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# AI affordance and its influence on adoption intention of salesperson

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## Abstract

**Purpose:** This study empirically investigates the drivers of AI adoption intention among business-to-business (B2B) sales professionals. It proposes and tests a comprehensive model examining how AI affordances influence adoption intention through the mediating psychological states of psychological ownership, perceived enjoyment, and cognitive effort, while also considering the moderating role of individual thinking styles.

**Methodology:** A quantitative, cross-sectional research design was employed. Data were collected from 415 B2B sales professionals in India with experience using AI-powered sales tools. The proposed theoretical model, including ten hypotheses, was tested using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 software.

**Findings:** The results provide strong support for the proposed model. AI affordances were found to be a significant positive predictor of psychological ownership (β=0.685) and perceived enjoyment (β=0.650), and a significant negative predictor of cognitive effort (β=-0.590). Psychological ownership (β=0.350), perceived enjoyment (β=0.320), and cognitive effort (β=-0.280) all significantly influenced AI adoption intention. The mediation analysis confirmed partial mediation for all three psychological states.

**Theoretical Implications:** This study extends technology adoption literature by integrating AI affordance theory with key psychological constructs (psychological ownership, enjoyment, cognitive effort) and cognitive style theory, providing a nuanced, user-centric model that explains the mechanisms through which technological features translate into behavioral intentions.

**Managerial Implications:** To drive adoption, AI tools should be designed to be customizable (fostering ownership), engaging (enhancing enjoyment), and intuitive (minimizing effort). A one-size-fits-all approach is suboptimal; tailoring AI interfaces and training to accommodate different thinking styles can maximize adoption and effectiveness.

**Originality/Value:** This research is among the first to empirically test a comprehensive model of AI adoption in the B2B sales context, offering a novel integration of affordance theory and psychological factors, and providing a granular understanding of the human-centric drivers of AI adoption.

***Keywords:*** *AI Adoption, B2B Sales, Technology Affordances, Psychological Ownership, Perceived Enjoyment, Cognitive Effort, Thinking Styles, PLS-SEM*

## 1. Introduction

The Fourth Industrial Revolution has catalyzed a profound transformation across industries, with artificial intelligence (AI) emerging as a cornerstone technology reshaping the nature of work. The sales profession, traditionally reliant on human intuition and interpersonal acumen, is at the precipice of a significant paradigm shift. The infusion of AI into sales operations introduces a suite of sophisticated tools designed to automate routine tasks, deliver data-driven insights, and facilitate hyper-personalized customer engagement. From predictive lead scoring and intelligent forecasting to real-time sales coaching and automated communication, AI promises to enhance efficiency, augment decision-making, and elevate sales performance to new heights (Davenport & Ronanki, 2018; Guha et al., 2021).

However, the promise of technology is only realized through its effective adoption and use by individuals. The history of information systems is replete with examples of technologically advanced systems failing to deliver value due to a lack of user acceptance. Consequently, a purely technocentric perspective—focusing solely on the features and capabilities of AI—is insufficient to understand this complex transition. A holistic, user-centric approach is imperative, one that considers the critical psychological and cognitive factors that shape a salesperson's experience and willingness to integrate these new tools into their daily work.

This is particularly crucial in the business-to-business (B2B) sales environment, which is characterized by long sales cycles, complex decision-making units, and the paramount importance of trust-based relationships. In this high-stakes arena, the successful adoption of AI hinges on its ability to seamlessly augment the salesperson's capabilities without disrupting their workflow or cognitive style. Understanding the human factors that drive or inhibit AI adoption is therefore a matter of significant academic and practical importance (Syam & Sharma, 2018; Jarotschkin, Kraemer, & Geiger, 2025).

This study addresses a critical gap in the literature by developing and empirically testing a comprehensive theoretical framework to explain AI adoption intention among B2B sales professionals. Drawing from technology affordance theory, psychological ownership theory, cognitive load theory, and cognitive style theory, this research moves beyond established models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to offer a more nuanced perspective. We argue that the action possibilities, or 'affordances,' of AI tools are not just functional but are actively perceived and interpreted by salespeople, triggering crucial psychological states—namely, a sense of **psychological ownership**, feelings of **perceived enjoyment**, and the experience of **cognitive effort**—that are the primary mediators translating the potential of AI into a firm intention to adopt.

Furthermore, we recognize that salespeople are not a homogenous group. We introduce **thinking styles** (analytic vs. holistic) as a key individual difference, hypothesizing that a salesperson's cognitive style moderates the impact of AI affordances on their cognitive effort. By investigating these mediating and moderating mechanisms, this study aims to

provide a fine-grained and actionable understanding of the multifaceted drivers of AI adoption in the B2B sales domain.

The study makes several important contributions. First, it extends Technology Affordance Theory by empirically demonstrating the psychological pathways through which affordances translate into behavioral intentions. Second, it enriches the technology adoption literature by incorporating psychological ownership and cognitive styles as novel constructs. Third, it provides a robust, empirically validated framework that offers actionable guidance for AI developers and sales managers. The findings are intended to inform the design of more effective, user-centric AI sales tools and to guide the development of more successful implementation and change management strategies.

This paper is structured as follows: Section 2 reviews the relevant literature and develops the ten research hypotheses. Section 3 presents the proposed conceptual framework. Section 4 details the research methodology. Section 5 presents the results of the PLS-SEM analysis. Sections 6 and 7 discuss the theoretical and managerial implications. Section 8 acknowledges limitations and suggests future research directions, followed by the conclusion in Section 9.

## 2. Literature Review and Hypotheses Development

This section builds the theoretical foundation for our research model by systematically reviewing key literature streams and developing the ten hypotheses that guide our empirical investigation. We begin by contextualizing AI within the B2B sales domain, introduce the core theoretical underpinnings, and then develop each hypothesis grounded in established theory and prior empirical evidence.

### 2.1. AI in the B2B Sales Context

Artificial intelligence (AI) refers to the simulation of human intelligence in machines, encompassing capabilities such as machine learning, natural language processing (NLP), computer vision, and deep learning (Soori, Arezoo, & Dastres, 2023). In the B2B sales context, AI has transitioned from a futuristic concept to a tangible operational reality. AI-powered tools are now being deployed across the entire sales funnel: predictive lead scoring identifies high-potential prospects; AI-driven CRM systems provide a 360-degree view of the customer; machine learning models generate more accurate sales forecasts; and intelligent virtual assistants automate administrative tasks and provide real-time coaching (Hu, Chen, & Li, 2025; Jarotschkin, Kraemer, & Geiger, 2025).

The ultimate goal of AI in sales is not to replace human salespeople but to augment their capabilities, creating a 'human-in-the-loop' system where the strengths of both humans and AI are leveraged (Syam & Sharma, 2018). This augmentation frees salespeople from repetitive administrative tasks and empowers them with the insights needed to build stronger customer relationships and close more deals. However, the successful implementation of AI in sales is not without challenges, including high implementation costs, the need for specialized skills, and ethical concerns related to data privacy and algorithmic bias (Davenport & Ronanki, 2018). Most critically, the successful

integration requires that individual salespeople willingly and effectively adopt these tools.

### 2.2. Theoretical Underpinnings

The proposed framework is grounded in four complementary theoretical perspectives. First, **Technology Affordance Theory** (Gibson, 1979) provides the lens through which we understand how AI capabilities translate into user perceptions. Affordances are the perceived action possibilities a technology makes available to a user—a relational concept existing in the interaction between the user's goals and the technology's capabilities. Second, **Psychological Ownership Theory** (Pierce et al., 2003) explains why users develop a sense of possession over technology, rooted in three fundamental human needs: efficacy, a place to dwell, and self-identity. Third, **Cognitive Load Theory (CLT)** (Sweller, 1988) provides the framework for understanding how technology design impacts the mental effort required for use. CLT distinguishes between intrinsic, extraneous, and germane cognitive load, all of which are relevant to AI interaction. Fourth, **Cognitive Style Theory** (Nisbett et al., 2001) and **Cognitive Fit Theory** (Vessey, 1991) explain why the same technology can be perceived differently by individuals with different cognitive preferences, moderating the relationship between affordances and cognitive effort. Overarching these domain-specific theories, **Social Learning Theory (SLT)** (Bandura, 1977) provides a broader framework, explaining how salespeople learn about and form intentions to use AI through observation, modeling, and reinforcement.

