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AI Captain: Set Sail for Safer Shores!

A Quantitative Study on AI Usage and Psychological Safety in the Top Management Team

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Abstract

Artificial Intelligence (AI) is increasingly integrated into strategic decision-making, yet limited research has examined how AI usage relates to psychological safety (PS) within top management teams (TMTs). This thesis investigates the relationship between AI usage and perceived PS in TMTs, and examines whether this relationship is shaped by the Unified Theory of Acceptance and Use of Technology (UTAUT) and Task-Technology Fit (TTF).

Drawing on literature on TMT, UTAUT, TTF, Decision Support Systems, and PS, the study employs a quantitative cross-sectional survey design based on 198 respondents across 50 Sweden-based TMTs. The data were analyzed using Ordinary Least Squares regression, moderation analysis, and supplementary polynomial regression with Response Surface Analysis (RSA).

The findings show a positive but weak direct relationship between AI usage and PS, contradicting the initial expectation that AI usage would reduce PS. This suggests that AI usage alone is not necessarily harmful, but explains limited PS variation. All UTAUT constructs positively moderated this relationship and showed highly similar empirical patterns suggesting that they functioned as related expressions of a broader AI adoption climate. Across these constructs, AI usage is more positively associated with PS when AI tools are perceived as useful, easy to use, socially supported, and institutionally enabled. TTF shows a different pattern: it is positively associated with PS, but does not significantly moderate the AI usage-PS relationship.

Supplementary RSA reveals divergent alignment patterns. UTAUT alignment shows increasingly favorable PS outcomes when AI usage and adoption conditions rise together, whereas TTF alignment appears beneficial but bounded, with diminishing returns emerging when AI usage continues increasing under already high TTF conditions. The thesis contributes by showing that AI-supported strategic decision-making depends less on AI usage alone than on the surrounding adoption and fit conditions.

Keywords: Artificial Intelligence, Psychological Safety, Top Management Teams, Strategic Decision-Making, Unified Theory of Acceptance and Use of Technology, Task-Technology Fit, Decision Support Systems

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Abbreviations and Descriptions

Term	Abbreviation	Description
Artificial Intelligence	AI	Computer-based systems used as decision-support tools and socially embedded in organizational adoption.
Decision Support Systems	DSS	Information systems designed to support managerial and strategic decision-making.
Intraclass Correlation Coefficient	ICC	Measure used to assess similarity within groups and justify aggregation.
Ordinary Least Squares	OLS	Regression estimation method used to model relationships between variables.
Psychological Safety	PS	"...the [individual] belief that the work [group] environment is safe for interpersonal risk taking" (Edmondson, 2018).
Response Surface Analysis	RSA	Statistical method used to analyze congruence and incongruence effects between variables.
Task-Technology Fit	TTF	Degree to which technological capabilities align with task requirements.
Top Management Team	TMT	Small group of senior executives at the strategic apex with overall responsibility for the organization.
Unified Theory of Acceptance and Use of Technology	UTAUT	Technology adoption framework explaining users' acceptance and usage behavior of new technologies.
Upper Echelons Theory	UET	Theory suggesting organizational outcomes reflect the characteristics of top executives.

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1. Introduction

1.1 Background

"Nothing is so painful to the human mind as a great and sudden change" (Shelley, 1818, p. 125). Organizations today operate amid rapid technological change, as digital technologies reshape core activities, structures, and decision-making processes (Hanelt et al., 2021; Besio et al., 2024). These changes increase complexity and uncertainty, requiring continuous adaptation (Matsunaga, 2024; Mavunda, 2025). Nowhere is this more evident than in *top management teams*, where decisions are made under conditions of uncertainty and constant change (Hambrick & Mason, 1984). At the center of today's technologies lies *Artificial Intelligence (AI)* (United Nations Economic and Social Council, 2026), which is increasingly used as an advanced *decision support system* that augments human judgment through analytical insight (Soori et al., 2026).

Two central lenses for studying AI usage and adoption are *Unified Theory of Acceptance and Use of Technology* (Venkatesh et al., 2003) and *Task-Technology Fit* (Goodhue & Thompson, 1995). Unified Theory of Acceptance and Use of Technology suggests that perceptions of usefulness, ease of use, social support, and facilitating conditions shape technology adoption (Venkatesh et al., 2003), including AI-enabled tool adoption in organizational contexts (Jain et al., 2022). A complement to this theory is Task-Technology Fit, which emphasizes that technologies, such as AI (Parsons et al., 2025), create value when their capabilities align with the tasks they are meant to support (Goodhue & Thompson, 1995).

As strategic decision-making becomes data-driven, AI tools may influence both decisions and team interactions (Onwujekwe & Weistroffer, 2025). Research on AI adoption among top managers has mainly focused on organizational AI implementation (Pinski et al., 2024) and the leadership capabilities required to support adoption (Bevilacqua et al., 2026). However, little attention has been paid to psychological dimensions and intrateam dynamics when new technologies enter decision processes (e.g. Wiersema & Hernsberger, 2021; Li & Shao, 2023).

Scholars have further highlighted that top management team research often overrelies on demographic and structural proxies for psychological and sociological decision processes

(Priem et al., 1999; Cannella et al., 2009). This calls for greater attention to the interpersonal interactions and team dynamics that shape executive decision processes (Wiersema & Hernsberger, 2021). One central concept for interpersonal team dynamics is *psychological safety* (Edmondson, 1999; Edmondson & Bransby, 2023), defined as *"the [individual] belief that the work [group] environment is safe for interpersonal risk taking"* (Edmondson, 2018, p. 8). Contemporary research suggests that psychologically safe environments foster open dialogue, knowledge sharing, and the critical evaluation of alternatives, all of which are considered essential for effective team decision-making (Edmondson & Lei, 2014; Frazier et al., 2017). While traditionally being examined through interpersonal dynamics, contemporary psychological safety research must account for increasingly digital contexts (Seth & Edmondson, 2026; Hofvander & Hydén Karlsson, 2023).

Although previous research has examined AI usage, psychological safety, and employee outcomes jointly, the primary focus has been on broader organizational or employee-level implications of AI (Kim et al., 2025). As more decisions are being augmented by AI, a growing body of literature has begun examining its effects on decision-making outcomes (Csaszar et al., 2024; Huang & Niyomsilp, 2025; Bevilacqua et al., 2025). Yet, a critical gap remains: limited attention has been given to how AI-augmented decision-making in top management teams may influence interpersonal dynamics that underpin psychological safety (Seth & Edmondson, 2026; Kim et al., 2025).

Thus, the central issue is not that AI is entering the management room, but what happens when it does. As AI tools become part of how strategic decisions are evaluated, justified, and challenged, they may reshape the very conditions that allow executives to speak up, question assumptions, and take interpersonal risks. The question is therefore not only whether TMTs are ready for AI, but how AI usage relates to psychological safety within the most central team of the organization.

1.2 Aim & Research Question

This study contributes to the research intersection of top management teams, AI-supported strategic decision-making, and psychological safety. Drawing on Upper Echelons Theory, which positions top executives as central to strategic choices and organizational outcomes (Hambrick & Mason, 1984), the study examines top management teams as the focal arena in which AI-supported strategic decisions are made. Building on decision support systems research (Keen & Scott Morton, 1978; Simon, 1977), Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003), and Task-Technology Fit (Goodhue & Thompson, 1995), AI usage is conceptualized both as a decision support tool and a socially embedded adoption phenomenon. Psychological safety (Edmondson, 1999) enables analysis of how AI usage relates to executive voice, challenge, and collective judgment.

The study makes three contributions: (i) to top management team research by studying psychological safety directly, rather than inferring team dynamics from demographic or structural characteristics (Hambrick & Mason, 1984); (ii) to AI and decision support research by moving beyond adoption, capability, and performance outcomes toward psychosocial consequences (Venkatesh et al., 2003; Goodhue & Thompson, 1995; Keen & Scott Morton, 1978; Simon, 1977); and (iii) to psychological safety research by extending Edmondson's construct into an AI-mediated top management team context, where interpersonal risk-taking may be shaped by algorithmic support and shifting human-machine authority (Edmondson, 1999).

Together, these perspectives clarify how AI usage relates to top management team psychological safety, and whether this depends on adoption conditions and task-technology fit. In doing so, the thesis examines not only whether AI supports strategic decision-making, but also how it reshapes the team conditions under which strategic decisions are made. To achieve this purpose, the thesis will therefore answer the following research question:

How does the use of AI tools relate to the perceived level of psychological safety within top management teams?

1.3 Delimitation

This study focuses exclusively on top management teams, thereby excluding other organizational levels. While this aligns with the aim of understanding how AI usage relates to psychological safety in strategic decision-making contexts, it means that the findings may not be applicable to lower-level teams or more operational settings where decision processes differ (Wiersema & Hernsberger, 2021).

As the empirical data are collected from firms with main operations in Sweden, observations do not include global collaboration across multiple time zones or extensive socio-cultural differences, which could otherwise influence psychological safety (Edmondson, 2018). This geographic focus allows for greater consistency across the sample but limits the ability to capture cross-cultural effects.

