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How Different Forms of Human–AI Interaction Shape Team Innovation: The Mediating Role of Knowledge Domain Coupling in AI-Enabled New Product Development

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Abstract

Against the backdrop of deep digital transformation and the increasing integration of AI into new product development (NPD), understanding the associations between different forms of human–AI interaction and team innovation has become an important organizational challenge. Grounded in the knowledge-based view and the Stimulus–Organism–Response (SOR) framework, this study investigates the associations between different forms of human–AI interaction and team innovative behavior, and the mediating role of knowledge domain coupling. Drawing on survey data collected from 268 NPD team managers serving as key informants for their respective teams in Chinese manufacturing firms, we examine two distinct forms of human–AI interaction: enhanced human–AI interaction (EHI) and impeded human–AI interaction (IHI). The results show that EHI is positively and significantly associated with both knowledge domain coupling and team innovative behavior, whereas IHI exhibits an inverted U-shaped relationship with knowledge domain coupling and team innovative behavior. Furthermore, complementary knowledge coupling and iterative knowledge coupling jointly serve as the knowledge-processing mechanisms linking human–AI interaction and team innovative behavior. This study contributes to the human–AI interaction and team innovation literature by explaining how different forms of human–AI interaction are associated with team innovation through distinct knowledge-processing mechanisms. The findings also offer practical guidance for managers seeking to dynamically balance different forms of human–AI interaction to foster innovation in AI-enabled NPD teams.

Keywords: human–AI interaction; NPD teams; team innovation behavior; knowledge domain coupling



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1. Introduction

Team success depends on its ability to continuously generate innovative ideas and products, and enhancing innovative behavior has become a core objective for new product development (NPD) teams [1,2]. Innovative behavior refers to the conscious efforts of members to develop, promote, and apply new ideas, products, processes, and procedures that benefit the team [3]. However, there is still insufficient exploration into the innovative behavior of NPD teams and their antecedent mechanisms. The rapid development of AI technology is profoundly reshaping the technological environment of NPD and has become a significant force associated with innovation [4,5]. Although AI excels in data processing,

efficiency enhancement, and predictive analysis, it still lacks uniquely human capabilities such as critical thinking, ethical judgment, and contextual insight [6]. Consequently, effective human–AI interaction is regarded as key to contributing to a continuous, adaptive feedback loop between human capabilities and algorithmic precision, thereby having the potential to be associated with team innovative behavior [7,8]. However, the impact of human–AI interaction is not always positive [9,10]. Over-reliance on AI outputs or excessive AI decision authority may gradually reduce meaningful human participation in decision-making, thereby constraining human judgment and creating coordination challenges within teams. Team members may also struggle to interpret complex algorithmic suggestions or feel that their creative space is limited by the solution scope defined by the AI system [11]. These issues are particularly salient in the highly complex and interconnected NPD innovation process. The aforementioned inconsistent findings highlight an important limitation in current human–AI interaction research. Therefore, it is necessary to examine the complex effects of different forms of human–AI interaction on NPD team innovation behavior (TIB), which is also crucial for understanding the human side of AI integration.

Despite growing interest in this topic, existing research still provides limited insights into the association between different forms of human–AI interaction and TIB in NPD teams. Although recent studies acknowledge the importance of human–AI interaction, AI is frequently treated mainly as a technological tool that is viewed as enhancing human capabilities [12]. Much of the literature focuses on efficiency improvements, data-processing advantages, and decision-support functions, thereby portraying AI primarily as an enabler of innovation outcomes [13–15]. However, how human and AI systems synergize through interaction to support innovative behavior, particularly the mechanisms through which different forms of collaboration may be associated with team-level innovative behavior, remains undertheorized. Second, the existing literature has focused primarily on the individual-level outcomes of human–AI interaction, such as employee creativity, job performance, and mental health [9,16–18]. In the NPD context, human–AI interaction and collaboration are also closely associated with team dynamics and collective innovation processes. Therefore, shifting the level of analysis from the micro individual to the collective team is particularly necessary. Nevertheless, few studies have examined how human–AI interaction is associated with collective innovative behavior at the team level. Third, existing research tends to explain AI-enabled innovation from perspectives such as dynamic capabilities, absorptive capacity, and iterative learning [15,19,20]. While these frameworks illuminate important organizational processes, they pay comparatively less attention to the knowledge integration mechanisms through which AI-enabled interaction reshapes how teams acquire, integrate, and recombine knowledge across domains. Given that NPD innovation depends significantly on knowledge exchange and boundary spanning [1], a more explicit knowledge-based explanation is therefore needed to clarify how human–AI interaction is associated with innovative behavior in NPD teams.

To better understand these issues, this study draws on the knowledge-based view (KBV) of the firm and the SOR framework to explain how human–AI interaction is associated with TIB within NPD teams. The KBV emphasizes that innovation emerges from the creation, integration, and recombination of diverse knowledge resources in organizations. Improving innovative behavior often requires NPD teams to combine expertise from multiple domains, including engineering, environmental management, product design, and manufacturing. Building on this knowledge perspective, the SOR framework provides an analytical structure for explaining how interaction patterns may be related to innovation behavior [21,22]. The SOR framework posits that external stimuli influence behavioral responses through internal cognitive or interpretive processes. Human–AI interaction in NPD teams acts as an external stimulus that may shape internal knowledge integration processes,

thereby being associated with innovation behavior. Within the KBV and SOR framework, knowledge domain coupling (KDC) is proposed as the key mediating mechanism linking human–AI interaction to TIB. KDC refers to the extent to which teams effectively integrate and align heterogeneous knowledge domains—such as engineering, environmental management, design, and manufacturing—during product development [23–25]. human–AI interaction may reshape how such cross-domain knowledge is surfaced, connected, and recombined within teams. By conceptualizing KDC as the “organism” in the SOR framework, this study provides a knowledge-based explanation of how interaction structures between humans and AI systems are associated with innovative behavior at the team level.

Using survey data collected from 268 NPD team managers serving as key informants for their respective NPD teams in Chinese manufacturing firms, this study develops and tests a team-level model linking human–AI interaction to TIB through the mediating role of KDC. This research highlights three main contributions. First, it advances understanding of AI-driven innovation by emphasizing the interactive dynamics between humans and AI rather than viewing AI merely as a technological tool. Specifically, we distinguish between two forms of human–AI interaction: enhanced human–AI interaction (EHI), in which humans retain primary decision authority while AI provides analytical support, and impeded human–AI interaction (IHI), in which AI assumes greater decision authority, thereby limiting human participation primarily to monitoring, validation, and implementation activities. We then examine how each type is associated with TIB. Second, this research shifts the focus of human–AI interaction from the individual level to the team level, reflecting the inherently collective and cross-functional nature of product development. Third, by integrating the KBV and the SOR framework, this study develops a mechanism-based explanation of how different forms of human–AI interaction are associated with TIB through KDC. In doing so, it highlights KDC as the central mechanism linking human–AI interaction and TIB in NPD teams.

2. Theory and Hypotheses

2.1. SOR Theory and the Knowledge-Based View

The SOR framework was originally developed in environmental psychology to explain how environmental cues influence behavioral outcomes through internal psychological processes [21]. Organizational and innovation scholars often employ the SOR framework to examine how technological or environmental stimuli affect cognitive and behavioral responses at individual and organizational levels [26–29]. However, innovation activities—particularly in NPD—are fundamentally collective processes that depend on the coordination and integration of diverse expertise within teams. In such settings, technological systems and interaction patterns can be conceptualized as external stimuli that are associated with differences in internal knowledge-processing structures within teams, thereby being associated with innovation behavior.

To more clearly specify the internal mechanism represented by the “organism” component, this study integrates the KBV of the firm with the SOR framework. The KBV posits that organizations are repositories of heterogeneous knowledge resources and that innovation primarily arises from the integration and recombination of diverse knowledge domains within collaborative settings. From this perspective, effective innovation depends not only on the availability of knowledge but also on the mechanisms through which heterogeneous knowledge is integrated and recombined across domains within teams. Building on this knowledge perspective, we conceptualize KDC as the key organismic mechanism in the SOR framework. KDC reflects the extent to which NPD teams effectively integrate and align heterogeneous knowledge domains—such as engineering, environmental management, design, and manufacturing—during product development. Human–AI interaction may be

associated with differences in how teams access, interpret, and recombine knowledge, as different interaction structures provide varying opportunities for information exploration and cross-domain linkage. Consequently, variations in human–AI interaction are expected to be associated with the degree of KDC within teams, which subsequently is associated with TIB.