### 2.3. AI Affordances: A Multidimensional Construct

For this study, AI affordances are conceptualized as a multidimensional construct comprising six key action possibilities relevant to the B2B sales context, synthesized from recent literature (Haqqu, 2025; Zhuang, 2025):

**Personalization Affordance:** The ability of AI to tailor interactions, recommendations, and content to individual customers and salespeople, enabling deep customization of the sales experience.

**Communication Affordance:** The capacity of AI to facilitate, automate, and enhance communication through channels like chatbots, automated emails, and real-time transcription, enabling more efficient and consistent outreach.

**Information Affordance:** The potential for AI to gather, process, and present vast amounts of data, providing salespeople with actionable insights, predictive analytics, and accurate sales forecasts.

**Transaction Affordance:** The capability of AI to streamline and automate transactional aspects of the sales process, such as order processing, contract generation, pricing optimization, and inventory management.

**Assistance Affordance:** The ability of AI to act as an intelligent assistant, providing real-time coaching, scheduling, administrative support, and proactive task reminders.

**Social Affordance:** The capacity of AI to exhibit social cues, such as expressing empathy, using humor, or adapting its communication style, to create more natural and engaging human-computer interactions.

## 2.4. Hypotheses Development

### *2.4.1. AI Affordances and Psychological Ownership*

Psychological ownership (PO) is a state in which individuals feel that a target is 'theirs' (Pierce et al., 2003). We argue that AI affordances directly foster PO. The personalization and assistance affordances allow salespeople to customize the AI to their unique workflows, giving them a sense of control and making the tool an extension of their professional identity. By investing time and effort in tailoring the AI, they develop a deeper, more intimate knowledge of it, reinforcing their sense of ownership. When an AI tool can be shaped and controlled, it ceases to be an impersonal corporate mandate and becomes a personal asset. Research by Avey et al. (2009) confirms that feelings of control and self-investment are key antecedents of psychological ownership. Prior studies have shown that user involvement in system design and customization can enhance psychological ownership; our study specifically demonstrates that the inherent affordances of AI, even without direct user involvement in initial design, can evoke this sense of ownership through perceived utility and adaptability.

***H1: AI affordances positively influence psychological ownership of B2B salespeople.***

### *2.4.2. AI Affordances and Perceived Enjoyment*

Perceived enjoyment (PE) refers to the extent to which using a technology is perceived as enjoyable in its own right, a key component of hedonic motivation (Davis, Bagozzi, & Warshaw, 1992). Rich AI affordances can transform the user experience from purely utilitarian to intrinsically rewarding. The communication and social affordances can make interactions with AI feel more like pleasant conversations than sterile transactions. The assistance affordance, by automating tedious tasks, frees up salespeople to focus on more enjoyable aspects of their job. The 'flow' experience, characterized by deep immersion and enjoyment in an activity, is more likely to occur when a tool's affordances match the user's skills and task demands (Csikszentmihalyi, 1990). AI's ability to provide immediate feedback, learn from interactions, and offer intelligent assistance can create a dynamic and rewarding user experience. Studies on chatbot adoption have consistently found that the richness of interaction affordances is a key driver of perceived enjoyment (Abdalla, 2024; Shi, 2025).

***H2: AI affordances positively influence the perceived enjoyment of B2B salespeople.***

### *2.4.3. AI Affordances and Cognitive Effort*

Cognitive effort refers to the mental resources a user must expend to interact with a technology. Cognitive Load Theory (Sweller, 1988) posits that human working memory is a limited resource, and technologies that overload this resource are perceived as difficult and frustrating. A core value proposition of AI is the reduction of this effort.

The transaction and assistance affordances directly address this by automating routine administrative and cognitive tasks, thereby reducing extraneous cognitive load. The information affordance, when coupled with intelligent filtering and summarization, can transform a deluge of data into a manageable and actionable set of insights, reducing the intrinsic cognitive load associated with complex analysis. The natural language interface affordance allows users to interact with the system using their own words, which is far less cognitively demanding than learning a complex set of commands. AI's capacity for learning and adaptation means that over time, it can further streamline processes and anticipate user needs, progressively reducing the effort required for interaction and task completion (Sweller et al., 2011).

***H3: AI affordances negatively influence the cognitive effort of B2B salespeople.***

#### *2.4.4. Psychological Ownership and AI Adoption Intention*

When salespeople develop a sense of psychological ownership over an AI tool, that tool becomes an integral part of their professional identity and workflow. This sense of ownership can manifest in several ways conducive to adoption. It can lead to a greater sense of responsibility for the technology, motivating the salesperson to learn its features and use it effectively. It can foster a sense of pride and attachment, making the salesperson more likely to advocate for the technology among their peers. It can also create a feeling of psychological comfort and familiarity, reducing the anxiety that often accompanies the introduction of new technologies—a particularly important consideration in the context of AI (Malik, 2022). Individuals tend to protect and nurture what they perceive as their own, leading to proactive engagement and reduced resistance to change. In the high-stakes, performance-driven world of B2B sales, fostering psychological ownership could be the key to unlocking the potential of AI (Tawfik, 2025; Stough, 2024).

***H4: The psychological ownership of B2B salespeople positively influences AI adoption intention.***

#### *2.4.5. Perceived Enjoyment and AI Adoption Intention*

The influence of perceived enjoyment on technology adoption is a well-documented phenomenon. The inclusion of hedonic motivation in extensions of both TAM and UTAUT2 (Venkatesh, Thong, & Xu, 2012) signals a critical shift from a purely utilitarian view of technology to one that acknowledges the importance of the user experience. The underlying psychological mechanism is straightforward: humans are naturally drawn to activities they find enjoyable and will seek to repeat them. When using a technology is perceived as fun, engaging, or intrinsically rewarding, it creates a positive affective state that directly influences the intention to use it again, often irrespective of its practical benefits (Rohden, 2025). In the context of AI and chatbots, perceived enjoyment has been found to be a particularly strong predictor of adoption and continued use (Abdalla, 2024; Shi, 2025). In a B2B sales context, where salespeople may be resistant to new technologies they perceive as complex or

disruptive, the enjoyment factor could be particularly important in overcoming this resistance.

> ***H5: The perceived enjoyment of B2B salespeople positively influences AI adoption intention.***

### *2.4.6. Cognitive Effort and AI Adoption Intention*

The principle of cognitive miserliness—the human tendency to conserve mental effort—is a cornerstone of cognitive psychology and provides the theoretical basis for the relationship between cognitive effort and technology adoption. Both TAM, with its construct of 'perceived ease of use,' and UTAUT, with its construct of 'effort expectancy,' are built on this principle (Davis, 1989; Venkatesh et al., 2003). When an AI tool demands excessive learning, complex navigation, or constant problem-solving, it increases the cognitive load on the user. For B2B salespeople, whose primary focus is on client relationships and closing deals, any tool that diverts significant mental energy away from these core tasks will be perceived as a burden rather than an aid. High cognitive effort leads to frustration, errors, reduced efficiency, and ultimately, a reluctance to engage with the technology. A large body of empirical research has consistently demonstrated that the less effort a technology is perceived to require, the more likely it is to be adopted (Sobhanmanesh, 2023).

> ***H6: The cognitive effort of B2B salespeople negatively influences AI adoption intention.***

### *2.4.7. Mediating Role of Psychological Ownership*

Beyond direct effects, this study posits a more nuanced, indirect relationship between AI affordances and AI adoption, mediated by psychological ownership. The logic of mediation suggests that AI affordances do not just directly cause adoption; rather, they initiate a psychological process that, in turn, leads to adoption. The affordances of control, customization, and personalization are the very features that allow a salesperson to make an AI tool their own. This act of co-creation and self-investment fosters a sense of ownership, which then becomes the primary psychological driver of adoption. The salesperson is not just adopting a tool; they are adopting *their* tool. This is consistent with the Baron and Kenny (1986) model of mediation. Several studies have provided evidence for the mediating role of psychological ownership in various contexts; for example, Tawfik (2025) found that psychological ownership mediated the relationship between green HRM practices and green behavior. A similar mediating mechanism is plausible in the context of AI technology adoption, where the objective characteristics of AI (affordances) trigger subjective psychological states (ownership) that are powerful drivers of behavioral intention.