Furthermore, the study examines AI usage in terms of how such tools are integrated into decision-making processes rather than focusing on the technical characteristics of specific AI systems. Examples of AI tools include generative AI systems (e.g., ChatGPT, Microsoft Copilot, and Gemini), AI-powered analytics software, recommendation systems, and other AI-enabled decision-support technologies. Rather than distinguishing between individual applications, this study conceptualizes these tools collectively, as the objective is to examine how AI-supported decision-making relates to psychological safety within top management teams. Thus, algorithm design, data quality, and system sophistication are not considered, although they may influence team dynamics.

The study further includes factors related to Task-Technology Fit (Goodhue & Thompson, 1995) and Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) to explore potential moderating effects, while other variables such as leadership style, organizational culture, or prior experience with AI are not controlled for and may also influence the studied relationships.

2. Literature Review

2.1 Top Management Teams

2.1.1 Defining Top Management Teams

The top management team (TMT) has been defined and operationalized differently across previous studies (Krause et al., 2022). Many researchers draw on Mintzberg's (1979) broader conceptualization (Krause et al., 2022; Cannella et al., 2009), defining the TMT as a relatively small group of top executives at the strategic apex with *"overall responsibility for the organization"* (Mintzberg, 1979, p. 24). TMT composition also varies across literature (Carpenter et al., 2004; Krause et al., 2022). Some studies include the CEO, for example by using the top five highest-paid executives (e.g. Carpenter et al., 2001; Carpenter et al., 2003), whereas others define TMTs as senior executives distinct from the CEO (e.g. Buyl et al., 2014; Xu, 2023). In some cases, broader definitions have included members of the board of directors (Finkelstein & Hambrick, 1990; Haleblian & Finkelstein, 1993).

Given variation in TMT definitions, researchers should specify and justify their operationalization (Cannella et al., 2009). Thus, this study limits TMT membership to C-suite and executive management, following Guadalupe et al.'s (2012) focus on senior managerial roles. This boundary aligns with TMT research positioning such actors as central to strategic choices (Hambrick & Mason, 1984; Carpenter et al., 2004).

2.1.2 TMTs as a Research Context

Since Hambrick and Mason's (1984) introduction of Upper Echelons Theory (UET), the TMT has become a central unit of analysis in strategic leadership research (Carpenter et al., 2004; Cannella et al., 2009). At its core, UET suggests that organizational outcomes reflect executives' cognitions, values, and perceptions, which shape strategic choices and performance (Carpenter et al., 2004; Hambrick & Mason, 1984). This cognitive emphasis is closely linked to bounded rationality (Simon, 1947), as Hambrick and Mason (1984) argue that strategic choices are not made under conditions of perfect rationality, but are filtered through executives' limited fields of vision, selective perception, and interpretation.

Because such cognitive characteristics are difficult to observe directly, Hambrick and Mason (1984) initially emphasized observable managerial characteristics, such as age, education, and socioeconomic background, as proxies for executives' underlying cognitions, values, and perceptions. Building on this logic, subsequent TMT research has further examined demographic and functional attributes, including gender and functional background, in relation to organizational outcomes (Carpenter et al., 2004; Cannella et al., 2009; Wiersema & Hernsberger, 2021). While this stream has generated extensive insight into how executive attributes relate to organizational outcomes, it has also been criticized for relying too heavily on such attributes as surrogates for the psychological and sociological processes underlying strategic decision-making (Krause et al., 2022; Wiersema & Hernsberger, 2021; Carpenter et al., 2004).

2.1.3 Strategic Decision-Making in TMTs

Strategic decision-making is central to TMT research since UET treats strategic choices as filtered through executives' cognition, values, and perceptions, meaning that *"the situation a strategic decision maker faces is complex"* (Hambrick and Mason, 1984, p. 195). As such, strategic decision-making within TMTs involves significant resource commitments and has long-term performance consequences (Papadakis et al., 1998).

While much TMT research has relied on demographic and structural attributes to infer underlying executive processes, a more process-oriented stream has begun to explore the interactional dynamics through which strategic decisions are made. Carmeli and Schaubroeck (2006) relate TMT behavioral integration to strategic decision quality, while Simsek et al. (2005) conceptualize behavioral integration as the extent to which TMT members engage in mutual and collective interaction. Similarly, TMT behavioral integration is described as "*mutual and collective interaction"* (Hambrick, 2007, p. 336), suggesting that executive decision-making should not be understood as purely individual. Vandekerkhof et al. (2018) further show that strategic decision-making in TMTs depends on cooperation, communication, and the ability to express disagreement, with psychological safety supporting these interaction conditions.

However, the aforementioned studies establish the importance of interactional and psychosocial conditions within TMT decision-making, rather than explaining how such conditions may be reshaped as strategic decision processes become increasingly guided by new analytical tools. Thus, strategic decision-making provides a relevant setting for examining how changing decision-support conditions may relate to TMT psychosocial dynamics, as strategic decision processes are shaped by both managerial and contextual factors and involve consequential evaluations, choices, and outcomes (Papadakis et al., 1998; Elbanna et al., 2020). Since TMTs shape the direction of the firm (Wiersema & Hernsberger, 2021), studying their internal dynamics is especially important.

2.2 AI Adoption & Decision Support Literature

2.2.1 Defining AI Tools in Managerial Decision-Making

AI tools refer to software applications that perform tasks requiring capabilities commonly associated with human intelligence, such as generating content, recognizing patterns, producing predictions, and supporting decision-making (Russell & Norvig, 2021). Within organizations, AI tools increasingly function as decision-support technologies that augment rather than replace managerial judgement by assisting users in processing information, evaluating alternatives, and generating recommendations (Shrestha et al., 2019; Jarrahi, 2018).

In managerial settings, AI tools encompass a broad range of applications, including generative AI systems such as ChatGPT, Microsoft Copilot, and Gemini, AI-enabled analytics platforms, recommendation systems, and other AI-supported decision-support software (Davenport & Mittal, 2022). Although these applications differ in their technical capabilities, they share the common purpose of supporting managerial decision-making through information processing, analytical insight, and decision support.

Accordingly, this thesis conceptualizes AI tools collectively as AI-enabled decision-support technologies used by top management teams during strategic decision-making processes. The focus is therefore on how AI tools are used within decision-making rather than on the technical characteristics or differences between specific AI applications.

2.2.2 Unified Theory of Acceptance and Use of Technology - Capturing Both Technological and Social Dimensions

To understand why individuals accept and use new technologies, technology adoption research has developed several theoretical models (Venkatesh et al., 2003; Venkatesh et al., 2012; Williams et al., 2015). Early contributions included the Technology Acceptance Model (Davis, 1989), the Theory of Reasoned Action (Ajzen & Fishbein, 1975), and Innovation Diffusion Theory (Rogers, 1962), among others, which contributed to theoretical fragmentation (Venkatesh et al., 2003). As a response, the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed to synthesize key determinants of technology acceptance and use into a unified framework (Venkatesh et al., 2003).

UTAUT explains behavioral intention and technology use through four central determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003; Venkatesh et al., 2012). Performance expectancy captures perceived performance benefits, effort expectancy reflects perceived ease of use, social influence concerns perceived expectations from important others, and facilitating conditions refer to the organizational and technical resources available to support use (Venkatesh et al., 2003; Venkatesh et al., 2012). Rather than forming a single homogeneous climate, these shared perceptions are distinct but related mechanisms shaping technology use (Venkatesh et al., 2003; Venkatesh et al., 2016), meaning any higher-order aggregation requires separate theoretical and empirical justification (Johnson et al., 2011). UTAUT explains substantial variance in intention and usage, outperforms earlier models (Williams et al., 2015; Dwivedi et al., 2019), and remains widely applied (Venkatesh et al., 2016; Xue et al., 2026).

Building on the original framework, UTAUT2 adds hedonic motivation, price value, and habit to enhance explanatory power (Venkatesh et al., 2012). Moreover, UTAUT provides a flexible adoption framework because it captures both technical and social conditions shaping technology use (Venkatesh, 2022; Rana et al., 2024). Although originally developed to explain individual technology acceptance and use, the constructs are context- and environment-dependent (Venkatesh et al., 2003). This supports a cautious extension beyond the individual level, especially considering multilevel AI research showing that group-level sensemaking, technology frames, and organizational support shape how AI is interpreted and integrated at work (Bankins et al., 2024). Therefore, this thesis treats the UTAUT dimensions as adoption-related perceptions that may reflect the local adoption environment within TMTs.

In AI contexts, innovation, learning support, and experimentation are associated with greater AI familiarity (Chugunova et al., 2026; Khanfar et al., 2025), while supportive organizational climates can reduce resistance by framing AI as augmenting rather than undermining work (Bankins et al., 2024; Raisch & Krakowski, 2021). At the team level, shared technology assumptions shape whether AI is integrated into work practices or resisted, emphasizing the collective nature of AI usage (Bankins et al., 2024). AI adoption studies further suggest that UTAUT-related perceptions can support AI uptake, although the relative importance of each construct appears context-dependent (Jain et al., 2022; Chugunova et al., 2026).