Accordingly, this study conceptualizes human–AI interaction as the external stimulus (S), KDC as the internal team-level organismic mechanism (O), and TIB as the response (R). By integrating the SOR framework with the KBV, this study provides a knowledge-based explanation of how human–AI interaction is associated with TIB through knowledge integration processes within NPD teams. Figure 1 provides an overview of the conceptual model.

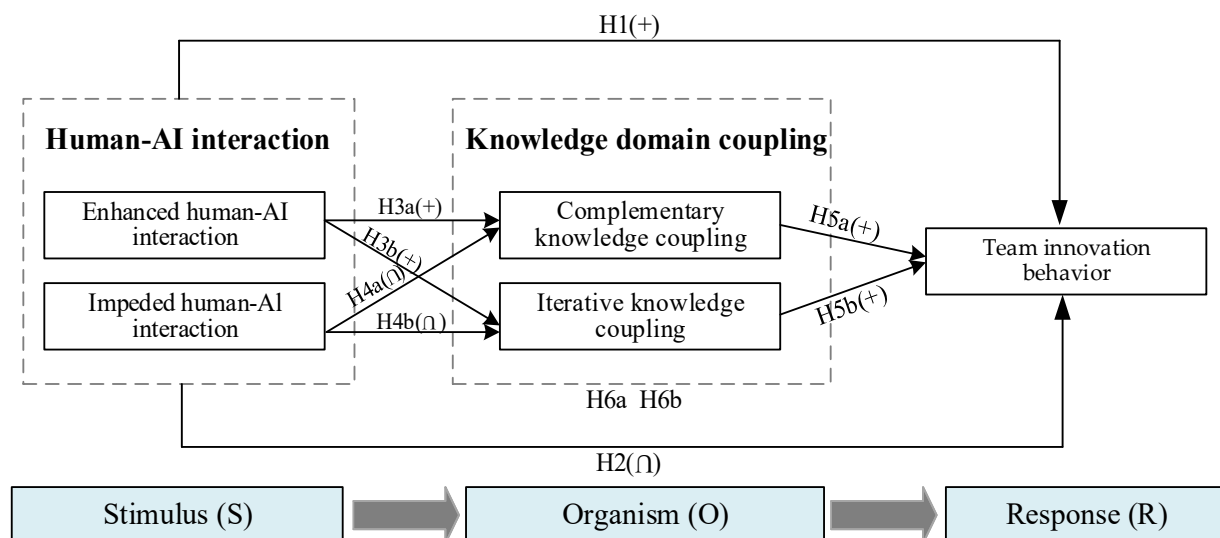


Figure 1. Conceptual model.

2.2. Human–AI Interaction and Team Innovation Behavior

Human–AI interaction refers to the ongoing collaborative engagement between team members and AI systems during the NPD process [7,11]. Prior research suggests that such interaction is not homogeneous; rather, its implications depend on how decision authority and task responsibilities are distributed between humans and AI systems within team workflows [16]. In particular, IHI refers to interaction arrangements in which AI assumes greater decision authority, thereby limiting the extent of meaningful human participation in decision making. Different interaction patterns may therefore be associated with the process through which teams proactively generate, promote, and implement new ideas and products. To clarify the conceptual distinction between EHI and IHI, Table 1 compares the two interaction modes in terms of decision authority, human involvement, knowledge-processing patterns, and their potential implications for innovation outcomes.

As summarized in Table 1, EHI and IHI differ not only in the allocation of decision authority between humans and AI, but also in the cognitive and knowledge-processing mechanisms underlying their associations with team innovation. Specifically, EHI is consistently associated with higher levels of team innovation, as human decision authority is preserved while AI provides information processing and analytical support. IHI, characterized by greater AI decision authority and correspondingly reduced human participation, exhibits a nonlinear association with team innovation. Based on these distinctions, we develop separate hypotheses for the two interaction modes.

Table 1. Comparison of EHI and IHI.

Dimension	EHI	IHI
Decision authority	Humans retain primary decision authority	AI assumes greater decision authority
Primary role of AI	Analytical assistant	Decision-dominant collaborator
Primary role of humans	Interpretation, judgment, final decision	Monitoring, validation, contextual adjustment, with reduced decision-making participation
Human cognitive involvement	Continuously high	Initially stimulated through critical evaluation, but gradually weakened under excessive AI decision authority
Knowledge-processing pattern	Human-led integration supported by AI	AI-generated insights requiring human interpretation and coordination
Innovation mechanism	AI is intended to support human creativity and decision-making	Moderate AI decision authority is associated with greater critical evaluation and cross-domain knowledge integration, whereas excessive AI decision authority is associated with lower human initiative and collaborative learning
Expected relationship with TIB	Positive	Inverted U-shaped

EHI occurs when team members retain primary decision authority while AI systems function as analytical assistants that support human decision-making [16]. In such situations, AI is often used to handle routine or data-intensive tasks while producing analytical insights that assist teams in evaluating alternative solutions [13,30,31]. Instead of substituting human judgment, these systems primarily serve a supportive role by expanding teams' information-processing capacity and offering analytical input during decision-making processes. Team members, however, remain responsible for interpreting AI-generated outputs, integrating information from multiple sources, and ultimately making innovation-related decisions. From the perspective of SOR theory, EHI represents an external stimulus that is associated with internal team states related to cognition and knowledge processing. By potentially reducing the time required for information search and data analysis [32], EHI may be associated with greater work autonomy, enabling teams to allocate more cognitive resources to creative problem-solving, which may be associated with TIB [33,34]. Therefore, we propose the following:

H1. *EHI is positively associated with TIB.*

Consistent with the above definition, IHI arises when AI systems assume greater decision authority in key decision processes, while human team members mainly supervise, verify, or implement AI-generated outputs [16]. Under such interaction arrangements, algorithmic recommendations often play a central role in shaping design decisions, problem-solving approaches, and development priorities. Although greater AI decision authority may be associated with higher analytical efficiency and faster analytical activities, it may also be associated with changes in how team members engage with knowledge during innovation processes [35]. From the perspective of the SOR framework, external stimuli affect outcomes by shaping internal team states. When AI assumes a moderate level of decision authority, algorithmic recommendations still require human interpretation, contextual judgment, and cross-functional coordination. As a result, team members are more likely to engage in critical evaluation of AI-generated outputs, reconcile them with domain expertise, and collaboratively refine potential solutions [36]. Such cognitive engagement may be associated with greater cross-domain knowledge integration, broader exploration of alter-

native solutions, and conditions conducive to TIB [7]. In other words, moderate AI decision authority may complement rather than substitute human cognition, allowing AI-generated insights and human expertise to be jointly integrated during innovation activities.

However, as AI decision authority continues to increase, this positive association may weaken. Excessive reliance on AI-generated recommendations may be associated with reduced human discretion, weaker independent judgment, and less proactive knowledge exploration [37,38]. Team members may become increasingly dependent on algorithmic outputs rather than actively questioning, refining, or extending them. Consequently, opportunities for collaborative learning and creative problem solving may be associated with lower levels of TIB [39]. Taken together, these arguments suggest that the relationship between IHI and TIB may be nonlinear and contingent on the level of AI decision authority. Moderate levels of AI decision authority are associated with higher levels of critical evaluation and knowledge integration, whereas excessive AI decision authority is associated with lower levels of human initiative and collaborative learning, resulting in an inverted U-shaped relationship between IHI and TIB. Therefore, we propose the following:

H2. *There is an inverted U-shaped relationship between IHI and TIB.*

2.3. Human–AI Interaction and Knowledge Domain Coupling

KDC refers to the extent to which NPD teams integrate and align heterogeneous knowledge domains during the product development process [25]. TIB requires the coordination of diverse expertise. Following Chen et al. [25], KDC can be conceptualized as consisting of two complementary forms. Complementary knowledge coupling (CKC) refers to the integration of knowledge that originates from different organizations or domains and provides complementary expertise for problem-solving. Another form, iterative knowledge coupling (IKC) refers to the refinement and recombination of knowledge that shares similar domains or technological foundations with a team's existing expertise.