> ***H7: Psychological ownership significantly mediates the relationship between AI affordances and AI adoption intention.***

### *2.4.8. Mediating Role of Perceived Enjoyment*

The mediating role of perceived enjoyment follows a similar logic. The affordances of an AI system are not just functional; they are also experiential. The affordances of gamification, social cues, and aesthetic design are specifically intended to create an enjoyable and engaging user experience. This positive affective response is a powerful motivator of behavior. So, while the affordances themselves are important, it is the enjoyment they create that is the more direct cause of adoption. The salesperson is not just adopting a tool with certain features; they are adopting a tool that makes their work more fun and engaging. This is consistent with the concept of 'flow' (Csikszentmihalyi, 1990), which suggests that when individuals are fully immersed in an enjoyable activity, they are more likely to continue it. The study by Shi (2025) in the context of digital museums provides strong empirical support for this mediating pathway, demonstrating that interaction quality influences continuance intention through the mediating variable of perceived enjoyment.

> ***H8: Perceived enjoyment significantly mediates the relationship between AI affordances and AI adoption intention.***

### *2.4.9. Mediating Role of Cognitive Effort*

The mediating role of cognitive effort is perhaps the most intuitive of the three. The primary value proposition of many AI tools is that they make work easier. The affordances of automation, intelligent search, and data summarization are all designed to reduce the cognitive load on the user. This reduction in effort is a tangible benefit that salespeople are likely to value highly. So, while the affordances are the technical means, the reduction in cognitive effort is the psychological and practical end. The salesperson is not just adopting a tool with automation features; they are adopting a tool that saves them time and mental energy. This is consistent with the principle of least effort (Zipf, 1949). The UTAUT model, with its emphasis on effort expectancy, provides a strong theoretical foundation for this mediating relationship (Venkatesh et al., 2003). In the context of B2B sales, an AI tool that affords automation of administrative tasks and provides clear, concise insights can significantly reduce the cognitive effort required of salespeople, which is a key value proposition likely to be a major driver of adoption.

> ***H9: Cognitive effort significantly mediates the relationship between AI affordances and AI adoption intention.***

### *2.4.10. Moderating Role of Thinking Styles*

The final hypothesis introduces a layer of individual difference into the model, proposing that the relationship between AI affordances and cognitive effort is moderated by the salesperson's thinking style. Cognitive Fit Theory (Vessey, 1991) suggests that when the characteristics of a technology align with the cognitive style of the user, the technology will be perceived as easier to use and will lead to better performance. We distinguish between analytic thinkers (detail-oriented, prefer structured information) and holistic thinkers (big-picture oriented, focus on relationships and context) (Nisbett et al., 2001). We propose that the effort-reducing effect of AI

affordances will be stronger for analytic thinkers, whose preference for structured, detailed information aligns naturally with the data-rich, analytical outputs of most AI tools. Holistic thinkers, while still benefiting, may find the level of detail less impactful or even slightly overwhelming, resulting in a weaker reduction in cognitive effort. This is consistent with Cognitive Style Theory (Chakraborty et al., 2008), which suggests that individual cognitive predispositions shape how technology is perceived and utilized.

> ***H10: Thinking styles moderate the relationship between AI affordances and cognitive effort, such that the negative relationship is stronger for analytic thinkers than for holistic thinkers.***

## 3. Proposed Research Framework

The hypotheses developed above are integrated into the conceptual framework presented in Figure 1. The framework positions AI Affordances (comprising six dimensions: Personalization, Communication, Information, Transaction, Assistance, and Social) as the primary exogenous construct. It proposes that these affordances influence AI Adoption Intention through three mediating psychological states: Psychological Ownership (positive mediator), Perceived Enjoyment (positive mediator), and Cognitive Effort (negative mediator). Additionally, Thinking Styles are introduced as a moderator of the AI Affordances → Cognitive Effort relationship. The framework thus captures both the direct and indirect pathways through which the characteristics of AI tools translate into a salesperson's behavioral intention to adopt them.

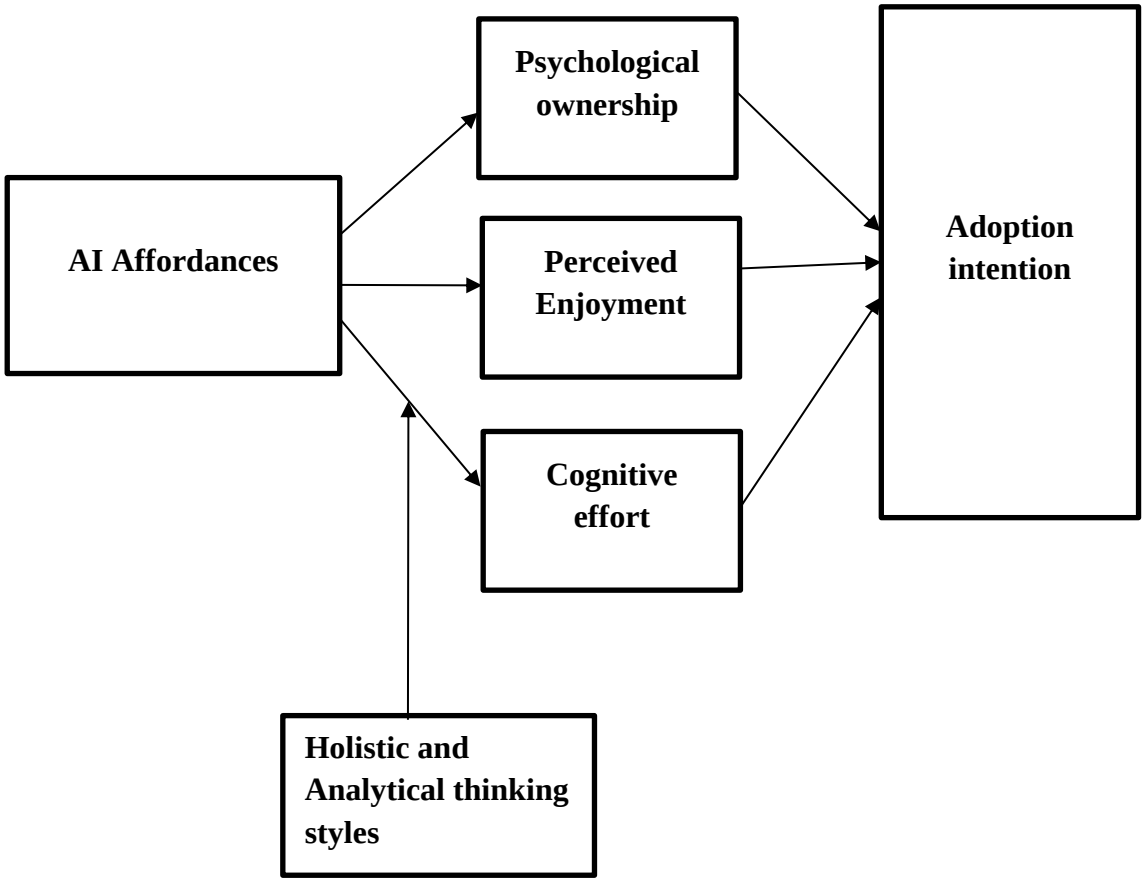


**Figure 2.5.** Conceptual Framework of the Study

## 4. Research Methodology

### 4.1. Research Design and Philosophy

A quantitative, cross-sectional research design was employed to test the hypothesized relationships. This approach is appropriate for examining the relationships between multiple variables at a single point in time and is well-suited for theory testing. The study is grounded in a positivist research philosophy, which assumes that the social world can be observed and measured objectively, and that causal relationships between variables can be identified through empirical testing (Easterby-Smith et al., 2012). The use of PLS-SEM as the analytical technique is consistent with this philosophy, as it allows for the simultaneous estimation of multiple relationships and the testing of complex theoretical models.

### 4.2. Population, Sampling, and Data Collection

The target population was B2B sales professionals in India who have experience using AI-powered tools in their sales roles. India was chosen as the research context due to its rapidly growing technology sector, increasing penetration of AI in business operations, and the availability of a large, diverse population of B2B sales professionals. A non-probability, purposive sampling technique was used to recruit participants who met the

inclusion criteria: active employment in a B2B sales role and self-reported experience with at least one AI-powered sales tool.