2.2.3 Task-Technology Fit - The Technological Side of Adoption Theory

Whereas UTAUT captures technical and social adoption conditions, Task-Technology Fit (TTF) focuses on perceived technical fit. TTF emphasizes that performance effects of information systems depend on the degree to which technological capabilities align with task requirements (Goodhue & Thompson, 1995). Rather than assuming inherent technological value, TTF highlights that benefits arise when systems effectively support the activities users perform (Zigurs & Buckland, 1998). TTF therefore shifts attention from general acceptance attitudes toward whether the technology is perceived to support the task (Goodhue & Thompson, 1995), with prior research linking TTF to perceived usefulness and ease of use (Dishaw & Strong, 1999; Howard & Hair, 2023).

Moreover, TTF is typically conceptualized through the fit between task characteristics, technology characteristics, and individual capabilities (Goodhue & Thompson, 1995; Zhou et al., 2010). Task characteristics reflect the complexity, interdependence, and information-processing requirements of work activities, which in turn determine what functionalities are required (Zigurs & Buckland, 1998). Technology characteristics instead refer to functionality, accessibility, and usability, which must match the task characteristics (Zhou et al., 2010). Lastly, individual capabilities, including experience and self-efficacy, shape how effectively users can leverage the technology (Wu & Chen, 2017).

Empirically, strong TTF consistently links with improved task performance and enhanced decision effectiveness (Goodhue & Thompson, 1995; Dishaw & Strong, 1999). When users perceive that a technology supports their task execution, they are more likely to adopt and continue using it (Zhou et al., 2010; Oliveira et al., 2014). Conversely, even highly advanced technologies may be rejected if they do not align with task requirements, underscoring that practical utility is important for technology use (Zhou et al., 2010).

Furthermore, TTF complements UTAUT by emphasizing task-technology alignment beyond user perceptions (Wu & Chen, 2017; Oliveira et al., 2014). Research suggests that integrating TTF with other constructs improves the explanatory power for both adoption and continuance intentions (Zhou et al., 2010; Wu & Chen, 2017).

Lastly, TTF is particularly relevant in strategic decision-making because technology use improves decision outcomes only when system capabilities fit the task’s information-processing requirements, rather than through use alone (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998). This is especially salient for AI-based decision support, where appropriateness depends on alignment between algorithmic outputs and the decision task's methodological, managerial, and ethical demands (Parsons et al., 2025; Strohmeier et al., 2025).

2.2.4 AI as Decision Support Systems

Decision Support Systems (DSS) are interactive information systems designed to assist decision-makers in solving semi-structured and unstructured problems by integrating data, models, and user interaction (Keen & Scott Morton, 1978). This is especially relevant for TMTs, where decisions require both analysis and human judgment under uncertainty and high consequence (Keen & Scott Morton, 1978; Simon, 1977, 1997). Early DSS research emphasized structured data processing, analytical modelling, and user interfaces that enable decision-makers to explore alternatives and evaluate outcomes (Keen & Scott Morton, 1978). DSS support problem structuring, alternative generation, and evaluation (Simon, 1997), where neither purely algorithmic nor intuitive approaches are sufficient (Phillips-Wren, 2013). Consequently, DSS have been applied across complex and ambiguous domains such as strategic management, health care, and operations (Arnott & Pervan, 2005).

AI has expanded DSS into AI-based decision support systems (e.g. Gupta et al., 2006; Phillips-Wren, 2013; Onwujekwe & Weistroffer, 2025). AI-based DSS differ by processing large-scale, distributed datasets and supporting real-time decisions in complex environments (Phillips-Wren, 2013; Onwujekwe & Weistroffer, 2025). By using machine learning, predictive analytics, and simulation, AI-based DSS can improve decision quality and efficiency by identifying patterns, generating forecasts, and providing data-driven recommendations (Phillips-Wren, 2013; Onwujekwe & Weistroffer, 2025). DSS have therefore become useful for conceptualizing AI-supported strategic decision-making (Onwujekwe & Weistroffer, 2025).

However, while DSS literature traditionally has focused on decision performance, it often neglects the social and interpersonal dynamics of decision-making processes (Arnott & Pervan, 2005). While AI enhances computational power and analytical depth, it does not inherently address how decisions are discussed, challenged or validated within teams (Shrestha et al., 2019). This limitation suggests that, despite technological advancements, DSS research remains primarily task- and performance-oriented, leaving an important gap concerning team-level processes (Arnott & Pervan, 2005).

2.3 Psychological Safety

2.3.1 Conceptualizing Psychological Safety

As interpersonal and intrateam dynamics gained prominence in organizational research, the construct of psychological safety (PS) has emerged from research on team learning and organizational behavior (Schein & Bennis, 1965; Edmondson, 1999). The dominant definition describes PS as *"...the [individual] belief that the work [group] environment is safe for interpersonal risk taking."* (Edmondson, 2018, p. 8). By capturing freedom to speak up without interpersonal penalty, PS has become especially important in managerial studies because it supports constructive dialogue (Edmondson, 1999; 2018).

Since its inception, PS has predominantly been conceptualized within a team-based framework (Edmondson & Lei, 2014; Newman et al., 2017). While some studies extend PS to the organizational level (Baer & Frese, 2003; Carmeli, 2007), recent literature reaffirms its meso-level conceptualization (e.g., Kuske et al., 2024; Lechner & Mortlock, 2022; Vella et al., 2024). Since PS is shaped by proximal interpersonal conditions, leadership behaviors, and task context, organization-level aggregation may obscure meaningful between-team variation (Edmondson & Lei, 2014; Newman et al., 2017). Empirical research also shows that PS varies between teams within organizations, highlighting its team-level nature (Chen & Tjosvold, 2012; Edmondson, 2018).

Similarly, individual-level conceptualizations face limitations related to measurement validity and theoretical consistency (Newman et al., 2017). Many micro-level studies rely on in-house, adapted or context-specific scales, which risks reducing comparability and construct validity across studies (DeVellis, 2003; Newman et al., 2017). Lastly, isolating PS at the individual level risks neglecting its inherently relational and socially constructed nature (Edmondson & Lei, 2014).

2.3.2 Psychological Safety in Team Decision Processes

In general team contexts, PS supports open communication and learning behavior (Edmondson, 1999), individual efficiency (Liang et al., 2012), and creativity by enabling voice and interpersonal risk-taking (Kark & Carmeli, 2009). This relevance also extends to digitally mediated work, where PS supports technology acceptance, trust, and adoption (Kuske et al., 2024), and facilitates collaboration in virtual teams (Lechner & Mortlock, 2022).

However, the effects of PS are not uniform across all settings. Although PS is generally associated with positive team outcomes (Edmondson & Bransby, 2023; Newman et al., 2017), its role may be context-dependent in agile and critical decision-making processes, where it does not always moderate team dynamics and performance in the same way (Verwijs & Russo, 2024). Still, evidence from high-stakes healthcare contexts suggests that PS remains particularly relevant when uncertainty, interdependence, and consequential decisions make voice, error reporting, and upward challenge essential (O'Donovan et al., 2020). This raises the question of how PS operates in other high-stakes decision settings, such as TMTs.

Strategic decision-making is characterized by consequential, ambiguous, and often irreversible outcomes (Papadakis et al., 1998). In such settings, the willingness to express uncertainty, challenge assumptions, and raise concerns becomes important for avoiding decision errors and unchallenged assumptions (Edmondson, 2018; Edmondson & Bransby, 2023). Yet PS is not unconditionally beneficial: when accountability is low, high PS may produce diminishing or even negative returns for decision performance (Eldor et al., 2023). Under higher accountability, however, PS supports collective learning, which is important in uncertain and information-intensive environments (Frazier et al., 2017). In strategic contexts marked by incomplete information and competing interpretations, PS may therefore help reduce information withholding and unchallenged assumptions (Mogård et al., 2023; Chinyuku & Qutieshat, 2025; Edmondson & Lei, 2014). This is especially relevant in TMTs, where members bring diverse judgments to unstructured problems (Carmeli et al., 2012). Since PS functions as an emergent state that enables interpersonal risk-taking in decision processes (Vandekerkhof et al., 2018), it may also help reduce defensive decision-making among managers (Artinger et al., 2025). PS should therefore not only be seen as a general team outcome, but as a condition shaping how TMTs engage in strategic decision-making.

AI-mediated environments add a further layer to this logic. While AI can support decision outcomes, it may also introduce concerns around accountability, fairness, transparency, and trust (Shrestha et al., 2019). AI-integrated applications may reduce workload and improve accuracy, but can also harm PS through job insecurity, upskilling pressure, and professional identity uncertainty (Gao & Zamanpour, 2024). Similarly, embedded AI can reduce mundane work while threatening agency, increasing surveillance, and reducing willingness to speak up (Webber, 2025). These risks are reinforced by AI trust research, which shows that confidence in algorithmic systems may deteriorate when outputs are opaque, imperfect, or difficult to interpret (Dietvorst et al., 2015; Glikson & Woolley, 2020). Taken together, AI usage may challenge the open communication and critical evaluation that underpin PS (Edmondson, 2018).

