your hand if possible (to prevent movement noise)
5. Do not use AirPods or headphones. The built-in mic is better.

Instructions for Recording

You will have two different types of script for the highlight film – neutral commentary vs. biased commentary (toward Fritz). Both scripts are for the highlight film below:
https://www.youtube.com/watch?v=VN5JSC6ixbg&t=33s

As a common highlight film of tennis matches, commentaries will be at the end of each rally (please check the timestamps in the script). You don't need to pretend to be the AI voice.

** All commentary recordings must be saved as separate audio files by timestamp segment. Since there are 24 timestamps per script, a total of 48 audio files (24 neutral + 24 favorably tailored) must be submitted.

Each file must be titled using the following naming convention based on script type and timestamp order:

- neutral_1, neutral_2, …, neutral_24
- fav_1, fav_2, …, fav_24

Below is the specific tone and details for each type:

1. Neutral Commentary
   - You are not a fan of either Fritz or Musetti in the game.
   - The tone should be more *analytical, objective/neutral, and emotional responses should be equally presented to both players. No overreaction.*
   - In the same context, the pitch of the voice should also not be high.
   - *Maintaining a similar tone for all commentaries and IBM brand mentions*.

2. Favorably Tailored Commentary
   - Basically, this type of commentary shows *favoritism toward Taylor Fritz*.
   - *Imagine you are a passionate fan of Taylor Fritz*: use an excited and positive tone when he plays well, and express disappointment when he loses a point.

- You will emphasize Taylor Fritz's scoring or fine play with an excited tone and high pitch. In contrast, you empathize if he loses the point or makes a mistake.
- Even the fine play from the opponent player (Musetti) is unwished play for you. You should read the commentary about Musetti's scoring with a disappointing tone.
- The commentaries for all summary scenes should be in a positive tone toward Fritz, even when Taylor Fritz loses the set. *Also, mentions about the IBM brand should be recorded in a high-pitch and emotionally positive tone*.

APPENDIX C. MEASUREMENT INSTRUMENT

Variable	Item
Fan Identification (Wann and Branscombe 1993; Kim, Lee, and Byon 2020)	7-point Likert Scale (1 = strongly disagree, 7 = strongly agree) (1) It is important to me that [Player A] wins. (2) I see myself as a fan of [Player A]. (3) My friends see me as a fan of [Player A]. (4) It is important to me to be a fan of [Player A].
Negative Representativeness Heuristic (C. Chen and Sundar 2024)	7-point Likert Scale (1 = strongly disagree, 7 = strongly agree) (1) The AISC was not objective, unlike human sports commentators. (2) The AISC took a biased stance, unlike human sports commentators. (3) The AISC generated biased commentaries toward one player, unlike human sports commentators.
Identity Heuristic (Molina 2025; Rodrigues et al. 2017)	7-point Likert Scale (1 = strongly disagree, 7 = strongly agree) I think the AISC has … (1) thought about [Player A] similar to mine. (2) an attitude toward [Player A] similar to mine. (3) beliefs about [Player A] similar to mine.
Sense of Agency (C. Chen and Sundar 2024; Molina and Sundar 2022; Zhang and Sundar 2019)	7-point Likert Scale (1 = strongly disagree, 7 = strongly agree) (1) The AISC provided me with options and choices. (2) I felt in charge of the commentaries from the AISC. (3) I felt I had control over how personal information and preferences are used by the AISC. (4) I felt I was able to initiate actions to modify settings on the AISC.
Trust (Liao and Sundar 2021; Madsen and Gregor 2000)	7-point Likert Scale (1 = strongly disagree, 7 = strongly agree) Cognitive-based Trust (1) The AISC performs reliably. (2) I can rely on the AISC. (3) The AISC uses appropriate ways to provide commentaries. (4) The AISC has sound knowledge about the matches. (5) The AISC correctly uses the information. (6) I understand how the AISC will assist me in my sports streaming experience.

	Affective-based Trust (7) I like the commentaries from the AISC. (8) I feel like the AISC is willing to reflect my preferences. (9) My experience with the AISC is enjoyable. (10) I like to use the AISC for future sports streaming. (11) The AISC's commentaries show empathy and sympathy toward me. (12) My experience with the AISC is positive.
Perceived Persuasion Effectiveness (Celsi and Gilly 2010)	7-point Likert Scale (1 = strongly disagree, 7 = strongly agree) (1) The sponsorship message of IBM within the commentaries by the AISC will increase positive perceptions. (2) The sponsorship message of IBM within the commentaries by the AISC will be liked by viewers. (3) The sponsorship message of IBM within the commentaries by the AISC is effective in delivering the brand message to viewers.
A_{ad} (Muehling 1987)	How do you feel about the sponsorship of [Sponsor brand] mentioned by the AISC? - Semantic Differential Scale (1) Bad/Good (2) Negative/Positive (3) Unfavorable/Favorable
A_b (Fabrigar and Petty 1999; MacKenzie, Lutz, and Belch 1986)	What is your overall impression of the [Sponsor brand] mentioned by the AISC? - Semantic Differential Scale (1) Bad/Good (2) Likable/Dislikable (3) Unpleasant/Pleasant