From the perspective of SOR theory, human–AI interaction structures function as external stimuli that may be associated with internal cognitive and knowledge states of teams (the organism), thereby being associated with how knowledge is integrated across domains. In particular, different distributions of decision authority between humans and AI systems may be associated with how teams coordinate expertise and recombine knowledge during product development [35].

First, EHI is associated with CKC. When human team members retain primary decision authority while AI systems provide analytical assistance, teams can leverage AI-generated insights without relinquishing human interpretive control [39]. In such interaction structures, AI tools may help identify potential external partners, analyze information from multiple knowledge sources, and process large volumes of technical and market data related to product development. Because human members remain responsible for interpreting these insights and coordinating collaborative activities, they actively engage with external partners to acquire complementary expertise and specialized knowledge. Through such collaboration, NPD teams are able to combine externally sourced knowledge with their internal capabilities, thereby enriching their existing knowledge base [40]. In addition, AI-supported analysis may facilitate the organization of heterogeneous information obtained from different partner firms, making it easier for teams to recognize complementarities across knowledge sources. Through these mechanisms, EHI may support the acquisition and integration of complementary external knowledge, which is associated with CKC [41].

Second, EHI is associated with IKC. During later stages of product development, teams frequently refine existing knowledge by incorporating external knowledge that shares similar technological foundations or expertise [5]. AI systems may support this process by rapidly processing technical information, analyzing experimental results, and generating

analytical feedback that informs incremental improvements in product solutions. Because human team members retain decision authority, they actively interpret AI-generated insights and evaluate how newly obtained knowledge relates to their prior expertise. When external knowledge shares similar structures or technological domains with the team's existing knowledge base, it can be more easily understood, matched, and integrated into ongoing development activities. Through repeated cycles of interpretation, evaluation, and refinement, teams gradually update and improve their knowledge structures [31]. In this way, AI may expand the information available to the team while human members contextualize and incorporate these insights into their existing knowledge base, which may contribute to IKC. Therefore, we propose the following:

H3a. *EHI is positively associated with CKC.*

H3b. *EHI is positively associated with IKC.*

In contrast, IHI occurs when AI systems assume greater decision authority in key tasks while human team members primarily monitor, validate, or implement AI-generated outputs. Under such interaction structures, algorithmic recommendations and AI-generated solutions play a dominant role in guiding design choices and development priorities. Although AI-led decision processes may increase analytical efficiency, they also may reshape how human members engage in knowledge integration activities within the team.

First, the relationship between IHI and CKC may be nonlinear. Moderate levels of AI decision authority may be associated with productive cognitive engagement and cross-functional coordination within NPD teams. When AI systems provide recommendations that require human monitoring and contextual interpretation, team members are often prompted to critically evaluate algorithmic outputs and reconcile them with their own domain-specific knowledge [7]. Such cognitively stimulating interactions may be associated with deeper cross-domain discussion among functional specialists. At the same time, AI-generated design alternatives may broaden the search space for potential solutions by introducing diverse analytical insights and technical possibilities. This expanded exploration may enable team members from different domains to identify complementarities among their expertise and coordinate around AI-generated solutions, which may be associated with the alignment and coordination of heterogeneous knowledge domains and CKC [42]. When AI systems assume a high level of decision authority, the dynamics of human–AI interaction may change in ways that may weaken knowledge coordination within NPD teams. Excessively high AI decision authority may lead to automation bias, meaning that team members may rely excessively on algorithmic outputs and reduce their critical assessment of AI-generated recommendations. As a result, human participation in cross-functional communication and collaborative interpretation of design choices may gradually decline. Lower levels of cognitive involvement may be associated with weaker coordination among specialists and reduced alignment of complementary expertise across domains. Under such conditions, the integration of heterogeneous knowledge resources becomes more challenging, which may be associated with lower levels of CKC.

Second, the relationship between IHI and IKC may be nonlinear. When AI systems hold a moderate level of decision authority, human–AI interaction can be associated with iterative learning and collective interpretation during the innovation process. In situations where AI-generated outputs require monitoring, evaluation, and contextual adjustment, team members often engage in repeated cycles of discussion, feedback interpretation, and solution refinement [43]. These interactions may be associated with teams reconsidering algorithmic suggestions and gradually refining their understanding of technical information, which supports the continuous recombination and improvement of existing knowledge

structures. In addition, generative AI systems may generate diverse analytical insights and alternative design options, enabling teams to explore a wider range of technological knowledge. Such iterative exploration may be associated with ongoing recombination of expertise across domains and IKC during product development. However, when AI systems assume excessive decision authority, human participation in these iterative learning cycles may decline. Overreliance on algorithmic outputs may reduce team members' motivation to critically examine or refine AI-generated solutions. As a result, opportunities for cross-domain dialogue and collaborative problem solving may diminish. Reduced human engagement may be associated with disruptions in the iterative learning processes through which teams continuously recombine knowledge throughout the development cycle [44]. Consequently, excessive AI decision authority may be associated with lower levels of IKC. Therefore, we propose the following:

H4a. *There is an inverted U-shaped relationship between IHI and CKC.*

H4b. *There is an inverted U-shaped relationship between IHI and IKC.*

2.4. Knowledge Domain Coupling and Team Innovation Behavior

According to the SOR framework, internal team-level knowledge states translate external stimuli (human–AI interaction) into innovation outcomes. Within this context, the association between human–AI interaction and TIB may operate through KDC. KDC comprises CKC and IKC [25], two forms of team-level knowledge integration processes that may be associated with TIB.

First, CKC and TIB. CKC emphasizes the initial alignment and integration of heterogeneous knowledge from diverse domains, such as engineering, design, manufacturing, and environmental management [25]. In practice, CKC manifests when NPD teams obtain new knowledge from partner firms, acquire partners' specialized experience and skills, integrate partners' methods to solve practical problems, and leverage complementary knowledge resources [45]. Through these activities, teams may identify complementarities between technical and functional knowledge, reduce knowledge silos, and clarify cross-functional dependencies. This form of coordinated knowledge integration may be associated with enhanced team effectiveness in generating innovative ideas, developing solutions, and optimizing implementation, which may be associated with innovative behavior.

Second, IKC and TIB. IKC captures the repeated, cyclical integration and refinement of knowledge throughout the NPD process. As reflected in our measurement items, IKC is evident when NPD teams build upon partners' similar knowledge and skills, align knowledge structures, iteratively integrate newly acquired knowledge, and continuously refine their knowledge base [46]. These activities may be associated with adaptive learning, iterative refinement of design solutions, anticipation of lifecycle challenges, and incorporation of emerging environmental standards. In contrast to CKC, which mainly concerns the initial integration of complementary knowledge, IKC reflects the ongoing refinement of knowledge during the development process. Through repeated cycles of knowledge recombination, feedback interpretation, and solution adjustment, teams may gradually improve their understanding of technical problems and development requirements. This iterative process may be associated with continuous updating of team knowledge structures and may be associated with the generation of innovative product ideas and solutions [25,47]. Therefore, we propose the following:

H5a. *CKC is positively associated with TIB.*

H5b. *IKC is positively associated with TIB.*

2.5. The Mediating Role of Knowledge Domain Coupling

According to the SOR framework, external technological stimuli are associated with behavioral responses through changes in internal cognitive and knowledge-processing states. Taken together, the theoretical relationships proposed in H3–H5 can be integrated into an overall mediation framework in which CKC and IKC represent the knowledge-processing mechanisms linking human–AI interaction and TIB. Specifically, human–AI interaction is associated with teams’ ability to acquire, integrate, and iteratively refine heterogeneous knowledge, which subsequently is associated with TIB. Accordingly, H6a and H6b are not intended as independent theoretical propositions but rather summarize the overall association mechanism implied by the relationships specified in H3–H5. Therefore, we propose the following:

H6a. *CKC plays a mediating role in the association between human–AI interaction and TIB.*

H6b. *IKC plays a mediating role in the association between human–AI interaction and TIB.*

3. Methods

3.1. Sampling and Data Collection

Data were collected through a survey of NPD team managers serving as key informants for NPD teams in manufacturing firms in China. The study focused on firms actively engaged in product development. Respondents were NPD team managers (including team leaders), who served as key informants for their respective teams. NPD team managers were selected because they are closely involved in coordinating cross-functional collaboration, overseeing AI-supported task allocation, and evaluating overall team innovation outcomes. Compared with individual team members, they are generally regarded in prior NPD research as being better positioned to provide holistic assessments of team-level processes, including human–AI interaction, knowledge integration, and team innovative behavior. Therefore, the key-informant approach commonly used in NPD and innovation research was adopted in this study. This key-informant approach has been widely adopted and empirically validated in prior NPD and innovation management research [48]. As only one knowledgeable informant was surveyed per team, the data represent key-informant evaluations of team characteristics rather than aggregated multi-member responses. Accordingly, the unit of analysis is the NPD team, while the unit of observation is the NPD team manager.