2.4 Integrating the Literature & Research Gap

2.4.1 A Three-Stream Intersection

Following the literature review, this study integrates three research streams: TMT, AI adoption & decision support, and PS. PS is explicitly adopted from Edmondson's studies (1999; 2018) and the AI stream incorporates UTAUT (Venkatesh et al., 2003), TTF (Goodhue & Thompson, 1995) as well as DSS research (Keen & Scott Morton, 1978). Moreover, TMT research, stemming from UET (Hambrick & Mason, 1984), sets the context in which strategic decisions emerge (Hambrick & Mason, 1984; Simsek et al., 2005). Integrating these perspectives, this thesis examines how AI-supported strategic decision-making relates to PS within TMTs.

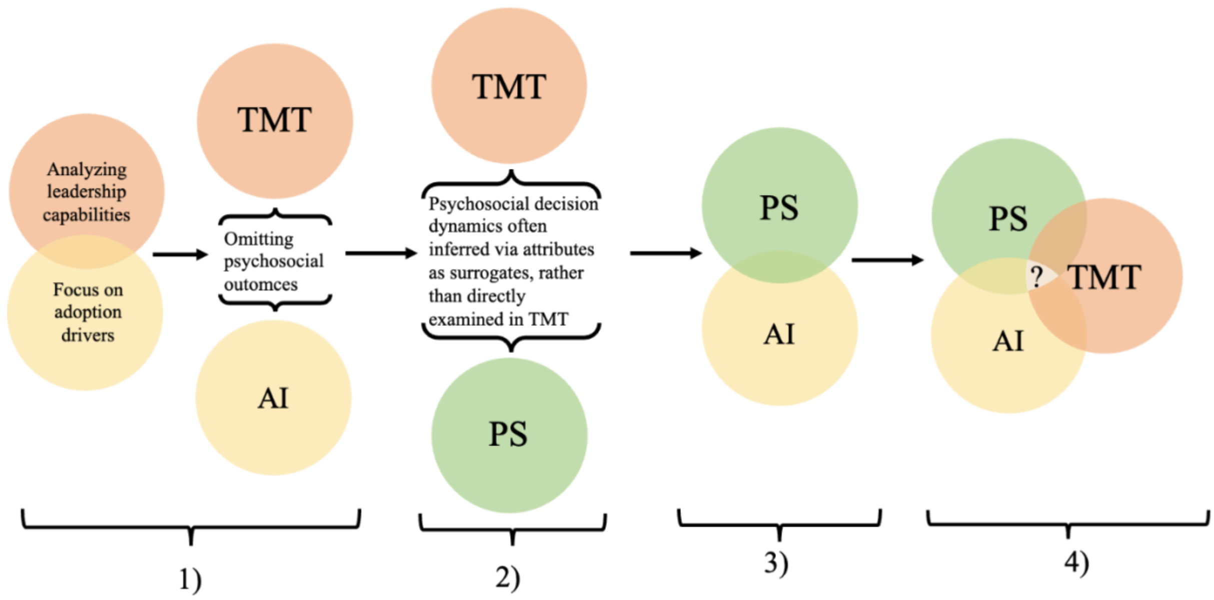

Figure 1: Deductive Research & Research Gap

The figure above presents the a priori research in a chronological sequence:

1) **Research Gap: AI in TMTs**
   AI-TMT research indicated focus on AI as a tool for improving decision-making and how to enable adoption. Limited attention has been given to how AI reshapes intrateam psychosocial dynamics, such as PS.
2) **Research Gap: Psychological Safety and Strategic Decision-Making in TMTs**
   Further review revealed that TMT research often infers psychosocial decision dynamics from observable team attributes, rather than studying outcomes, such as PS, directly. This leaves limited insight into how psychosocial team-level outcomes such as PS are affected in TMTs, and especially how external factors such as AI shape these outcomes.
3) **Intersection: AI and Psychological Safety**
   Emerging studies on AI usage and PS exist but are fragmented and context specific.
4) **Integrating the Research Streams**
   The sections above were integrated to develop the research question (1.2) & hypotheses (3.4).

2.4.2 Research Gap: AI in TMTs

Research on digital extensions of strategic decision-making includes DSS literature, where AI is conceptualized as a tool which enhances information processing, structuring of complex problems, and improves evaluation of strategic alternatives (Keen & Scott Morton, 1978; Simon, 1977; Shrestha et al., 2019). Within TMT research, this perspective has been extended by situating AI usage in executive-level decision processes and how digital capabilities, AI orientation, and managerial characteristics shape strategic, rather than psychosocial outcomes (Bevilacqua et al., 2025). This is highlighted by Li & Shao (2023, p. 10) who claim that TMT research should investigate *"the impact of factors such as social environment"* on digital orientation.

Moreover, while UTAUT primarily explains how technosocial conditions shape individual usage behavior (Venkatesh et al., 2003; Williams et al., 2015), TTF has been adapted to group-level contexts by using group performance as an outcome (Zigurs & Buckland, 1998). However, these outcomes remain primarily technology- and performance-oriented; thus, TTF is functionally limited and has been criticized for *"its lack of focus on individuals' psychological and situational factors"* (Marikyan & Papagiannidis, 2026a, p. 12). Similarly, calls for multi-level analysis have been voiced by UTAUT scholars (Williams et al., 2015). For this reason, the adoption literature provides little explanation of how AI usage shapes intra-team processes, leaving a gap in understanding outcomes such as PS within teams, particularly since TMTs play a central role in organizational strategic leadership (Carpenter et al., 2004).

2.4.3 Research Gap: Psychological Safety and Strategic Decision-Making in TMTs

Carpenter et al. (2004, p. 749) describe UET both as a theoretical framework and a methodology that relies on executive demography as a proxy for "*underlying individual and group cognitions and behaviors*" and further call for research to examine the deeper constructs that TMT demographic characteristics are presumed to represent. Similarly, Wiersema and Hernsberger (2021, p. 358) state that "*TMT scholars rely on attributes of the team as surrogates for the psychological and sociological processes that underlie decision-making",* and that this does not fully show what transpires within TMTs. As such, current TMT research is limited in its ability to explain underlying psychological processes, such as how communication, interaction, and influence shape members' cognitive perspectives (Wiersema & Hernsberger, 2021).

As such, TMT research mainly indicates how demographic or structural attributes relate to inferred or adjacent team processes instead of capturing psychosocial team-level states directly. Vandekerkhof et al. (2018) explicitly position PS as an emergent TMT state that facilitates cooperation, communication, shared decision-making, and the expression of disagreement without fear of negative judgment. Therefore, the gap is not that TMT research ignores team dynamics, but that much of the broader tradition infers them from attributes, while direct research on psychosocial team-level states such as PS remains limited.

2.4.4 Intersection: AI usage and Psychological Safety

While adoption frameworks such as UTAUT and TTF offer limited insight into intrateam dynamics, Seth & Edmondson (2026) have highlighted that broader research on links between PS and AI usage is emerging. AI-integrated applications may foster PS through employee confidence, but also undermine it through role ambiguity (Gao & Zamanpour, 2024). Simultaneously, embedded AI systems may increase monitoring and data transparency in ways that erode trust and constrain PS (Webber, 2025), while AI adoption may also be linked to lower PS under unfavorable support conditions (Kim et al., 2025). At the team level, digital transformation research indicates that perceived PS is shaped by uncertainty, technological design, trust, and digital literacy (Kuske et al., 2024; Minartz et al., 2024).

Moreover, AI usage has been associated with anxiety, privacy concerns, and technology distrust, with PS being important for AI adoption (Shen et al., 2025). Employee-level research likewise suggests that AI can provoke reactions of trust and threat, with the latter weakening adaptive collaboration (Duong et al., 2026). At the same time, broader research suggests that in periods of technological change, PS remains essential for adaptation and experimentation (Cazan, 2023).

2.4.5 Integrating the Research Streams

Despite research within each intersection, the combined nexus remains underexplored. AI in decision-making has often been conceptualized through DSS (Phillips-Wren, 2013; Onwujekwe & Weistroffer, 2025) or focused on capabilities required for effective AI navigation at the executive level (e.g. Bevilacqua et al., 2026). However, the studies overlook how AI integration reshapes intrateam dynamics such as PS within TMTs. Furthermore, studies on TMTs and PS are limited since UET focuses on observational attributes as proxies for psychosocial processes (Wiersema & Hernsberger, 2021). At the same time, intersecting research on AI and PS remains nascent and fragmented, with most studies focusing on non-executive contexts or specific industries rather than strategic leadership teams (e.g. Seth & Edmondson, 2026; Shen et al., 2025).

Taken together, research simultaneously examining AI usage, PS, and TMT strategic decision-making dynamics is notably absent. This limits the understanding of how AI adoption not only supports but also alters social and behavioral foundations of strategic decision-making within TMTs; hence representing a critical gap and avenue for research (Figure 1).