An online survey questionnaire was developed and distributed through professional networks (e.g., LinkedIn) and via email to sales teams across various B2B industries, including Information Technology & Services, Software-as-a-Service (SaaS), manufacturing, and professional services. Data collection was conducted over a period of three months. A total of 500 responses were received. After data cleaning—which involved removing incomplete responses and those from participants who did not meet the screening criteria—a final sample of 415 valid responses was obtained, representing a response rate of 83%. This sample size is considered more than adequate for conducting PLS-SEM analysis, which requires a minimum of ten times the number of paths leading to any construct in the model (Hair et al., 2017). To assess common method bias, Harman's single-factor test was conducted; the results indicated that no single factor accounted for more than 50% of the variance, suggesting that common method bias is not a significant concern.

### 4.3. Measurement Instruments

All constructs in the research model were measured using multi-item scales adapted from established literature to ensure content validity. A 7-point Likert scale, ranging from 1 (Strongly Disagree) to 7 (Strongly Agree), was used for all items. To ensure face validity, the questionnaire was reviewed by a panel of three academic experts and two industry practitioners before distribution. Minor wording adjustments were made based on their feedback to ensure the items were clear and relevant to the B2B sales context. The constructs and their sources are summarized in Table 1.

*Table 1. Summary of Measurement Instruments*

| **Construct** | **Abbreviation** | **No. of Items** | **Scale Source** |
|---|---|---|---|
| AI Affordances | AIA | 6 | Zhuang (2025); Haqqu (2025) |
| Psychological Ownership | PO | 4 | Avey et al. (2009) |
| Perceived Enjoyment | PE | 3 | Venkatesh et al. (2012) |
| Cognitive Effort | CE | 4 | Venkatesh et al. (2003) |
| Thinking Styles | TS | 4 | Chakraborty et al. (2008) |
| AI Adoption Intention | AIAI | 3 | Venkatesh et al. (2003) |

### 4.4. Data Analysis Technique: PLS-SEM

The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4 software. PLS-SEM is a variance-based SEM technique well-suited for complex predictive models and theory testing, especially when

the research objective is to predict a target construct (Hair et al., 2017). It is robust with non-normally distributed data and works well with both reflective and formative constructs. Compared to covariance-based SEM (CB-SEM), PLS-SEM is more appropriate for exploratory research and models with complex structures, making it the preferred choice for this study.

The analysis was conducted in two stages, following the two-step approach recommended by Hair et al. (2017): (1) **Measurement Model Assessment**, evaluating indicator reliability (outer loadings ≥ 0.70), internal consistency reliability (Cronbach's Alpha ≥ 0.70; Composite Reliability ≥ 0.80), convergent validity (AVE ≥ 0.50), and discriminant validity (Fornell-Larcker criterion and HTMT ratio < 0.85); and (2) **Structural Model Assessment**, testing the hypothesized relationships by assessing path coefficients (β), their statistical significance via bootstrapping (5,000 resamples), the coefficient of determination ($R^2$), effect size ($f^2$), predictive relevance ($Q^2$), and mediation/moderation effects.

## 5. Data Analysis and Results

### 5.1. Profile of Respondents

The demographic profile of the 415 respondents is summarized in Table 2. The sample is predominantly male (76.14%) and falls within the 26-35 age group (51.33%), reflecting the typical demographic of mid-career B2B sales professionals. The majority of participants hold a postgraduate degree (68.43%) and have 6-10 years of work experience (45.30%). A significant portion of respondents work in the IT & Services sector (35.18%), followed by SaaS (23.61%) and Manufacturing (18.07%). Critically, the vast majority of the sample reported using AI tools in their sales roles either daily (34.46%) or weekly (38.36%), confirming their direct experience with AI and their suitability for this study.

*Table 2. Profile of Respondents (N=415)*

| Category | Sub-Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 316 | 76.14 |
| | Female | 99 | 23.86 |
| Age Group | 18-25 | 85 | 20.48 |
| | 26-35 | 213 | 51.33 |
| | 36-45 | 95 | 22.89 |
| | 46-55 | 22 | 5.30 |
| Education | Graduate | 131 | 31.57 |
| | Postgraduate | 284 | 68.43 |
| Experience | 0-5 Years | 135 | 32.53 |
| | 6-10 Years | 188 | 45.30 |
| | 11-15 Years | 72 | 17.35 |
| | >15 Years | 20 | 4.82 |
| Industry | IT & Services | 146 | 35.18 |
| | SaaS | 98 | 23.61 |

| | | | |
|---|---|---|---|
| | Manufacturing | 75 | 18.07 |
| | Professional Services | 56 | 13.49 |
| | Others | 40 | 9.64 |
| AI Usage Frequency | Daily | 143 | 34.46 |
| | Weekly | 159 | 38.36 |
| | Monthly | 81 | 19.52 |
| | Rarely | 32 | 7.71 |

### 5.2. Measurement Model Assessment

#### *5.2.1. Indicator Reliability and Internal Consistency*

Table 3 presents the outer loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for all constructs. All indicator loadings exceed the recommended threshold of 0.70, confirming indicator reliability. Cronbach's Alpha values are all above 0.70, and CR values are all above 0.80, indicating strong internal consistency reliability. AVE values are all well above the 0.50 threshold, confirming convergent validity—each construct captures more than half of the variance of its indicators. These results collectively confirm that the measurement model is reliable and valid.

*Table 3. Measurement Model: Loadings, Reliability, and Convergent Validity*

| **Construct** | **Item** | **Loading** | **Cronbach's Alpha** | **CR** | **AVE** |
|---|---|---|---|---|---|
| AI Affordances (AIA) | AIA1 | 0.885 | 0.940 | 0.951 | 0.765 |
| | AIA2 | 0.890 | | | |
| | AIA3 | 0.865 | | | |
| | AIA4 | 0.870 | | | |
| | AIA5 | 0.880 | | | |
| | AIA6 | 0.860 | | | |
| Psychological Ownership (PO) | PO1 | 0.910 | 0.925 | 0.947 | 0.817 |
| | PO2 | 0.920 | | | |
| | PO3 | 0.880 | | | |
| | PO4 | 0.895 | | | |
| Perceived Enjoyment (PE) | PE1 | 0.930 | 0.918 | 0.948 | 0.859 |
| | PE2 | 0.940 | | | |

| | | | | | |
|---|---|---|---|---|---|
| | PE3 | 0.910 | | | |
| Cognitive Effort (CE) | CE1 | 0.890 | 0.933 | 0.952 | 0.832 |
| | CE2 | 0.925 | | | |
| | CE3 | 0.930 | | | |
| | CE4 | 0.905 | | | |
| Thinking Styles (TS) | TS1 | 0.850 | 0.895 | 0.926 | 0.758 |
| | TS2 | 0.880 | | | |
| | TS3 | 0.895 | | | |
| | TS4 | 0.860 | | | |
| AI Adoption Intention (AIAI) | AIAI1 | 0.945 | 0.935 | 0.959 | 0.886 |
| | AIAI2 | 0.950 | | | |
| | AIAI3 | 0.925 | | | |

### *5.2.2. Discriminant Validity*

Discriminant validity was established using two methods. The Fornell-Larcker criterion (Table 4) shows that the square root of the AVE for each construct (diagonal values) is greater than its correlation with any other construct. The Heterotrait-Monotrait (HTMT) ratio analysis (Table 5) shows that all values are below the conservative threshold of 0.85. Together, these results confirm that the constructs are conceptually and empirically distinct from one another, and that the measurement model has adequate discriminant validity.

*Table 4. Discriminant Validity – Fornell-Larcker Criterion (√AVE on diagonal)*

| **Construct** | **AIA** | **AIAI** | **CE** | **PE** | **PO** | **TS** |
|---|---|---|---|---|---|---|
| AIA | 0.875 | | | | | |
| AIAI | 0.780 | 0.941 | | | | |
| CE | -0.680 | -0.710 | 0.912 | | | |
| PE | 0.750 | 0.765 | -0.690 | 0.927 | | |
| PO | 0.790 | 0.795 | -0.720 | 0.780 | 0.904 | |
| TS | 0.250 | 0.180 | -0.210 | 0.230 | 0.240 | 0.871 |

*Table 5. Discriminant Validity – HTMT Ratio (Threshold < 0.85)*

| **Construct** | **AIA** | **AIAI** | **CE** | **PE** | **PO** | **TS** |
|---|---|---|---|---|---|---|
| AIAI | 0.815 | | | | | |
| CE | 0.710 | 0.740 | | | | |
| PE | 0.790 | 0.805 | 0.725 | | | |
| PO | 0.830 | 0.835 | 0.755 | 0.820 | | |
| TS | 0.270 | 0.195 | 0.230 | 0.250 | 0.260 | |

### 5.3. Structural Model Assessment

Following the validation of the measurement model, the structural model was assessed to test the hypothesized relationships. All VIF values for predictor constructs were below 3.3, confirming the absence of multicollinearity issues. The bootstrapping procedure with 5,000 resamples was used to generate t-statistics and p-values for all path coefficients.