The measurement items used in this study were adapted from previously validated scales and adjusted to fit the context of NPD teams and human–AI interaction. Because the original scales were developed in English, a translation and back-translation procedure was carried out to ensure semantic consistency in the Chinese questionnaire.

A pilot test involving several experienced NPD team managers was conducted before the main survey to assess the clarity of the questionnaire. Respondents were asked to review the questionnaire and indicate whether the items were understandable, relevant, and representative of practices in NPD teams. Based on their feedback, minor wording revisions were made to improve clarity and contextual suitability.

Data collection took place between October 2025 and January 2026 through both online and offline surveys. To reduce common method bias (CMB), respondents were informed that the survey was anonymous, that there were no right or wrong answers, and that all responses would be used solely for academic research. They were also encouraged to answer honestly based on their team’s actual practices. A total of 335 NPD team managers were initially contacted through industry associations, professional networks, and referrals from participating firms. After removing incomplete or inconsistent questionnaires,

268 valid responses remained, representing an effective response rate of about 80%. The final sample comprises 268 key-informant evaluations, each representing one NPD team, provided by NPD team managers from firms of different sizes, product categories, and levels of digitalization, providing sufficient variation for empirical analysis. Descriptive information about the participating teams is reported in Table 2.

Table 2. Descriptive Statistics of NPD Team Sample (N = 268).

Characteristic	Item	N	%
Team experience (years)	1–5	72	26.9
	6–10	123	45.9
	More than 10	73	27.2
Team size (number of members)	Less than 5	11	4.1
	6–10	28	10.4
	11–15	48	17.9
	16–20	115	42.9
	More than 20	66	24.6
Manufacturing sector	Consumer electronics	74	27.6
	Industrial equipment	63	23.5
	Household appliances	81	30.2
	Others	50	18.7
Technological level	High-tech	189	70.5
	Non-high-tech	79	29.5

3.2. Measures

The questionnaire employed a seven-point Likert scale (see Appendix A). All adapted constructs were measured from the team perspective, with NPD team managers serving as key informants to evaluate collective team characteristics. Accordingly, all responses reflect managers' assessments of team-level characteristics rather than aggregated perceptions obtained from multiple team members.

Human–AI interaction (HI): HI was adapted from Li et al. [16], which originally measured human–AI interaction at the individual level. Following prior team-level research, all items were revised using a referent-shift approach by replacing individual-focused wording (e.g., “I”) with team-oriented wording (e.g., “Our NPD team”), so that managers evaluated the collective characteristics of their teams rather than their own individual experiences. Following Li et al. [16], HI was further divided into two distinct dimensions, EHI and IHI, each measured with four items.

Team innovation behavior (TIB): TIB was measured using established scales from Monnens et al. [3], comprising 4 items. The scale captures the extent to which NPD teams proactively introduce and apply new ideas, products, processes, and procedures. To align with the specific context of NPD teams, the wording of some items was appropriately adapted. Likewise, the items were phrased from the team perspective so that managers evaluated the innovative behavior of the NPD team as a whole rather than their own individual innovative behavior.

Knowledge Domain Coupling (KDC): The KDC scale was adapted from Chen et al. [25], originally designed for R&D teams. Items were revised to match the context of NPD teams, and the construct was conceptualized with two complementary dimensions: **CKC** and **IKC**, each measured with 6 items. CKC captures the initial alignment and integration of heterogeneous knowledge from diverse domains, while IKC reflects the repeated, cyclical recombination of knowledge throughout the NPD process. Likewise, the wording of all items was adapted to capture knowledge integration processes at the collective team level rather than individual knowledge activities.

Control variables: Following prior studies [48], four control variables were included: team experience, team size, manufacturing sector, and technological level.

3.3. Non-Response Bias and Common Method Bias

All statistical analyses were conducted using IBM SPSS Statistics 22.0 (IBM Corp., Armonk, NY, USA) and IBM SPSS Amos 24.0 (IBM Corp., Armonk, NY, USA).

3.3.1. Non-Response Bias

To assess the potential influence of non-response bias, two complementary approaches were employed.

First, the final sample was compared with benchmark information on NPD teams in manufacturing contexts reported in industry surveys (e.g., manufacturing and innovation reports published by consulting firms and industry organizations) and prior empirical studies on manufacturing and new product development. The participating NPD teams exhibited substantial heterogeneity in terms of team size, team experience, manufacturing sector, and technological level. These characteristics were broadly consistent with those reported in prior empirical studies and industry reports, suggesting that the sample is reasonably representative of the target population.

Second, following Armstrong and Overton (1977) [49], an early–late respondent analysis was conducted as a statistical test of non-response bias. Early respondents were defined as those who completed the survey during the initial stage of data collection, whereas late respondents were those who responded after follow-up reminders. Independent-samples *t*-tests were performed to compare the key constructs between the two groups. As reported in Table 3, no statistically significant differences were observed between early and late respondents across any of the focal constructs (all $p > 0.05$), indicating that non-response bias is unlikely to threaten the validity of the findings.

Table 3. Early–late response comparison.

Variable	Early (n = 134)	Late (n = 134)	t	p
EHI	4.560	4.460	0.610	0.540
IHI	3.810	3.740	0.280	0.780
CKC	4.390	4.310	0.410	0.680
IKC	4.210	4.180	0.160	0.870
TIB	4.240	4.180	0.350	0.720

3.3.2. Common Method Bias

Because all variables were collected from a single knowledgeable informant for each NPD team, both procedural and statistical remedies were adopted to minimize the potential influence of CMB.

Procedurally, respondent anonymity was guaranteed, participation was voluntary, and respondents were informed that there were no right or wrong answers. They were also encouraged to provide objective evaluations of their teams, thereby helping reduce evaluation apprehension and social desirability bias.

Statistically, two complementary diagnostic approaches were employed. First, Harman’s single-factor test was conducted using exploratory factor analysis. The results show that five factors with eigenvalues greater than one were extracted, jointly accounting for 68.24% of the total variance. The first unrotated factor explained only 26.35% of the total variance, well below the commonly adopted threshold of 50%, suggesting that no single factor accounted for the majority of the covariance among the measures.

Second, an unmeasured latent method factor (ULMF) was incorporated into the confirmatory factor analysis (CFA) to further examine the potential influence of common method variance. As shown in Table 4, the inclusion of the latent method factor resulted in only negligible improvements in model fit ($\Delta\text{CFI} = 0.006$; $\Delta\text{TLI} = 0.002$; $\Delta\text{IFI} = 0.001$). In addition, the standardized loadings on the latent method factor were uniformly small (ranging from 0.044 to 0.071) relative to the substantive trait factor loadings (see Table 5), suggesting that the diagnostic tests did not indicate substantial common method variance in the present data. Taken together, these procedural and statistical diagnostics suggest that CMB is unlikely to be a major concern in the present study.

Table 4. Result of the unmeasured latent method factor test.

Model	χ^2	df	χ^2/df	CFI	TLI	IFI	ΔCFI	ΔTLI	ΔIFI
Five-factor model	865.725	485	1.785	0.964	0.952	0.965	-	-	-
Model including the five factors and the method factor	837.425	475	1.763	0.970	0.954	0.966	0.006	0.002	0.001

Table 5. Standardized Trait Factor Loadings and Method Factor Loadings (ULMF Test).