3. Theoretical Frameworks & Hypotheses

3.1 TMTs & UET

Hambrick & Mason's (1984) UET provides the starting point for this study by positioning strategic choices as reflections of top executives' cognitive bases, values, and perceptions; hence, TMTs, as a level of analysis, are treated as the central locus through which organizational outcomes are shaped. Therefore, UET is used to justify TMTs as an important unit of analysis, as they shape the direction of the firm (Wiersema & Hernsberger, 2021) and exert strong influence over strategic outcomes (Carpenter et al., 2004).

3.2 AI Usage & Adoption Theories

3.2.1 UTAUT

To address the research gap (2.4), UTAUT is used to theorize the adoption conditions surrounding AI use in TMTs. It explains how technology becomes accepted, legitimized, and embedded in organizational practice, rather than merely available for use (Venkatesh et al., 2003). Following Venkatesh et al. (2012), habitual use was included to account for routinized use tendencies (AI-U1, Appendix 1.5). UTAUT therefore informs the contextual adoption construct used in H2 (3.4.2) and the corresponding survey items in Appendix 1.6.

3.2.2 TTF

TTF is used to theorize whether AI use becomes meaningful for TMT decision-making by depending on the fit between technological capabilities and task requirements (Goodhue &

Thompson, 1995). This complements UTAUT by shifting attention from adoption conditions to task alignment, thereby capturing whether AI tools are perceived as appropriate for the decision tasks they support (Dishaw & Strong, 1999; Venkatesh et al., 2003). As Oliveira et al. (2014) show that TTF can strengthen explanations of technology adoption and use outcomes, TTF provides the theoretical basis for H3 and the corresponding measurement items (Appendix 1.7).

3.2.3 DSS

DSS literature is used to contextualize AI usage within TMT strategic decision-making. It complements UTAUT and TTF by specifying AI use as engagement with decision support inputs, including outputs, recommendations, and analyses used to evaluate alternatives, support judgment, and assess decision outcomes (Keen & Scott Morton, 1978; Shrestha et al., 2019). Since technology-use measures require adaptation to the specific technology and context studied (Marikyan & Papagiannidis, 2026b), DSS informs the AI usage items (Appendix 1.5).

3.3 Psychological Safety

PS is used as the study's core psychosocial outcome because the construct is theoretically mature, consistently defined, and widely measured across prior research (Edmondson & Bransby, 2023). Edmondson's (1999) framework is therefore adopted as the main theoretical basis for PS, including its team-level orientation, its definition as "*the [individual] belief that the work [group] environment is safe for interpersonal risk taking"* (Edmondson, 2018, p. 8), and the seven-item measurement scale (Appendix 1.8). This framework also supports general hypotheses development by linking PS to related team behaviors such as voice, trust, learning, and interpersonal risk-taking (Newman et al., 2017; Edmondson & Bransby, 2023).

3.4 Hypotheses Formulation

3.4.1 Direct Relationship Hypothesis

Although AI and DSS research shows that AI can support information processing, forecasting, and alternative evaluation (e.g. Phillips-Wren, 2013; Onwujekwe & Weistroffer, 2025), these benefits are mainly framed around performance outcomes within TMTs (Bevilacqua et al., 2025), rather than on psychosocial team dynamics. AI usage may negatively affect PS as AI-generated trust ambiguity "*directly threatens the psychological safety*" of teams and "*inhibits* *willingness to speak up*" within the same teams (Seth & Edmondson, 2026, p. 3). Moreover, while embedding AI in teams may reduce mundane work and support feedback, it can increase surveillance, weaken trust, and make members less willing to speak openly (Webber, 2025). Similarly, AI use can reduce perceived discretion and agency through monitoring, recommendation, and control mechanisms, which constrain users' willingness to question or deviate from system outputs (Kellogg et al., 2020; Raisch & Krakowski, 2021). Lastly, people may lose confidence in algorithmic systems when outputs are opaque, imperfect, or difficult to interpret (Glikson & Woolley, 2020; Dietvorst et al., 2015). As such, we hypothesize that:

H1:	AI usage is **negatively** related to psychological safety within top management teams

3.4.2 Moderation Hypotheses UTAUT

Moderator variables capture conditions under which the relationship between a predictor and an outcome changes. Sharma et al. (1981) define a moderator as a variable that systematically alters the strength and/or form of such a relationship. Moreover, a moderator does not influence other variables, and it is not influenced by other variables, the only thing it does is to influence associations between variables. Accordingly, this study examines the UTAUT constructs and TTF as potential moderators of the relationship between AI usage and psychological safety within TMTs.

UTAUT suggests that technology use is more consequential when perceived as useful, easy, socially supported, and organizationally enabled, rather than merely adopted (Venkatesh et al., 2003; Venkatesh et al., 2016). Studies on AI tool use for strategic decision-making extend this logic by linking performance expectancy, effort expectancy, and facilitating conditions to AI uptake (Cao et al., 2021). Organizational research further finds support for all constructs in shaping managers' AI attitudes for collaboration and team management (Jain et al., 2022), which is relevant since PS links to behavioral integration (Mogård et al., 2023) and helps make collaboration more likely (Edmondson & Lei, 2014).

Furthermore, the UTAUT constructs represent distinct but interrelated mechanisms through which users evaluate technology; as such, prior research often treats these dimensions as 4 separate but interrelated constructs (Venkatesh et al., 2016; Williams et al., 2015). Therefore, the moderating role of UTAUT constructs is examined at the component level:

***H2a**:* Performance Expectancy **moderates** the negative relationship between AI usage and psychological safety

H2b: Effort Expectancy **moderates** the negative relationship between AI usage and psychological safety

***H2c**:* Social Influence **moderates** the negative relationship between AI usage and psychological safety

***H2d**:* Facilitating Conditions **moderates** the negative relationship between AI usage and psychological safety

3.4.3 Moderation Hypothesis TTF

The moderating role of TTF follows prior research showing that technology use depends on whether the tool fits the task it supports. TTF theory argues that technology creates value when its capabilities match task requirements, rather than through use alone (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998). Since fit is also linked to perceived usefulness, ease of use, and continued use (Dishaw & Strong, 1999; Zhou et al., 2010; Wu & Chen, 2017), AI tools that fit strategic decision tasks should be experienced as more appropriate and less disruptive. Higher TTF is therefore expected to reduce the negative implications of AI usage for voice, trust, and interpersonal risk-taking, weakening the negative AI usage-PS relationship proposed in H1.

H3: TTF **moderates** the relationship between AI usage and psychological safety

3.5 Unified Theoretical Framework

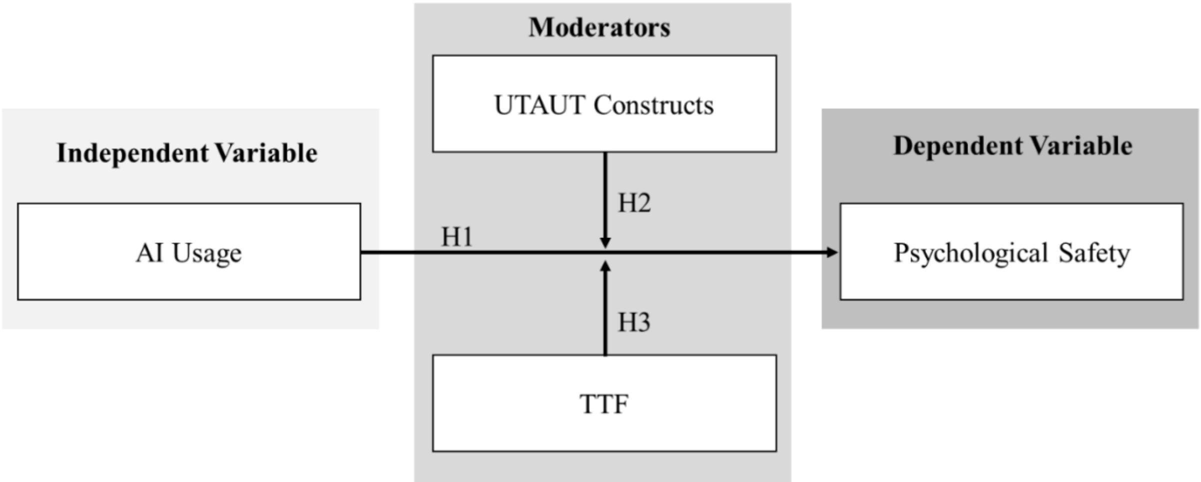

Figure 2: Hypothesized Theoretical Framework

By integrating research on TMT, UTAUT, TTF, DSS, and PS, the theoretical framework addresses the research gaps (2.4) by moving beyond adoption, fit, and decision-performance perspectives to examine how AI usage relates to PS within TMTs.

4. Method

4.1 Research Design & Methodological Fit

This study adopts a positivist approach, treating the relationship between AI usage and PS in TMTs as observable, measurable, and empirically testable (Straub et al., 2014). The hypotheses were developed deductively from existing theory and examined through a quantitative cross-sectional survey design, enabling predefined constructs to be measured systematically across respondents (Creswell & Creswell, 2017). Given the study timeframe, a longitudinal design was not feasible, as too few measurement points could risk inconsistent findings (Wang et al., 2017).