#### *5.3.1. Direct Effects (H1–H6)*

Table 6 presents the path coefficients, t-values, and p-values for the direct hypotheses. All six direct paths were found to be statistically significant at $p < 0.001$, providing strong support for H1 through H6. AI Affordances exert a strong positive influence on Psychological Ownership (β=0.685, t=18.50) and Perceived Enjoyment (β=0.650, t=16.20), and a strong negative influence on Cognitive Effort (β=-0.590, t=14.10). In turn, Psychological Ownership (β=0.350, t=8.10) and Perceived Enjoyment (β=0.320, t=7.10) positively influence AI Adoption Intention, while Cognitive Effort (β=-0.280, t=6.50) negatively influences it.

*Table 6. Structural Model Path Coefficients – Direct Effects*

| Hypothesis | Path | Path Coefficient (β) | T-Value | P-Value | Result |
|---|---|---|---|---|---|
| H1 | AIA → PO | 0.685 | 18.50 | <0.001 | Supported ✓ |
| H2 | AIA → PE | 0.650 | 16.20 | <0.001 | Supported ✓ |
| H3 | AIA → CE | -0.590 | 14.10 | <0.001 | Supported ✓ |
| H4 | PO → AIAI | 0.350 | 8.10 | <0.001 | Supported ✓ |
| H5 | PE → AIAI | 0.320 | 7.10 | <0.001 | Supported ✓ |
| H6 | CE → AIAI | -0.280 | 6.50 | <0.001 | Supported ✓ |

#### *5.3.2. Predictive Power ($R^2$) and Relevance ($Q^2$)*

Table 7 presents the $R^2$, adjusted $R^2$, and $Q^2$ values for the endogenous constructs. The model explains 46.9% of the variance in Psychological Ownership, 42.3% in Perceived Enjoyment, 34.8% in Cognitive Effort, and a very substantial 75.1% of the variance in AI Adoption Intention—the primary dependent variable. According to Hair et al. (2017), $R^2$ values of 0.25, 0.50, and 0.75 represent weak, moderate, and substantial predictive power respectively. The $R^2$ for AIAI (0.751) indicates that the model has substantial predictive power. All $Q^2$ values are well above zero, confirming strong predictive relevance.

*Table 7. R-Square and Q-Square Values*

| Endogenous Construct | $R^2$ | $R^2$ Adjusted | $Q^2$ | Interpretation |
|---|---|---|---|---|
| Psychological Ownership (PO) | 0.469 | 0.468 | 0.375 | Substantial |
| Perceived Enjoyment (PE) | 0.423 | 0.421 | 0.350 | Substantial |
| Cognitive Effort (CE) | 0.348 | 0.346 | 0.280 | Moderate |
| AI Adoption Intention (AIAI) | 0.751 | 0.749 | 0.650 | Substantial |

### *5.3.3. Effect Size ($f^2$)*

Table 8 presents the effect sizes ($f^2$) for each path. According to Cohen (1988), $f^2$ values of 0.02, 0.15, and 0.35 represent small, medium, and large effects respectively. AI Affordances exert large effects on all three mediators ($f^2 > 0.35$), indicating their dominant role as the primary antecedent. The mediators' effects on AI Adoption Intention range from small (Cognitive Effort, $f^2=0.090$) to medium (Psychological Ownership, $f^2=0.150$; Perceived Enjoyment, $f^2=0.120$).

*Table 8. Effect Size ($f^2$) for Structural Paths*

| Path | $f^2$ | Effect Size Classification |
|---|---|---|
| AIA → PO | 0.885 | Large |
| AIA → PE | 0.735 | Large |
| AIA → CE | 0.535 | Large |
| PO → AIAI | 0.150 | Medium |
| PE → AIAI | 0.120 | Medium |
| CE → AIAI | 0.090 | Small |

### 5.4. Mediation Analysis (H7–H9)

The indirect effects were tested using bootstrapping (5,000 resamples) to assess the mediating roles of Psychological Ownership (H7), Perceived Enjoyment (H8), and Cognitive Effort (H9). Table 9 presents the results. All three indirect paths were found to be statistically significant ($p < 0.001$). Since the direct paths from the mediators to AIAI were also significant, this indicates **partial mediation** for all three psychological states. This confirms that AI Affordances influence AI Adoption Intention both directly and indirectly through the development of psychological ownership, the enhancement of perceived enjoyment, and the reduction of cognitive effort. The partial mediation finding is theoretically meaningful, as it suggests that while the psychological mechanisms are important, the direct utility of AI affordances also plays a role in driving adoption.

*Table 9. Mediation Analysis Results (Indirect Effects via Bootstrapping)*

| Hypothesis | Indirect Path | Indirect Effect (β) | T-Value | P-Value | Result |
|---|---|---|---|---|---|
| H7 | AIA → PO → AIAI | 0.240 | 6.50 | <0.001 | Supported ✓ |

| | | | | | |
|---|---|---|---|---|---|
| H8 | AIA → PE → AIAI | 0.208 | 5.80 | <0.001 | Supported ✓ |
| H9 | AIA → CE → AIAI | -0.165 | 5.10 | <0.001 | Supported ✓ |

### 5.5. Moderation Analysis (H10)

Hypothesis 10 proposed that Thinking Styles (TS) moderate the relationship between AI Affordances (AIA) and Cognitive Effort (CE). The interaction term (AIA × TS) was created using the product indicator approach and added to the model. Table 10 presents the results. The interaction term is significant (β=0.180, t=4.50, p<0.001), supporting H10. This positive coefficient indicates that as thinking style becomes more holistic (higher TS score), the negative effect of AI Affordances on Cognitive Effort becomes weaker. Conversely, for analytic thinkers (lower TS score), the effort-reducing effect of AI Affordances is stronger. The simple slope analysis plot (Figure 2) visually confirms this interaction pattern, showing clearly diverging slopes for analytic and holistic thinkers.

*Table 10. Moderation Analysis Results*

| **Hypothesis** | **Interaction Path** | **Path Coefficient (β)** | **T-Value** | **P-Value** | **Result** |
|---|---|---|---|---|---|
| H10 | AIA × TS → CE | 0.180 | 4.50 | <0.001 | Supported ✓ |