Item	Trait Loading	Method Loading
EH11	0.782	0.061
EH12	0.716	0.044
EH13	0.766	0.057
EH14	0.775	0.071
IH11	0.861	0.052
IH12	0.827	0.049
IH13	0.844	0.058
IH14	0.859	0.055
CKC1	0.764	0.063
CKC2	0.844	0.047
CKC3	0.751	0.060
CKC4	0.805	0.051
CKC5	0.800	0.046
CKC6	0.811	0.056
IKC1	0.792	0.054
IKC2	0.777	0.059
IKC3	0.817	0.048
IKC4	0.810	0.050
IKC5	0.813	0.053
IKC6	0.804	0.045
TIB1	0.814	0.062
TIB2	0.781	0.057
TIB3	0.796	0.049
TIB4	0.749	0.065

4. Results

4.1. Reliability and Validity

First, Cronbach's alpha (CA) and composite reliability (CR) were used to assess internal consistency. As shown in Table 6, all CA and CR values exceeded the recommended threshold of 0.70, indicating satisfactory reliability. Second, the validity of the measurement model was evaluated using confirmatory factor analysis (CFA). The results indicate a good model fit ($\chi^2/\text{df} = 1.785$, CFI = 0.964, TLI = 0.952, IFI = 0.965), suggesting that the proposed measurement model adequately fits the data. Convergent validity was assessed based on average variance extracted (AVE). As reported in Table 6, all AVE values exceeded the recommended threshold of 0.50, and all standardized factor loadings were greater than 0.70, providing evidence of satisfactory convergent validity. Discriminant validity was examined

using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). As shown in Tables 7 and 8, the square roots of the AVE values exceeded the corresponding inter-construct correlations, and all HTMT values were below the recommended threshold of 0.85 [49], confirming adequate discriminant validity. Finally, all variance inflation factor (VIF) values were well below the recommended threshold of 10, indicating that multicollinearity was not a concern in the regression analyses.

Table 6. Reliability and convergent validity.

Variables	Measurement Items	Factor Loadings	Cronbach's Alpha	AVE	CR
EHI	EHI1	0.782	0.904	0.578	0.845
	EHI2	0.716			
	EHI3	0.766			
	EHI4	0.775			
IHI	IHI1	0.861	0.892	0.719	0.911
	IHI2	0.827			
	IHI3	0.844			
	IHI4	0.859			
CKC	CKC1	0.764	0.898	0.634	0.912
	CKC2	0.844			
	CKC3	0.751			
	CKC4	0.805			
	CKC5	0.800			
	CKC6	0.811			
IKC	IKC1	0.792	0.901	0.644	0.915
	IKC2	0.777			
	IKC3	0.817			
	IKC4	0.810			
	IKC5	0.813			
	IKC6	0.804			
TIB	TIB1	0.814	0.874	0.667	0.922
	TIB2	0.781			
	TIB3	0.796			
	TIB4	0.749			

Table 7. Descriptive statistics and discriminant validity.

Variables	1	2	3	4	5
1. EHI	0.760				
2. IHI	0.228 ***	0.848			
3. CKC	0.537 ***	0.301 ***	0.796		
4. IKC	0.587 ***	0.244 ***	0.546 ***	0.803	
5. TIB	0.513 ***	0.283 ***	0.502 ***	0.580 ***	0.817
M	4.511	3.774	4.354	4.193	4.213
SD	1.662	1.849	1.599	1.634	1.664
VIF	2.003	1.130	1.925	1.890	1.696

Notes: Diagonal entries (in bold) are the square root of the AVE (average variances extracted). Entries below the diagonal are correlations. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 8. HTMT of correlations.

Variables	1	2	3	4	5
1. EHI	-				
2. IHI	0.254	-			
3. CKC	0.618	0.336	-		
4. IKC	0.651	0.272	0.608	-	
5. TIB	0.530	0.331	0.531	0.631	-

4.2. Hypothesis Tests

4.2.1. Testing Direct Effects

As shown in Table 9, first, EHI is positively and significantly associated with TIB (M1, $\beta = 0.516$, $p < 0.001$), supporting **H1**. The standardized coefficient ($\beta = 0.516$) suggests that the positive association between EHI and TIB is not only statistically significant but also practically meaningful, indicating that higher levels of EHI are associated with higher levels of TIB. In Model 4, the linear term of IHI has a positive and significant coefficient with TIB ($\beta = 2.881$, $p < 0.001$), while the squared term of IHI has a negative and significant coefficient ($\beta = -0.349$, $p < 0.001$). These results provide initial evidence for **H2** but are not sufficient to establish an inverted U-shaped relationship [50]. To reduce potential multicollinearity between the linear and quadratic terms, IHI was mean-centered prior to the creation of the squared term (IHI^2). In addition, the variance inflation factor (VIF) statistics reported in Table 6 indicate that multicollinearity is not a concern in the regression models. Following Haans et al. (2016) [51], two additional conditions must be satisfied to establish an inverted U-shaped relationship. First, the slope below the inflection point (i.e., the left side of the curve) must be positive and significant, while the slope above the inflection point (i.e., the right side of the curve) must be negative and significant. Second, the inflection point must lie within the observed range of the independent variable. To test these conditions, we conducted the U-test procedure in Stata 16.0 [52] and calculated the slopes of the tangent lines at the lower and upper bounds of IHI (see Table 11). The results show that the slope at the lower bound is significantly positive (2.183, $p < 0.001$), whereas the slope at the upper bound is significantly negative (-2.005 , $p < 0.001$). The estimated inflection point is 4.128, which lies within the observed range of IHI [1,7]. Given that IHI was measured on a seven-point Likert scale, the estimated turning point of 4.128 suggests that the highest observed level of TIB was associated with a moderate-to-high level of IHI in the present sample. Beyond this point, further increases in AI decision authority are associated with lower levels of TIB, suggesting that managers should avoid excessive restrictions on human participation in AI-assisted decision making. To further ensure robustness of the curvilinear specification, we re-estimated the model using alternative specifications (e.g., non-centered quadratic term and bootstrapped standard errors), and the inverted U-shaped relationship remained consistent in both direction and significance. These findings confirm that the relationship between IHI and TIB follows an inverted U-shaped pattern. As illustrated in Figure 2, TIB increases as IHI increases up to the turning point, after which higher levels of IHI are associated with lower levels of TIB. Therefore, **H2** is supported.

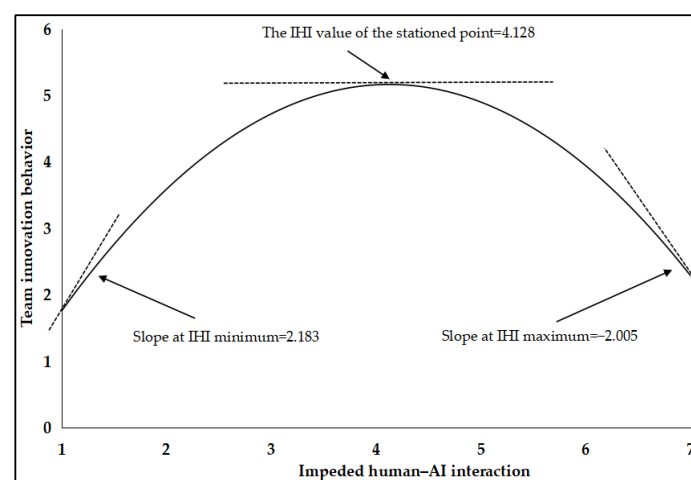


Figure 2. Inverted U-shaped relationship between IHI and TIB.

Table 9. Regression results for TIB.