Furthermore, surveys were suitable because they efficiently collect standardized data across a broader sample (Bryman & Bell, 2011). Although quantitative data cannot fully explain intrateam dynamics, the heterogeneous sample (N = 198) supports the identification of systematic patterns (Blackstone, 2012). Given that PS is shaped by local team dynamics (Edmondson, 1999, 2018), a team-level design is appropriate for examining TMTs.

Accordingly, AI usage, UTAUT constructs, and TTF were operationalized at the team level to align the independent and moderating variables with the dependent variable, PS. Although these constructs are often introduced at the individual level, the inclusion rule described in section 4.2.1, together with the ICC results reported in Appendix 11, supported aggregation to the team level (Bliese, 1998, 2000). Multilevel modelling was considered less appropriate given the small within-team sample sizes, which can produce unstable estimates in hierarchical models (Kreft & de Leeuw, 1998; Maas & Hox, 2005). Lastly, because responses to sensitive topics may be influenced by disclosure concerns, anonymity was ensured to reduce potential response bias (Ong & Weiss, 2000).

4.2 Research Method

4.2.1 Sample Selection

The sample was selected to match the study's TMT focus while ensuring sufficient variation in AI usage and adoption conditions. In line with section 2.1.1, respondents were limited to C-suite and executive management members. Since TMTs are typically small and difficult to access, the study prioritized collecting responses from several teams across different firms rather than restricting the sample to a single industry (Krause et al., 2022).

To preserve the credibility of team-level aggregation, only teams with at least three respondents or at least 50% team coverage were retained, consistent with aggregation logic in team-level research (Bliese, 2000). This inclusion rule was further supported by ICC estimates indicating meaningful between-team variance (Appendix 11).

A cross-industry sample was considered appropriate because both AI usage and technology adoption are relevant across sectors (Venkatesh et al., 2003; Williams et al., 2015). Although industry characteristics may influence organizational culture (Chatman & Jehn, 1994), such effects can be addressed analytically rather than through strict sampling restrictions (Sharp et al., 2013). The industry-diverse sample is therefore defensible, while acknowledging increased heterogeneity (Chaudhry et al., 2016). Also, as PS is shaped by local interaction dynamics, the relevance of PS across organizational contexts is supported (Edmondson, 1999; 2018; Newman et al., 2017). Lastly, to reduce external contextual variation, the sample was limited to Swedish firms and TMTs.

4.2.2 Survey Construction

The survey (Appendix 1) included 27 questions with the following structure:

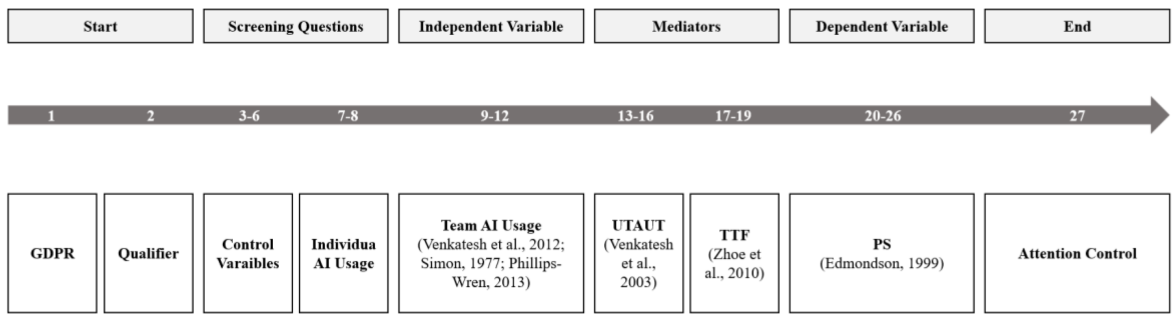

Figure 3: Survey Layout

Age, workgroup size, and organizational size controlled for relevant heterogeneity. Age reflects upper echelons researchers' use of executive demographics as proxies for cognitive and experiential differences (Hambrick & Mason, 1984), while workgroup size accounts for variation in TMT interaction dynamics (Amason & Sapienza, 1997). Organizational size was included as larger firms tend to differ in organizational structure and division of labor within senior management, which may shape the operational context of TMTs (Guadalupe et al., 2012). Lastly, individual AI usage was included descriptively because adoption and fit research is traditionally grounded in individual use behavior (Venkatesh et al., 2003; Goodhue & Thompson, 1995). Since AI usage was adapted to the TMT level, these items assessed whether personal AI exposure related to, yet differed from, team-level AI usage, consistent with multilevel composition logic (Chan, 1998).

For the dependent variable PS, the survey items followed Edmondson's (1999) scale since these items have been widely used and validated in prior research (Edmondson & Bransby, 2023; Newman et al., 2017). Although reliability may be optimized with 7-point Likert scales (Colman et al., 1997), this study uses 5-point scales. This choice aimed to increase response rates (Babakus & Mangold, 1992) and reduce frustration (Buttle, 1996). Furthermore, Edmondson (2018) states that reducing from 7- to 5-point scales does not affect PS measurements. Moreover, odd-numbered scales were used to avoid forcing indifferent respondents to choose sides (Kusmaryono et al., 2022) for all Likert scale questions.

AI usage was operationalized through a combination of UTAUT-based technology-use and DSS-based decision support logic. UTAUT and UTAUT2 informed the general usage foundation, particularly habitual use (Venkatesh et al., 2003; Venkatesh et al., 2012), while DSS literature specified what AI use entails in strategic decision-making (Keen & Scott Morton, 1978). Since technology-use and UTAUT measures are context-dependent, the items were reformulated to capture collective and decision-relevant AI use in TMTs (Venkatesh et al., 2016; Marikyan & Papagiannidis, 2026b). Thus, AI-U1 captures routinized use (Venkatesh et al., 2012), while AI-U2, AI-U3 and AI-U4 capture AI use for evaluating strategic options, analytically supporting or justifying decisions, and assessing performance-relevant outcomes (Simon, 1977; Phillips-Wren, 2013; Appendix 1.10 for logic).

For the UTAUT constructs, this study adopted one item per dimension from Venkatesh et al. (2003), while recognizing that UTAUT research generally relies on multi-item operationalizations (Venkatesh et al., 2016; Williams et al., 2015) and that multi-item scales usually provide stronger measurement properties (Diamantopoulos et al., 2012). This was a conscious design trade-off rather than an assumption of measurement equivalence. Since Diamantopoulos et al. (2012) argue that single-item measures should be limited to special circumstances, this choice is interpreted cautiously in light of the TMT setting, where executive survey access and response burden are known methodological challenges (Bednar & Westphal, 2006; Cycyota & Harrison, 2006). Following pilot feedback that two- and three-item UTAUT versions were repetitive and burdensome (4.2.3), brevity was prioritized to improve feasibility. The final items were also phrased close to respondents' everyday AI-supported decision tasks, making them relatively narrow and unambiguous, consistent with arguments that single-item measures may be acceptable when constructs are clear, and concrete (Wanous et al., 1997; Fisher et al., 2016).

For TTF, the items were adapted from Zhou et al. (2010) and readjusted to fit the strategic decision-making context within TMTs (Appendices 1.7 & 1.10). Individual capability-related items were excluded to keep TTF focused on the team-level fit between AI capabilities and strategic decision tasks, consistent with group-level TTF research emphasizing the fit between a group’s task and supporting technology (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998).

Since the respondents worked for companies operating in Sweden, the survey was translated into Swedish. This necessitated precautions as deviations in terminology, derived from faulty translations, could prevent respondents from comprehending the questions as intended (Sha & Immerwahr, 2018). Therefore, the translated survey was reviewed by four linguists and revised thereafter.

4.2.3 Pilot Testing and Instrument Refinement

Since expert reviews can identify ambiguous or weak items and strengthen measurement quality (Willis, 2005; Presser et al., 2004), initial input from experts in psychological measurement and quantitative methodological approaches was gathered. To further strengthen the survey, both the original and the translated draft were sent out to seven CHROs or HR representatives from the target firms for review. Pilot feedback emphasized brevity, especially for UTAUT, where two- and three-item versions were criticized as repetitive and burdensome. Therefore, the final survey retained one item per UTAUT construct as a conscious trade-off between construct depth and response feasibility. Once no further feedback was received, the survey was distributed to all targeted executives.

4.2.4 Data Distribution & Collection

To collect data, respondents within the authors’ professional networks were contacted and provided with separate anonymous links, allowing for team-level identification required for accurate aggregation of team-level constructs based on individual responses (Kozlowski & Klein, 2000; Bliese, 2000). Second, interested executives at a networking event were invited to sign up for participation and were subsequently sent separate links, which were redistributed to the respective TMTs within their organizations. While team-level identification slightly reduced respondent anonymity, this was necessary to conform with the team-level conceptualization of PS and accurately group individuals for valid aggregation (Edmondson, 1999).