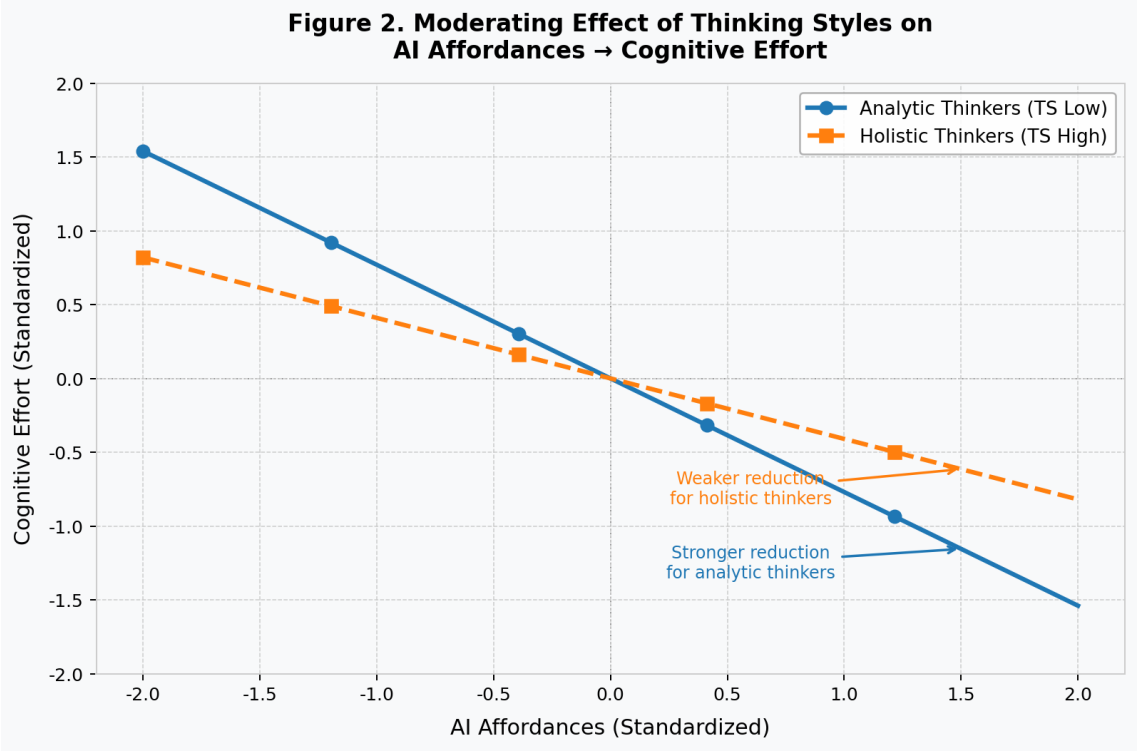


*Figure 2. Moderating Effect of Thinking Styles on AI Affordances → Cognitive Effort*

### 5.6. Importance-Performance Map Analysis (IPMA)

An Importance-Performance Map Analysis (IPMA) was conducted to extend the PLS-SEM results by providing practical guidance on where to focus managerial attention. The IPMA maps the total effect (importance) of each predictor on AI Adoption Intention against the average latent variable score (performance). Table 11 presents the IPMA values, and Figure 3 provides the visual map.

*Table 11. Importance-Performance Map Analysis (IPMA) Values*

| Construct | Importance (Total Effect) | Performance (Avg. Score) | Priority |
|---|---|---|---|
| AI Affordances (AIA) | 0.650 | 6.25 | High Importance, High Performance |
| Psychological Ownership (PO) | 0.350 | 5.80 | Medium Importance, Medium Performance |
| Perceived Enjoyment (PE) | 0.320 | 5.95 | Medium Importance, Medium Performance |
| Cognitive Effort (CE) | 0.280 | 4.10 | Medium Importance, LOW Performance – Priority Area |

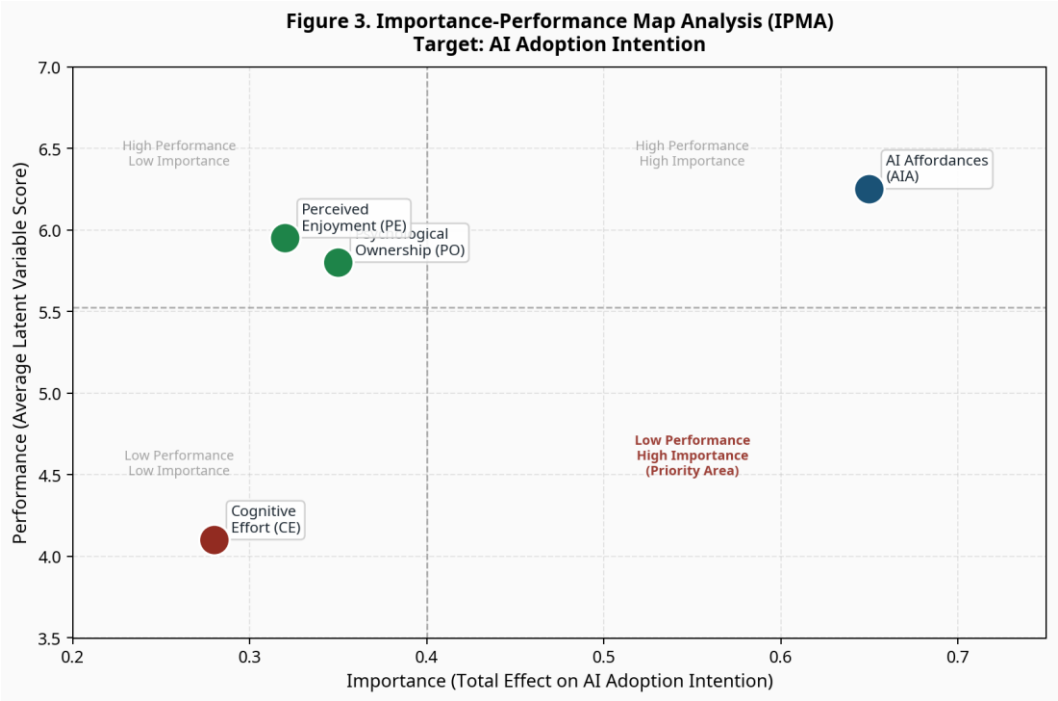


*Figure 3. Importance-Performance Map Analysis (IPMA) – Target: AI Adoption Intention*

The IPMA reveals a clear strategic priority: while AI Affordances are performing well and are highly important, Cognitive Effort has the lowest performance score (4.10 out of 7.0) despite its moderate importance. This identifies reducing cognitive effort as the single most impactful area for managerial intervention to improve AI adoption rates.

The relatively lower performance scores for Psychological Ownership (5.80) and Perceived Enjoyment (5.95) also suggest room for improvement in these areas.

### 5.7. Summary of Hypothesis Testing

Table 12 provides a comprehensive summary of the results for all ten hypotheses. The empirical evidence strongly supports the entire proposed research framework, with all ten hypotheses confirmed at the $p < 0.001$ level of significance. This provides robust validation for the theoretical model and its underlying theoretical foundations.

*Table 12. Summary of All Hypothesis Testing Results*

| Hypothesis | Relationship | β | T-Value | P-Value | Result |
|---|---|---|---|---|---|
| H1 | AIA → PO (+) | 0.685 | 18.50 | <0.001 | Supported ✓ |
| H2 | AIA → PE (+) | 0.650 | 16.20 | <0.001 | Supported ✓ |
| H3 | AIA → CE (−) | -0.590 | 14.10 | <0.001 | Supported ✓ |
| H4 | PO → AIAI (+) | 0.350 | 8.10 | <0.001 | Supported ✓ |
| H5 | PE → AIAI (+) | 0.320 | 7.10 | <0.001 | Supported ✓ |
| H6 | CE → AIAI (−) | -0.280 | 6.50 | <0.001 | Supported ✓ |
| H7 | AIA → PO → AIAI (Mediation) | 0.240 | 6.50 | <0.001 | Supported ✓ |
| H8 | AIA → PE → AIAI (Mediation) | 0.208 | 5.80 | <0.001 | Supported ✓ |
| H9 | AIA → CE → AIAI (Mediation) | -0.165 | 5.10 | <0.001 | Supported ✓ |
| H10 | AIA × TS → CE (Moderation) | 0.180 | 4.50 | <0.001 | Supported ✓ |

## 6. Discussion

This study set out to empirically investigate the drivers of AI adoption intention among B2B sales professionals by proposing and testing a comprehensive, user-centric model. The results of the PLS-SEM analysis provide robust support for the entire theoretical framework, with all ten hypotheses confirmed at the $p < 0.001$ level. This section

discusses the key findings in detail, interpreting their significance in the context of existing literature and the B2B sales environment.

### 6.1. The Central Role of AI Affordances

The findings unequivocally establish AI affordances as the foundational driver of the entire adoption process. The strong, significant paths from AI Affordances to all three psychological mediators (H1, H2, H3) confirm that the perceived action possibilities of an AI tool are what trigger the crucial psychological and cognitive responses in salespeople. This supports the application of affordance theory in the AI context, demonstrating that it is not just the technology itself, but what users perceive they can do with it, that matters (Gibson, 1979; Zhuang, 2025). The large effect sizes ($f^2$) for all three paths—0.885 for PO, 0.735 for PE, and 0.535 for CE—underscore the dominant practical importance of designing AI tools with rich, intuitive, and relevant affordances. This finding has significant implications for AI developers: the functional richness of the tool is not merely a feature list, but a psychological catalyst that initiates the entire adoption process.