Variables	TIB				
	M1	M2	M3	M4	M5
Control variables					
Team experience	0.054 (0.697)	0.046 (0.639)	0.046 (0.656)	0.103 (1.468)	0.078 (1.179)
Team size	0.074 (0.935)	0.070 (0.959)	0.079 (1.094)	−0.019 (−0.271)	0.017 (0.257)
Manufacturing sector	0.282 (1.498)	0.133 (0.765)	0.133 (0.773)	0.209 (1.226)	0.102 (0.634)
Technological level	−0.243 (−1.312)	−0.211 (−1.235)	−0.224 (−1.326)	−0.106 (−0.630)	−0.145 (−0.914)
Independent variable					
EHI	0.516 *** (9.783)		0.183 ** (2.754)		
IHI				2.881 *** (12.817)	1.915 *** (6.867)
IHI ²				−0.349 *** (−11.925)	−0.232 *** (−6.615)
Mediator variables					
CKC		0.291 *** (4.798)	0.206 ** (3.064)		0.187 ** (3.374)
IKC		0.427 *** (7.183)	0.362 *** (5.737)		0.302 *** (5.247)
R ²	0.284	0.396	0.413	0.413	0.491
Adjusted R ²	0.271	0.382	0.397	0.403	0.475
F value	20.815 ***	28.491 ***	26.121 ***	31.069 ***	31.226 ***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

4.2.2. Testing Mediation Effects

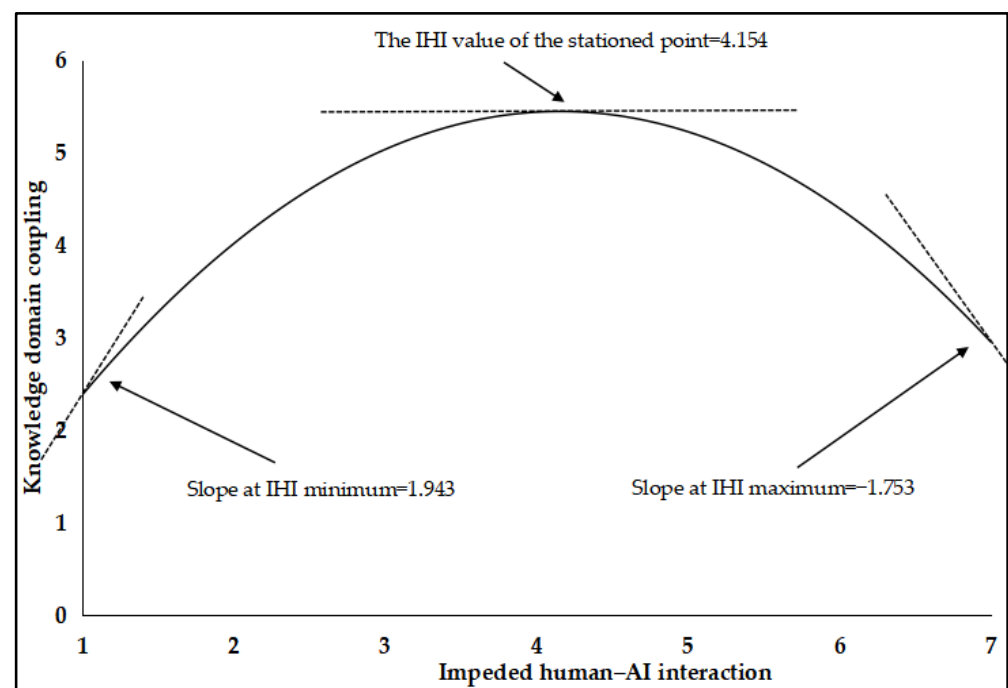
First, EHI is positively and significantly associated with KDC and its two dimensions. As shown in Table 10, EHI is positively and significantly associated with overall KDC (M6, $\beta = 0.589$, $p < 0.001$), CKC (M8, $\beta = 0.605$, $p < 0.001$), and IKC (M10, $\beta = 0.574$, $p < 0.001$), thereby supporting *H3a* and *H3b*. Second, the regression coefficient of the linear term of IHI on KDC is positive and significant (M7, $\beta = 2.559$, $p < 0.001$; M9, $\beta = 2.692$, $p < 0.001$; M11, $\beta = 2.426$, $p < 0.001$). Furthermore, the squared term of IHI is negative and significant (M7, $\beta = -0.308$, $p < 0.001$; M9, $\beta = -0.322$, $p < 0.001$; M11, $\beta = -0.293$, $p < 0.001$). These findings provide preliminary support for *H4a* and *H4b* but are not sufficient to establish a curvilinear relationship. All curvilinear terms were constructed using mean-centered variables to mitigate multicollinearity concerns. Following the same procedure as in Section 4.2.1, we computed the slopes of the tangent lines at the lower and upper bounds of IHI (see Table 11). The lower-bound slope is positive and significant (1.943, $p < 0.001$), whereas the upper-bound slope is negative and significant (−1.753, $p < 0.001$). The estimated inflection point is 4.154, which lies within the observed range of IHI [1,7]. This finding suggests that the highest observed level of KDC was associated with a moderate level of IHI in the present sample. Beyond this threshold, higher levels of IHI are associated with lower levels of KDC. These results confirm an inverted U-shaped relationship between IHI and KDC. As illustrated in Figure 3, higher levels of IHI are associated with higher levels of KDC up to the turning point (4.154), after which further increases in IHI are associated with lower levels of KDC, thereby supporting *H4a* and *H4b*. Finally, both dimensions of KDC are positively and significantly associated with TIB. As shown in Table 9, CKC (M2, $\beta = 0.291$, $p < 0.001$) and IKC (M2, $\beta = 0.427$, $p < 0.001$) are positively associated with TIB, supporting *H5a* and *H5b*.

Table 10. Regression results for KDC, CKC and IKC.

Variables	KDC		CKC		IKC	
	M6	M7	M8	M9	M10	M11
Control variables						
Team experience	0.002 (0.037)	0.042 (0.727)	−0.040 (−0.590)	0.001 (0.016)	0.044 (0.612)	0.083 (1.114)
Team size	−0.021 (−0.367)	−0.120 * (−2.041)	−0.065 (−0.949)	−0.166 * (−2.410)	0.023 (0.320)	−0.073 (−0.972)
Manufacturing sector	0.230 (1.698)	0.209 (1.489)	0.118 (0.721)	0.091 (0.548)	0.342 (1.962)	0.328 (1.812)
Technological level	−0.035 (−0.264)	0.102 (0.735)	−0.039 (−0.239)	0.109 (0.665)	−0.032 (−0.186)	0.096 (0.536)
Independent variable						
EH1	0.589 *** (15.499)		0.605 *** (13.175)		0.574 *** (11.724)	
IHI		2.559 *** (13.791)		2.692 *** (12.349)		2.426 *** (10.152)
IHI ²		−0.308 *** (−12.745)		−0.322 *** (−11.359)		−0.293 *** (−9.431)
R ²	0.490	0.456	0.413	0.407	0.361	0.316
Adjusted R ²	0.480	0.443	0.401	0.393	0.349	0.301
F value	50.369 ***	36.404 ***	36.797 ***	29.814 ***	29.605 ***	20.138 ***

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.**Table 11.** Curve equations, slope equations of tangents to curves, and analysis of stationary point.

Paths	Curve Equations	Slope Equations of Tangents to Curves	Stationary Points
IHI → TIB	$TIB = -0.349 \times IHI^2 + 2.881 \times IHI - 0.778$	$S = -0.698 \times IHI + 2.881$	4.128
IHI → KDC	$KDC = -0.308 \times IHI^2 + 2.559 \times IHI + 0.131$	$S = -0.616 \times IHI + 2.559$	4.154

**Figure 3.** Inverted U-shaped relationship between IHI and KDC.

To examine the integrated mediation framework derived from H3–H5, we tested whether CKC and IKC jointly mediate the relationship between human–AI interaction and TIB. After introducing the mediating variables into the regression model of EHI and TIB, CKC (M3, $\beta = 0.206$, $p < 0.01$) and IKC (M3, $\beta = 0.362$, $p < 0.001$) remain significantly positively associated with TIB, while the coefficient of EHI on TIB decreases from 0.516 (M1) to 0.183 (M3), remaining statistically significant. Consistent with the theoretical relationships proposed in H3a–H5b, these findings indicate that CKC and IKC jointly function as mediating mechanisms linking EHI to TIB, thereby providing empirical support for the integrated mediation framework (**H6a**). Similarly, after adding CKC and IKC into the regression model of IHI and TIB (M5), both CKC ($\beta = 0.187$, $p < 0.01$) and IKC ($\beta = 0.302$, $p < 0.001$) remain significantly positively associated with TIB. Meanwhile, the coefficient of the squared term of IHI decreases in magnitude from -0.349 to -0.232 . Together with the findings of H4a–H5b, these results further indicate that CKC and IKC jointly constitute the mediating mechanisms through which IHI influences TIB, thereby providing empirical support for the integrated mediation framework (**H6b**).