4.2.5 Testing the Relationships

To test the direct relationship between PS and AI usage, both constructs were aggregated by taking their respective mean values (Appendices 2.3 & 2.6). Moreover, workgroup size (WG_i), organizational size (OS_i), and age (Age_i), were included as control variables to account for potential heterogeneity (4.2.2). The relationship was tested using the specified linear regression below:

$$PS_i=\beta_0+\beta_1 AI\_Usage_i+\beta_2 Age_i+\beta_3 WG_i+\beta_4 OS_i+\varepsilon_i \quad (1)$$

For the moderation hypotheses, Baron and Kenny's (1986) moderation logic was used. The UTAUT dimensions were first tested as four separate moderators (Appendix 2.4), while TTF was calculated as the mean of the three TTF items (Appendix 2.5). AI usage and moderator variables were mean-centered before creating interaction terms as it improves interpretability of lower-order coefficients and reduces non-essential multicollinearity between interaction terms and their components (Aiken & West, 1991).

$$PS_i=\beta_0+\beta_1 AI\_Usage^i+\beta_2 UTAUT_i+\beta_3(AI\_Usage_i\times UTAUT_i)+\beta_4 Age_i+\beta_5 WG_i+\beta_6 OS_i+\varepsilon_i \quad (2)$$

$$PS_i=\beta_0+\beta_1 AI\_Usage_i+\beta_2 TTF_i+\beta_3(AI\_Usage_i\times TTF_i)+ \beta_4 Age_i+\beta_5 WG_i+\beta_6 OS_i+\varepsilon_i \quad (3)$$

4.2.6 Data Analysis & Assumptions

Survey data (Appendix 1) were coded in Excel (Appendix 2) and subsequently imported into Stata® for model specification and estimation. Ordered control variables were numerically coded as linear controls, assuming monotonic effects for parsimonious inclusion of non-focal ordinal covariates (Robitzsch, 2020; Williams, 2020). Also, given the team-level framing of the study, aggregation was assessed through respondent inclusion rules (4.2.1) and ICC analysis (Appendix 11). Because team sizes of TMTs are relatively small, the aggregated results are interpreted cautiously and OLS regressions were estimated with cluster-robust standard errors at the team-level (Wooldridge, 2020; Cameron & Miller, 2015).

To assess the robustness of the Ordinary Least Squares (OLS) regressions, the VIF values for the main linear models were first examined and found to be below conventional concern thresholds (Appendices 4.1–4.3), indicating no problematic multicollinearity (Marquardt, 1970; Hair et al., 2019). Cook's (1977) influence diagnostics indicated no serious influential observations for H1 and H3 (Appendix 5), while 12 observations exceeded the H2 threshold, leading to a robustness re-estimation (Appendix 15) that yielded highly similar results as the main model. Residual-versus-fitted plots showed some clustering (Appendix 6), likely reflecting the bounded survey-scale structure of the variables, but no severe functional-form misspecification (Robitzsch, 2020). Accordingly, the linear specification was considered acceptable, with inference based on cluster-robust standard errors at the team level (Wooldridge, 2020). Lastly, Q-Q plots indicated some deviations from perfect residual normality (Appendix 16), but this was treated as a supplementary diagnostic rather than a decisive assumption test, as such deviations are rarely problematic in practice under robust inference (Schielzeth et al., 2020; Wooldridge, 2020).

4.2.7 Complementary Response Surface Analysis & Assumptions

Following the main OLS and moderation analyses, polynomial regression with response surface analysis (RSA) was added as a complementary post-hoc analysis rather than as part of the original a priori hypothesis-testing design. The purpose was not to test new hypotheses, but to examine whether the observed patterns reflected nonlinear, asymmetric, or alignment-based relationships between AI usage, contextual conditions, and PS. This approach is appropriate when outcomes may depend on congruence or incongruence between constructs, as traditional interaction models can obscure such effects (Edwards, 1994; Edwards & Parry, 1993; Shanock et al., 2010). In this thesis, this logic is relevant because AI usage may relate differently to PS depending on whether it is matched by supportive adoption conditions (UTAUT) or adequate task fit (TTF), rather than through usage intensity alone. Since PS is also a socially embedded and context-dependent team state (Edmondson, 1999; Edmondson & Lei, 2014), and psychosocial outcomes may involve nonlinear or bounded effects (Eldor et al., 2023), RSA provides a useful supplementary lens for interpreting nonlinear and congruence-based patterns (Humberg et al., 2019). Accordingly, the following second-order polynomial model was specified:

$$PSi=b_0+b_1Xi+b_2Y_i+b_3X_i^2+b_4X_iY_i+b_5Y_i^2+ b_6Age + b_7WG\_Size + b_8Org.Size + \varepsilon_i \quad (4)$$

In the model, X_i represents centered AI usage, Y_i represents the centered moderator construct (UTAUT constructs or TTF), and the higher-order terms allow for the estimation of congruence and incongruence effects across the response surface. Centering was also retained for the RSA models, where it supports interpretation of higher-order terms (Shanock et al., 2010; Humberg et al., 2019).

To support cautious interpretation of the supplementary RSA models, additional diagnostics were conducted. VIF values were acceptable for both polynomial models (Appendices 4.4 & 4.5), and correlation matrices indicated no severe bivariate overlap between centered predictors and higher-order terms (Appendices 7.7 & 7.8; Shanock et al., 2010; Humberg et al., 2019). Bootstrap-based confidence intervals were also estimated for the surface parameters, with all a-parameters remaining significant (Edwards & Parry, 1993; Humberg et al., 2019; Appendices 8.1 & 8.2). Finally, because RSA surfaces can be misleading when interpreted outside the observed data range, the plots were interpreted only within empirically populated regions. Configuration coverage plots showed observations across the relevant low-low, high-high, high-low, and low-high regions for both AI usage-UTAUT and AI usage-TTF (Appendix 10), supporting cautious interpretation of congruence and incongruence patterns (Shanock et al., 2010; Humberg et al., 2019).

4.3 Ethical Considerations

Given the sensitive nature of PS and team dynamics, the choice of self-completion questionnaires rather than interviews is justified as respondents may withhold their genuine perceptions during interviews (Saunders et al., 2019). This is particularly important since the outcome variable of PS requires safeguarding of respondents' ability to express opinions without fear of judgment (Edmondson, 1999; 2018). Moreover, due to the sensitive nature of the information collected, the data collection aligned with current regulations of SSE and GDPR.

5. Empirics

5.1 Descriptive Statistics

The survey yielded 219 total responses from 55 different executive teams in 55 different organizations operating within financial, managerial, technological, and industrial practices in Sweden. 21 responses from 5 teams were deemed non-usable as shown below (Appendix 3 for specific team & respondent information):

	Sample Size (n)
Original sample	219
Omission of non-complete answers	-7
Omission of non-TMT	-10
Omission of members from team with ≤2 respondents and <50% of team	-4
Final Analysis Sample	198
# of teams	50

Table 1: Analysis Sample

The control variables below were included in the regressions to account for potential heterogeneity. Individual AI usage was used as a descriptive variable.

Control Variable	**Frequency (n)**	**Percentage (%)**	**Cumulative (%)**
Age Span	Frequency (n)	Percentage (%)	Cumulative (%)
18–29	9	4.55	4.55
30–39	71	35.86	40.40
40–49	103	52.02	92.42
50–59	15	7.58	100.00
Team Size	Frequency (n)	Percentage (%)	Cumulative (%)
2 people	1	0.51	0.51
3–6 people	76	38.38	38.89
7–9 people	100	50.51	89.39
10+ people	21	10.61	100.00
Organizational size	Frequency (n)	Percentage (%)	Cumulative (%)
Less than 20 people	25	12.63	12.63
20–49 people	36	18.18	30.81
50–199 people	66	33.33	64.14
200–500 people	42	21.21	85.35
500+ people	29	14.65	100.00

Usage Control 1	Frequency (n)	Percentage (%)	Cumulative (%)
Never	3	1.52	1.52
Less than 1h	30	15.15	16.67
1-2h	72	36.36	53.03
3-4h	78	39.39	92.42
4+h	15	7.58	100.00
Usage Control 2 (slider, grouped)	Frequency (n)	Percentage (%)	Cumulative (%)
0–20	22	11.11	11.11
21–40	42	21.21	32.32
41–60	49	24.75	57.07
61–80	64	32.32	89.39
81–100	21	10.61	100.00
Total	**198**	**100.00**	

Table 2: Control & Descriptive Measures

Descriptive distributions show variation in age, team size, organizational size, and individual AI usage. The correlations between individual and team-level AI usage were moderate to strong, but not near-perfect (r=0.679 and r=0.573; Appendix 7.1), indicating related but non-interchangeable constructs across levels, consistent with the multilevel composition logic in section 4.2.2 (Chan, 1998).

The main models therefore retain age, workgroup size, and organizational size as controls, as these map more directly onto the TMT and AI-adoption logic developed in section 4.2.2. Although the observed heterogeneity does not establish statistical generalizability, it supports assessment of external validity across persons and settings (Shadish et al., 2002).