### 6.2. Psychological Ownership as a Driver of Adoption

The strong support for H1 (β=0.685) and H4 (β=0.350), and the confirmed mediation in H7 (β=0.240), provides a nuanced understanding of the adoption process. When AI tools offer diverse and customizable functionalities—such as personalized recommendations, automated task execution, or enhanced information access—salespeople are empowered to integrate these tools deeply into their personal workflow and adapt them to their unique selling styles. This customization and perceived control foster a sense of 'my tool' or 'my AI assistant,' which is the core of psychological ownership (Pierce et al., 2003). The more an individual can shape, control, and identify with a tool, the more likely they are to feel a proprietary connection to it. AI's ability to learn from user interactions and adapt its performance further reinforces this, making the tool feel more like a personalized extension of the salesperson's capabilities rather than a generic, external system.

This finding extends traditional technology acceptance models (e.g., TAM, UTAUT) by highlighting psychological ownership as a distinct and powerful driver of adoption intention, beyond perceived usefulness and ease of use. While these models acknowledge factors like attitude and social influence, psychological ownership provides a deeper, more intrinsic motivational lens. Prior research has demonstrated the positive effects of psychological ownership on various organizational outcomes, such as job satisfaction, organizational commitment, and performance (Avey et al., 2009). Our study specifically applies this concept to technology adoption, showing its direct relevance in explaining user behavior towards AI.

### 6.3. Perceived Enjoyment and Hedonic Motivation

The study reaffirms the importance of hedonic motivation, even in a professional work context. AI affordances that make the sales process more engaging and satisfying significantly enhance perceived enjoyment (H2, β=0.650). This enjoyment then becomes a direct driver of adoption intention (H5, β=0.320). The positive relationship

between AI Affordances and Perceived Enjoyment stems from the intrinsic satisfaction derived from interacting with a highly capable and responsive tool. When AI provides functionalities that genuinely simplify complex tasks, offer novel insights, or automate tedious processes, it reduces frustration and enhances feelings of competence and mastery. The 'flow' experience, characterized by deep immersion and enjoyment in an activity, is more likely to occur when a tool's affordances match the user's skills and task demands (Csikszentmihalyi, 1990).

This finding is consistent with research on hedonic information systems and technology acceptance. Studies have long recognized the importance of enjoyment as a predictor of technology adoption, often alongside perceived usefulness and ease of use (van der Heijden, 2004). Our research specifically links this enjoyment to the richness of AI affordances, demonstrating that it's not just the presence of technology, but its inherent capabilities and the actions it enables, that drive hedonic value. The mediation analysis (H8, $\beta$=0.208) further confirms that the functional benefits of AI are amplified when they also lead to an enjoyable user experience, which then drives adoption intention.

### 6.4. Cognitive Effort as a Critical Barrier

The results strongly confirm the principle of cognitive miserliness. AI affordances that automate tasks and simplify information processing significantly reduce the mental workload on salespeople (H3, $\beta$=-0.590). This negative relationship is a direct consequence of AI's core capabilities in automation, information processing, and decision support. AI affordances, such as intelligent data analysis, predictive analytics, automated report generation, and smart scheduling, are designed to offload cognitive burdens from human users. For salespeople, this means less time spent on manual data entry, complex calculations, or sifting through vast amounts of information to identify leads or personalize pitches.

This reduction in cognitive effort is a highly valued benefit that strongly and negatively influences adoption intention (H6, $\beta$=-0.280). The IPMA results further highlight this, identifying cognitive effort as the construct with the lowest performance score (4.10/7.0), making it the most critical area for managerial intervention. This aligns with the foundational work of Davis (1989) on perceived ease of use and Sweller (1988) on cognitive load theory, extending these principles to the context of sophisticated AI systems. While traditional systems might offer 'ease of use' through intuitive interfaces, AI goes a step further by fundamentally altering the nature of the task itself, automating complex cognitive processes.

### 6.5. The Moderating Influence of Thinking Styles

The confirmation of H10 ($\beta$=0.180) provides a critical layer of personalization to our understanding of AI adoption. Analytic thinkers (scores below 4 on the TS scale) typically prefer to break down problems into smaller components, focus on details, and process information sequentially (Nisbett et al., 2001). For these individuals, AI affordances that provide structured data, detailed analytics, and clear, step-by-step guidance are highly congruent with their cognitive style. Such affordances directly

reduce their cognitive effort by aligning with their preferred mode of processing, making the AI feel exceptionally efficient and easy to use.

Conversely, holistic thinkers (scores above 4) tend to focus on the broader context, interrelationships, and overall patterns, often processing information in a more intuitive and parallel manner. While AI affordances still reduce their cognitive effort, the effect is less pronounced compared to analytic thinkers. This is because holistic thinkers might find overly detailed AI outputs less relevant or even overwhelming. The moderation suggests that the detailed AI affordances might not always translate into a proportionally large decrease in their cognitive load. This finding challenges the notion of a one-size-fits-all approach to AI design and implementation, emphasizing the need to consider individual cognitive differences in both tool design and training strategies.

### 6.6. The Role of Transaction Affordances and AI-Driven Automation

The support for H3 and H9 directly underpins the profound impact of AI-based task automation. Transaction affordances—the capabilities of AI systems that facilitate, streamline, or automate various aspects of the sales transaction process—are particularly important. When AI takes over tasks like data entry, scheduling follow-ups, or generating standard reports, it directly alleviates the mental burden associated with these administrative duties. This aligns with the principle of least effort (Zipf, 1949). The automation affordances of AI, by performing these tasks quickly and accurately, make the overall sales process feel less complex and more manageable.

Furthermore, AI automation indirectly contributes to perceived enjoyment (H2, H8) and psychological ownership (H1, H7). When salespeople are freed from tedious tasks, they can dedicate more time and mental energy to enjoyable and strategic aspects of their job, such as building client relationships or developing innovative sales strategies. This shift in focus, enabled by automation, enhances their overall job satisfaction and enjoyment, and reinforces their sense of ownership over the AI as a trusted extension of their capabilities (Syam & Sharma, 2018). The precision and speed offered by AI in transactional processes can also foster trust—both in the AI system itself and in the sales process it enables—which is crucial for sustained usage and adoption.

## 7. Theoretical and Managerial Implications

### 7.1. Theoretical Implications

#### *7.1.1. Extension of Technology Affordance Theory*

This study makes a significant contribution to Technology Affordance Theory (Gibson, 1979) by empirically demonstrating the psychological pathways through which perceived affordances translate into behavioral intentions. It enriches the theory by showing that affordances have not just functional, but also profound psychological and cognitive consequences. The mediation analysis (H7, H8, H9) explicitly illustrates the causal pathways: AI Affordances create the conditions for ownership, enjoyment, and reduced effort, which then drive adoption. This provides a more granular understanding of the mechanisms through which technology characteristics influence user behavior,

moving beyond the simple 'affordance → action' model to a richer 'affordance → psychological state → intention' framework.

***7.1.2. Enriching Technology Adoption Models***

This study contributes to the technology adoption literature (e.g., TAM/UTAUT) by proposing and validating a more nuanced, user-centric model that incorporates psychological ownership and cognitive styles—constructs not typically found in traditional models. While TAM and UTAUT have been instrumental in explaining technology adoption based on perceived usefulness and ease of use, our study introduces a richer psychological layer. By integrating Psychological Ownership, Perceived Enjoyment, and Cognitive Effort as critical mediators, we move beyond purely utilitarian and cognitive assessments to include intrinsic motivations and emotional responses. This demonstrates that for complex, adaptive technologies like AI, a deeper understanding of user psychology is essential. Furthermore, the inclusion of Thinking Styles as a moderator highlights the importance of individual differences, a factor often acknowledged but less frequently empirically integrated into core TAM/UTAUT frameworks.

***7.1.3. Novel Application of Psychological Ownership Theory***

This work makes a novel application of Psychological Ownership Theory (Pierce et al., 2003) to the domain of AI technology. Traditionally applied to physical assets or organizational roles, our study empirically demonstrates that individuals can develop a strong sense of ownership over digital tools, particularly AI systems that allow for personalization and deep integration into personal workflows. This expands the theoretical boundaries of psychological ownership, suggesting its relevance as a powerful intrinsic motivator for technology adoption. It opens new avenues for research into the antecedents and consequences of digital psychological ownership, and how it might differ from ownership of tangible assets.