4.2.3. Robustness Tests

We conducted a bootstrap analysis to test the linear mediation effect of KDC in the relationship between EHI and TIB (see Table 12). The results show that the indirect effect of EHI on TIB through KDC is significant (Effect = 0.348, Boot 95% CI = [0.258, 0.429]). The magnitude of the indirect effect (0.348) indicates that a substantial proportion of the association between EHI and TIB operates through KDC, underscoring the practical importance of KDC as a mechanism linking human–AI interaction to team innovation. Additionally, the mediation effects of the two dimensions of KDC are also presented in Table 12. The results indicate that the corresponding confidence intervals exclude 0, suggesting that both CKC and IKC significantly mediate the relationship between EHI and TIB. Therefore, the mediating role of KDC between EHI and TIB is supported, confirming **H6a**. Moreover, we employed Hayes’s Medcurve macro with 5000 bootstrap resamples to examine the nonlinear mediation effects of IHI on TIB through KDC. The results indicate that the three nonlinear indirect effects are -0.124 , -0.057 , and -0.099 , respectively, with 95% bootstrap confidence intervals of $[-0.180, -0.076]$, $[-0.103, -0.017]$, and $[-0.145, -0.058]$. None of these confidence intervals includes 0, indicating that the nonlinear mediation effects of KDC are significant. These findings further support **H6b**.

Table 12. Bootstrap results for linear and nonlinear mediation effects.

Paths	Effect	Boot 95% CI	
		LowerCI	UpperCI
EHI → KDC → TIB	0.348	0.258	0.429
EHI → CKC → TIB	0.187	0.097	0.280
EHI → IKC → TIB	0.249	0.166	0.330
IHI ² → KDC → TIB	-0.124	-0.180	-0.076
IHI ² → CKC → TIB	-0.057	-0.103	-0.017
IHI ² → IKC → TIB	-0.099	-0.145	-0.058

To further clarify the nonlinear mediation mechanism, we estimated the conditional indirect effects of IHI on TIB through KDC at three representative values of IHI (Mean $- 1$ SD, Mean, and Mean $+ 1$ SD) using 5000 bootstrap resamples. As reported in Table 13, the indirect effect was positive and strongest at a low level of IHI (Effect = 0.555, Boot 95% CI = [0.301, 0.813]). At the mean level of IHI, the indirect effect remained positive but was substantially weaker (Effect = 0.096, Boot 95% CI = [0.012, 0.194]). At a high level of IHI

(Mean + 1 SD), the indirect effect became significantly negative (Effect = -0.363 , Boot 95% CI = $[-0.547, -0.170]$). These findings indicate that the indirect effect of IHI on TIB through KDC gradually changes from positive to negative across increasing levels of IHI, providing additional evidence for the proposed curvilinear mediation mechanism.

Table 13. Conditional indirect effects of IHI via KDC.

IHI Value	Indirect Effect	Boot 95% CI	
		LowerCI	UpperCI
Mean – 1 SD	0.555	0.301	0.813
Mean	0.096	0.012	0.194
Mean + 1 SD	-0.363	-0.547	-0.170

5. Discussion and Conclusions

This study investigates how human–AI interaction is associated with TIB in NPD teams and explores the mediating role of KDC. Drawing on SOR theory, we conceptualize human–AI interaction as an external stimulus that is associated with internal team cognitive processes, which subsequently are associated with innovation behavior. Using survey data collected from 268 NPD teams in Chinese manufacturing firms, the empirical results provide several important findings. First, EHI has a positive and significant association with TIB. This finding suggests that higher levels of EHI are associated with higher levels of TIB in AI-enabled NPD teams. Second, IHI exhibits an inverted U-shaped relationship with TIB. Moderate levels of AI decision authority under IHI may be associated with increased critical evaluation, human oversight, and knowledge integration. However, when AI assumes excessive decision authority, further increases in IHI are associated with lower levels of TIB. Third, KDC plays an important mediating role. EHI is significantly associated with both CKC and IKC, which in turn are associated with TIB. Additionally, the relationship between IHI and KDC also follows an inverted U-shaped pattern.

5.1. Theoretical Contribution

First, this study makes a theoretical contribution by explaining how different forms of human–AI interaction are associated with TIB through distinct knowledge-processing mechanisms in AI-enabled NPD teams. Rather than introducing new dimensions of human–AI interaction, this study builds upon the established distinction between EHI and IHI to explain how these two interaction modes operate through distinct collaborative mechanisms at the team level. Existing research has largely focused on the instrumental role of AI in enhancing efficiency, data processing, and decision support [13–15]. Although some studies have begun to explore human–AI interaction, their focus remains mostly limited to its impact on individual outcomes, such as productivity, decision-making performance, and mental health [9,16–18]. How AI integration from a human–AI interaction perspective operates at the team level, particularly the mechanisms through which it is associated with innovative behavior in NPD teams, has not yet been sufficiently examined.

By distinguishing between EHI and IHI, the present study shows that IHI has an inverted U-shaped relationship with both KDC and TIB. In contrast to previous studies suggesting that IHI may lead to negative individual outcomes [16], our findings highlight the nonlinear role of AI decision authority in TIB. When the level of AI decision authority is moderate, AI-generated insights can stimulate critical evaluation, strengthen human oversight, and encourage teams to integrate knowledge across functional domains. However, when AI assumes excessive decision authority, team members may become overly dependent on algorithmic outputs, giving rise to several potential risks. Excessive reliance

on AI may encourage automation bias, whereby team members accept AI-generated recommendations without sufficient critical evaluation. It may also reduce human agency by limiting employees' autonomous judgment and creative decision-making. Moreover, excessive dependence on AI-generated solutions may overstandardize innovation processes and weaken the development and exchange of tacit knowledge during team collaboration. These potential risks may help explain why the positive association weakens beyond the estimated turning point, reinforcing the importance of maintaining an appropriate balance between AI support and human judgment [53]. Accordingly, the theoretical contribution of this study lies not in introducing new forms of human–AI interaction, but in explaining why and how different interaction modes are associated with distinct innovation outcomes at the team level. These findings suggest that the innovation benefits associated with IHI do not increase linearly with greater AI decision authority, but rather follow a nonlinear pattern, highlighting the importance of balancing human judgment and AI support.

Second, this study contributes to the application of the SOR framework by extending it from individual cognition to team-level knowledge-processing mechanisms in AI-enabled innovation. In the proposed framework, human–AI interaction represents the external technological stimulus, KDC reflects the internal cognitive and learning processes of the team, and TIB constitutes the behavioral response. By linking these elements, the study demonstrates how AI-related interaction structures are associated with innovation behavior through team-level knowledge processes. In this way, the proposed framework provides a process-based explanation of AI-enabled team innovation rather than merely validating statistical relationships among existing constructs.

Third, this study contributes to the knowledge integration literature by conceptualizing KDC as the central mechanism linking human–AI interaction and TIB. Much of the existing research on knowledge integration has focused on knowledge sharing or recombination, while the dynamic processes through which heterogeneous knowledge domains interact during innovation have received comparatively less attention. By distinguishing between CKC and IKC, this study provides a more detailed explanation of how cross-domain knowledge integration develops in AI-supported NPD teams and clarifies the pathways through which human–AI interaction is associated with TIB. By doing so, this study shifts the focus from examining relationships among established constructs to explaining the knowledge integration processes through which different forms of human–AI interaction are translated into TIB.

5.2. Managerial Implications

This study provides practical insights for organizations seeking to integrate AI technologies into NPD activities to enhance TIB. The practical implications of the proposed framework are primarily applicable to AI-enabled NPD teams characterized by cross-functional collaboration, intensive knowledge integration, and shared innovation responsibilities. Because the empirical evidence was obtained from Chinese manufacturing firms, the recommendations should be interpreted primarily within similar innovation-oriented organizational contexts. Organizations operating in substantially different institutional, industrial, or technological environments may need to adapt these recommendations to their specific circumstances.

A key managerial implication is that human–AI interaction should not be viewed as a single or fixed collaboration mode. Instead, NPD teams should recognize that EHI and IHI may coexist within the same team and even across different stages of the same innovation task. Rather than relying exclusively on one interaction mode, managers should flexibly configure and dynamically adjust the balance between EHI and IHI according to task characteristics, innovation stages, and AI decision requirements. For

example, EHI may be particularly valuable during the early stages of NPD, such as idea generation and opportunity exploration, where broad knowledge exploration, divergent thinking, and creative recombination are required. By contrast, a moderate degree of AI decision authority may be more appropriate during later stages involving concept evaluation, technical assessment, and solution refinement, where analytical consistency, risk evaluation, and evidence-based decision making become increasingly important.