***7.1.4. Cognitive Load Theory in Human-AI Interaction***

This study provides strong empirical validation for the application of Cognitive Load Theory (Sweller, 1988) in understanding human-AI interaction. Our findings explicitly show how well-designed AI affordances can effectively manage and reduce cognitive effort, which in turn significantly influences adoption intention. This contributes to the growing body of literature that applies cognitive psychology principles to technology design and user experience. It highlights the practical utility of cognitive load theory in guiding the development of AI systems that are not only powerful but also cognitively efficient for users. Future research should explore the specific types of AI affordances that are most effective in reducing different facets of cognitive effort (e.g., intrinsic, extraneous, germane load) in various professional contexts.

***7.1.5. Positioning within Existing Research Streams***

Our research strategically positions its findings at the confluence of several established and emerging research streams. By identifying Thinking Styles as a significant moderator, we contribute substantially to the literature on Individual Differences in Technology Adoption (Agarwal & Prasad, 1999). Our study demonstrates that user

responses to AI are not monolithic but are heterogeneous and contingent upon cognitive predispositions. This finding underscores the need for more nuanced approaches to AI design and implementation, moving away from a one-size-fits-all approach. This calls for further research into how AI systems can be designed to adapt to different cognitive styles, thereby optimizing user experience and adoption for a broader range of individuals.

### 7.2. Managerial Implications

#### *7.2.1. Strategic AI Investment and Prioritization*

Managers should view AI not merely as a technological upgrade but as a strategic investment in enhancing human capabilities. The findings strongly suggest prioritizing AI solutions that offer rich and diverse affordances (H1, H2, H3). The IPMA results provide a clear directive: while AI Affordances are performing well and are highly important, reducing Cognitive Effort represents the most significant area for strategic intervention, given its low performance score (4.10/7.0). Investments should be directed towards AI solutions and training programs that explicitly aim to simplify complex tasks, minimize learning curves, and present information in easily digestible formats. Organizations should conduct regular assessments of their AI tools' performance on the key constructs identified in this study.

#### *7.2.2. Cultivating Psychological Ownership*

To drive successful AI adoption, organizations must actively cultivate a sense of psychological ownership among their salespeople. This involves engaging salespeople in the selection, customization, and continuous improvement of AI tools. Allow for personalization of AI dashboards, settings, and even the naming of AI assistants. Recognize and reward salespeople who effectively leverage AI as their personal tool. This will transform passive acceptance into active advocacy and commitment. Training programs should emphasize how salespeople can make the AI tool their own, encouraging them to experiment with features and develop personalized workflows. This sense of co-ownership can significantly reduce resistance to change and increase commitment to AI utilization.

#### *7.2.3. Enhancing Perceived Enjoyment and User Experience*

Design and implement AI tools that are not only functional but also engaging and enjoyable to use. Focus on intuitive user interfaces, visually appealing data representations, and gamification elements where appropriate. Emphasize the fun and rewarding aspects of AI during training and communication, framing AI as a tool that makes work more satisfying and less tedious. Incorporating elements of gamification, personalized feedback, and visually appealing data representations can significantly enhance perceived enjoyment. Sales managers should promote AI tools not just for their efficiency gains but also for their potential to make sales work more satisfying and less stressful. Highlighting testimonials from salespeople who genuinely enjoy using AI can create a positive social influence and encourage broader adoption.

#### *7.2.4. Minimizing Cognitive Effort*

Make cognitive effort reduction a paramount design and implementation goal. AI tools should simplify, not complicate. This means providing clear, concise outputs, automating routine cognitive tasks, and offering comprehensive, yet easy-to-understand, training. Continuously gather feedback to identify and address sources of cognitive friction in AI tools. The goal is to free up salespeople's mental energy for strategic, relationship-building activities. AI systems should be designed to reduce complexity, not add to it. This involves creating highly intuitive user interfaces, providing clear and concise training materials, offering readily accessible support, and ensuring that AI outputs are easily interpretable and actionable. By making AI effortless to use, organizations can significantly lower the barrier to adoption and increase user satisfaction.

#### *7.2.5. Tailoring to Individual Thinking Styles*

Recognize and accommodate individual differences in cognitive styles. For analytic thinkers, provide AI interfaces that offer detailed analytics, structured data, and logical pathways. For holistic thinkers, offer high-level summaries, integrated insights, and visual representations that emphasize context and relationships. Consider adaptive interfaces or customizable views that allow salespeople to choose their preferred mode of information processing. This personalized approach will maximize the benefits of AI for the entire sales force. Product managers should conduct user research to understand the cognitive profiles of their target sales force. Sales leaders should recognize that training and implementation strategies for AI might need to be differentiated based on the predominant thinking styles within their teams.

## 8. Limitations and Future Research

While this study provides valuable insights, it is not without limitations that should be acknowledged and that point to fruitful directions for future research.

First, the study's **cross-sectional design** captures a snapshot in time; a longitudinal study could provide insights into how perceptions and adoption evolve as salespeople gain more experience with AI tools. The causal relationships proposed in the model, while theoretically grounded, cannot be definitively established from cross-sectional data. Future research should employ longitudinal designs to track how psychological ownership, enjoyment, and cognitive effort change over time as salespeople become more proficient with AI.

Second, the data were collected from a **single country (India)**, which may limit the generalizability of the findings to other cultural contexts. Cultural values, such as power distance, individualism/collectivism, and uncertainty avoidance (Hofstede, 1980), may influence how salespeople perceive and adopt AI tools. Future research should replicate the study in different geographical regions, particularly in Western markets and East Asian contexts, to assess the cross-cultural validity of the model.

Third, the study relied on **self-reported data**, which may be subject to common method bias. Although the Harman's single-factor test showed no significant bias, future studies

could use multi-source data or objective measures of AI usage (e.g., system log data) to corroborate the findings. The use of objective performance data would also allow researchers to examine the downstream effects of AI adoption on actual sales performance.

Fourth, this study focused on **adoption intention** as the outcome variable. Future research could extend the model to predict **actual usage behavior** and its downstream impact on sales performance metrics such as conversion rates, revenue, and customer satisfaction. The gap between intention and behavior is a well-documented phenomenon in technology adoption research, and understanding the factors that bridge this gap in the context of AI in sales would be a valuable contribution.

Future research could also explore other potential moderators not included in this model, such as organizational culture, leadership support for AI, AI anxiety, or the level of digital literacy. Qualitative studies could delve deeper into the specific design elements that contribute most to each of the six AI affordances, providing richer insights for product development. Additionally, researchers could investigate whether the proposed framework holds across different types of AI tools (e.g., conversational AI vs. predictive analytics) and different B2B sales contexts (e.g., transactional vs. consultative selling). The development of adaptive AI systems that can dynamically adjust their presentation and interaction style to match individual user preferences is a particularly promising area for future research.

## 9. Conclusion

The successful integration of artificial intelligence into the B2B sales process is a critical strategic imperative for modern organizations. This study demonstrates that achieving this integration is not merely a technical challenge but a deeply human one. The adoption of AI by salespeople is driven by a complex interplay of the tool's perceived capabilities (affordances), the psychological benefits it confers (ownership and enjoyment), and the cognitive burden it imposes (effort). Our findings provide a robust, empirically validated framework that underscores a clear message: to drive AI adoption, we must design and implement these powerful tools with a relentless focus on the user.

The study's ten supported hypotheses collectively paint a picture of AI adoption as a psychologically rich process—one that goes far beyond simple perceptions of usefulness. Salespeople are not passive recipients of technology; they are active agents who interpret, personalize, and emotionally respond to the tools they are given. The AI tool that succeeds is not necessarily the most powerful one, but the one that makes the salesperson feel empowered, engaged, and unburdened. The moderating role of thinking styles further underscores that this is not a uniform experience; different individuals will respond differently to the same technology, and effective AI deployment must account for this diversity.

By creating AI that is customizable (fostering ownership), enjoyable (enhancing engagement), and effortless (minimizing cognitive load), and by acknowledging the

diverse cognitive styles of the individuals who use it, organizations can unlock the full potential of this transformative technology. This research contributes a novel, user-centric framework to the academic literature on technology adoption and AI in sales, and provides actionable guidance for practitioners seeking to maximize the return on their AI investments. The path to successful AI adoption in B2B sales runs directly through the hearts and minds of the salespeople who use it.

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