Specifically, EHI is positively associated with TIB by enabling AI systems to function as collaborative partners that provide analytical support, knowledge recommendations, and data-driven insights while preserving human judgment and creativity. Such collaborative arrangements are particularly valuable during idea generation, knowledge exploration, and interdisciplinary problem solving. Managers can further strengthen these benefits by providing training programs that improve employees' capabilities to effectively collaborate with AI technologies. In addition, organizations should invest in AI literacy and human–AI collaboration capabilities so that employees are able to critically interpret AI-generated recommendations rather than relying on them uncritically. Such capabilities can help employees critically evaluate AI-generated recommendations, reduce automation bias, and more effectively integrate AI-generated insights with domain expertise throughout the innovation process.

At the same time, our findings indicate that IHI exhibits an inverted U-shaped relationship with innovation behavior. Importantly, the estimated turning point (4.128 on a seven-point scale) should be interpreted as a sample-based empirical estimate rather than a universal managerial threshold. The findings suggest that maintaining a moderate level of IHI, rather than continuously expanding AI decision authority, is generally more conducive to team innovation. Moderate AI decision authority enables teams to leverage AI's analytical capabilities while preserving human oversight, critical evaluation, and collaborative learning. However, once AI decision authority becomes excessively high, the benefits gradually diminish, as excessive reliance on AI may discourage human participation in knowledge integration and creative problem solving. Therefore, rather than continuously expanding AI decision authority, managers may consider establishing governance mechanisms that maintain AI involvement at a moderate level appropriate to their organizational context and task requirements while preserving meaningful human oversight and intervention. More specifically, organizations may consider establishing formal AI governance mechanisms that clearly define the allocation of decision authority between AI systems and human experts across different innovation activities. Managers should specify when AI serves primarily as a decision-support tool and when final decision authority should remain with human experts, particularly for strategic, creative, and highly uncertain decisions. Such governance mechanisms should be periodically reviewed and adjusted as AI capabilities and innovation tasks evolve, ensuring that the balance between AI autonomy and human judgment remains appropriate across different innovation contexts. In addition, such governance mechanisms can reduce the risks of automation bias, preserve employees' decision autonomy, and encourage continuous interpersonal knowledge exchange, thereby preventing innovation processes from becoming overly standardized or dependent on AI-generated solutions.

Finally, our results highlight the critical role of KDC in translating human–AI interaction into TIB. Both CKC and IKC serve as important mechanisms through which human–AI interaction is associated with TIB. Accordingly, managers should cultivate organizational environments that facilitate interdisciplinary collaboration, strengthen cross-functional communication, and implement digital platforms that enable teams to integrate, refine, and recombine heterogeneous knowledge. Beyond providing digital collaboration platforms, organizations should also establish regular cross-functional knowledge-sharing

routines and incentive mechanisms that encourage employees to critically evaluate, refine, and recombine AI-generated insights with their own domain expertise. Such practices can strengthen both collaborative knowledge coupling and interdisciplinary knowledge coupling, thereby enabling AI technologies to generate sustained innovation value rather than merely improving operational efficiency. By simultaneously optimizing the configuration of human–AI interaction and promoting KDC, organizations can better leverage AI technologies to promote TIB.

5.3. Limitations and Future Directions

The empirical analysis is based on cross-sectional survey data collected from NPD teams in Chinese manufacturing firms. Although this dataset provides valuable insights into human–AI interaction in product development contexts, the cross-sectional design limits causal inference. Furthermore, all variables were assessed by NPD team managers serving as key informants. Although managers are well-positioned to evaluate team-level constructs because they oversee product development activities, coordinate cross-functional collaboration, and possess a comprehensive understanding of team innovation processes, relying on a single key informant may still introduce perception bias.

In addition, because team-level constructs were operationalized using a single-informant key-respondent design rather than multi-member aggregation, the study does not capture within-team perceptual variability. Although this approach is consistent with prior NPD and innovation research, future studies could strengthen measurement robustness by collecting data from multiple team members and examining within-group agreement.

Although the procedural and statistical diagnostics adopted in this study did not indicate substantial CMB, some residual risk cannot be entirely ruled out because the data were collected from a single knowledgeable informant for each NPD team using a cross-sectional survey design. Future research could further reduce this risk by collecting data from multiple team members, combining survey responses with objective performance indicators, or employing longitudinal research designs. Moreover, focusing on a single national and industrial context may constrain the generalizability of the findings. In addition, the survey classified manufacturing firms into broad categories of high-tech and non-high-tech manufacturing, which may not fully capture the heterogeneity of innovation processes across different manufacturing sectors. Accordingly, future research could provide stronger evidence regarding causal relationships by employing longitudinal, experimental, or mixed-method research designs and by examining organizations across different countries, industries, and innovation contexts. Future studies may also adopt more fine-grained industry classification standards, such as the OECD manufacturing classification, to investigate whether the proposed relationships differ across manufacturing sectors with distinct technological and innovation characteristics.

A second limitation concerns the mediating mechanism examined in this study. We focus on KDC as the primary mechanism linking human–AI interaction and TIB. However, AI-enabled innovation is likely to involve multiple complementary team processes. Future studies could investigate additional mediating mechanisms, such as team learning, knowledge sharing, collaborative problem solving, psychological safety, or team reflexivity, to develop a more comprehensive understanding of how human–AI interaction influences innovation outcomes.

Finally, this study analytically distinguishes between EHI and IHI to examine their differential effects on TIB. However, in real organizational settings, these two interaction modes are likely to coexist within the same NPD team and may dynamically evolve across different innovation stages and task contexts. Accordingly, future research should move be-

yond examining their independent effects and instead investigate their joint configurations, dynamic interplay, and potential complementarities in AI-enabled innovation. In particular, future studies could examine whether synergistic effects between EHI and IHI generate innovation outcomes that cannot be fully explained by either interaction mode in isolation. To address this issue, longitudinal designs, configurational approaches, or multi-level research methods may be particularly useful for capturing the dynamic balancing process of human–AI interaction across time and contexts. Building on this line of inquiry, future research may also explore the potential dark side of greater AI decision authority under IHI. Specifically, future research may investigate how automation bias, loss of human agency, overstandardization of innovation processes, and tacit knowledge erosion influence team innovation outcomes under varying levels of AI involvement.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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Abbreviations

The following abbreviations are used in this manuscript:

HI	Human–AI interaction
EHI	Enhanced human–AI interaction
IHI	Impeded human–AI interaction
TIB	Team innovation behavior
NPD team	New Product Development team
KDC	Knowledge domain coupling
CKC	Complementary knowledge coupling
IKC	Iterative knowledge coupling
SOR	Stimulus–Organism–Response
KBV	knowledge-based view

Appendix A

EHI	• In our NPD team, AI is mainly responsible for autonomous data acquisition and collection. • In our NPD team, AI assists members with tedious tasks. • In our NPD team, AI assists members with repetitive tasks. • In our NPD team, AI reduces the overall workload of team members.
IHI	• In our NPD team, AI autonomously makes decisions among alternatives. • In our NPD team, AI makes decisions on important tasks. • In our NPD team, AI interferes with members' normal work processes. • In our NPD team, AI increases pressure and burden within the team.
CKC	• Our NPD team can obtain new knowledge and information through cooperation with other enterprises. • Our NPD team acquires partners' specialized experience and skills in product development or service provision • Our NPD team integrates partners' methods and practices to address practical problems. • Our NPD team collaborates with partners that possess unique and complementary knowledge resources. • Learning from partner firms helps our NPD team complement its existing knowledge base. • Our NPD team enhances its knowledge base by combining external complementary knowledge with existing expertise.
IKC	• Our NPD team shares similar knowledge domains and technical expertise with partner firms. • Our NPD team builds upon partners' similar experience and skills to refine its existing knowledge. • Our NPD team and partner firms share similar knowledge structures and technical foundations. • Our NPD team can easily understand external knowledge that is similar to its existing expertise. • Our NPD team can closely match and integrate newly acquired knowledge with its existing knowledge base. • The similarity between our NPD team's knowledge and that of partner firms facilitates continuous refinement of our knowledge base.
TIB	• Team members often implement new ideas to improve the quality of our products and services. • This team gives little consideration to new and alternative methods and procedures for doing their work (excluded item). • Team members often produce new services, methods or procedures. • This is an innovative team.

Figure A1. Measured items.

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