Lastly, all independent (AI Usage), moderator (UTAUT & TTF), and dependent (PS) variables are presented both at aggregate and component levels.

Variable	Obs	Mean	Std. Dev	Min	Max
PS	198	3.2078	1.5044	1	5
PS_1	198	3.2677	1.5228	1	5
PS_2	198	3.1162	1.6095	1	5
PS_3	198	3.3788	1.5090	1	5
PS_4	198	3.0101	1.6800	1	5
PS_5	198	3.1263	1.5801	1	5
PS_6	198	3.2525	1.5304	1	5
PS_7	198	3.3030	1.5476	1	5
AI_usage	198	3.5859	1.3220	1	5
AI_U1	198	3.6667	1.4532	1	5
AI_U2	198	3.7525	1.3308	1	5
AI_U3	198	3.3030	1.3515	1	5
AI_U4	198	3.6212	1.4402	1	5
UTAUT	198	3.5669	1.4794	1	5
AI_PE	198	3.6010	1.5891	1	5
AI_EE	198	3.4849	1.5601	1	5
AI_SI	198	3.7020	1.4168	1	5
AI_FC	198	3.4798	1.5633	1	5
TTF	198	2.7643	1.0844	1	5
TTF_1	198	2.8384	1.2234	1	5
TTF_2	198	2.6566	1.1764	1	5
TTF_3	198	2.7980	1.1878	1	5

Table 3: Descriptive Statistics for Dependent, Independent, and Moderator Variables

Inter-item correlations for PS were consistently high (r=0.875–0.936; Appendix 7.2), with Cronbach's alpha indicating very high internal reliability (α≈0.985; Appendix 9.1). Similarly, AI usage items exhibited strong intercorrelations (r=0.829–0.866; Appendix 7.3) and high reliability (α=0.962; Appendix 9.2). These values exceed conventional reliability thresholds (Cronbach, 1951; Nunnally & Bernstein, 1994). For the moderators, UTAUT components display strong associations (0.890-0.937; Appendix 7.4) alongside high reliability (α=0.975;

Appendix 9.3), while TTF shows moderate to strong intercorrelations ranging from 0.660–0.775 with acceptable reliability (α=0.892; Appendix 9.4).

5.2 Direct Relationship Between AI Usage and Psychological Safety

5.2.1 Empirical Results

VARIABLES	H1: Direct Effect (PS)
AI_usage	0.259** (0.104)
Age	-0.081 (0.148)
WG_Size	-0.005 (0.268)
Org_Size	-0.208* (0.111)
Constant	2.938*** (0.688)
Observations	198
R-squared	0.102
Clustered SE	Team_ID (50 teams)
Controls	Age, Workgroup Size, Org. Size

Cluster-robust errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 4: Direct Relationship of AI Usage on Psychological Safety

AI usage appears positively associated with PS (β=0.259**). While the magnitude of the coefficient is weak (Cohen, 1988), the relationship remains robust when controlling for age, workgroup, and organizational size. Among the controls, only organizational size is significant and negative (β=-0.208*), indicating that larger organizations may experience lower levels of PS. The weak explanatory power (R^2=0.102) suggests that AI usage alone explains limited PS variation (Hair et al., 2011). Lastly, as lower R^2 could indicate "*potential sources of* *heterogeneity*" which should be tested "b*y means of multigroup analysis or moderator analysis*" (Hair et al., 2011, p. 147), the subsequent analyses are empirically motivated.

5.2.2 Testing Hypothesis 1

Given that H1 proposed a negative relationship between AI usage and PS, the observed positive and significant coefficient contradicts the stated hypothesis; hence, H1 is rejected.

Hypothesis Test Result 1

H1	AI usage is **negatively** related to the perceived level of psychological safety within top management teams	**Not Supported**

5.3 Moderating Role of UTAUT

Although component-level UTAUT hypotheses remain primary, the aggregate model is reported for parsimony. This choice reflects the highly similar empirical patterns, as indicated by strong internal consistency (Cronbach's α=0.975; Appendix 9.3), high inter-item correlations (r=0.890–0.937; Appendix 7.4), high component VIFs (Appendix 4.6), and highly similar component-level checks (Appendix 14.1). The aggregate model was calculated as the mean score of the four UTAUT constructs (Appendix 2.4), in line with the view that higher-order multidimensional constructs should be assessed empirically rather than assumed (Johnson et al., 2011). Meaningful between-team variance for the aggregate UTAUT construct (ICC=0.166; Appendix 11) further supports its use in the team-level analysis, consistent with aggregation logic in organizational research (Bliese, 2000; LeBreton & Senter, 2008).

5.3.1 Data Empirics

VARIABLES	H2: AI usage × UTAUT → PS
AI_usage_c	0.247*** (0.044)
UTAUT_c	0.373*** (0.031)

AI_usage × UTAUT	0.583*** (0.020)
Age	0.057 (0.064)
Workgroup Size	0.025 (0.078)
Org. Size	0.045 (0.049)
Constant	3.126*** (0.189)
Observations	198
R-squared	0.871
Clustered SE	Team_ID (50 teams)
Controls	Age, Workgroup Size, Org. Size

Cluster-robust errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Table 5: Moderating Effect of UTAUT on AI Usage and PS

Table 5 indicates that both mean-centered AI usage (β=0.247***) and UTAUT constructs (β=0.373***) exhibit positive and significant relationships with PS. The AI usage x UTAUT interaction is also positive (β=0.583***), indicating that AI usage becomes more positively related to PS at higher UTAUT levels. Complementary component analyses support this pattern, with all UTAUT dimensions showing positive, significant interactions (β=0.531***–0.564***; Appendix 14.1).

The model's strong explanatory power (R^2=0.871) indicates that incorporating UTAUT captures large shares of the variance in PS (Hair et al., 2011). Although R^2 should be interpreted cautiously as model fit rather than explanatory strength alone (Figueiredo Filho et al., 2011; Ijomah, 2019), the substantial increase from H1 suggests that UTAUT explains additional PS variance beyond AI usage. Together with the significant interaction term, this strengthens the interpretation that the AI usage-PS relationship is conditional on UTAUT-related adoption conditions (Hair et al., 2011).

Lastly, as Cook's (1977) influence diagnostics showed 12 influential observations, the model was re-estimated without them (Appendix 15). The interaction remained highly similar (β=0.572***) to the original results presented above; thereby supporting the choice of keeping the original sample as the results appear not to be driven by influential observations.

5.3.2 Testing Hypothesis 2

Since H2 proposed that UTAUT would weaken a negative AI usage-PS relationship, the observed results provide empirical support for a moderating effect. However, rather than merely attenuating a negative relationship, the interaction indicates that UTAUT constructs shift the relationship in a positive direction (in line with the findings for H1); suggesting that alignment between AI usage and UTAUT constructs enhances PS within TMTs. The same patterns can be seen for all UTAUT components in Appendix 14.1 indicating that each UTAUT dimension reinforces this moderating mechanism.

Overall, these results suggest that UTAUT constructs are strongly associated with the way AI usage relates to intrateam outcomes, supporting the theoretical expectation that adoption conditions influence behavioral consequences of technological use. Therefore, the moderation logic is supported, but not the hypothesized direction of H2.

Hypothesis Test Results 2

H2a	Performance Expectancy **moderates** the negative relationship between AI usage and psychological safety	**Moderation supported (direction reversed)**
H2b	Effort Expectancy **moderates** the negative relationship between AI usage and psychological safety	**Moderation supported (direction reversed)**
H2c	Social Influence **moderates** the negative relationship between AI usage and psychological safety	**Moderation supported (direction reversed)**
H2d	Facilitating Conditions **moderates** the negative relationship between AI usage and psychological safety	**Moderation supported (direction reversed)**

5.4 Moderating Role of TTF

5.4.1 Empirical Results

VARIABLES	H3: AI usage × TTF (PS)
AI_usage_c	-0.011 (0.067)
TTF_c	1.046*** (0.057)
AI_usage × TTF	-0.007 (0.047)
Age	-0.059 (0.117)
Workgroup Size	-0.060 (0.121)
Org. Size	-0.081 (0.091)
Constant	3.626*** (0.341)
Observations	198
R-squared	0.594
Clustered SE	Team_ID (50 teams)
Controls	Age, Workgroup Size, Org. Size

Cluster-robust errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 6: Moderating Effect of TTF on AI Usage and PS

TTF is strongly and positively associated with PS (β=1.046***), linking higher TTF to higher PS in TMTs. Mean-centered AI usage (β=-0.011) and the AI usage x TTF interaction (β=-0.007) are insignificant, indicating no observable moderating effect or significant controls. This suggests that functional fit contributes to PS independently of usage intensity, with moderate explanatory power (R^2=0.594).

5.4.2 Testing Hypothesis 3

The absence of a significant interaction effect provides no empirical support for the moderating role of TTF in relation to H3. While TTF itself appears to be an important predictor of PS, the results suggest that it does not influence how AI usage translates into PS within TMTs; therefore, H3 is not supported.

Hypothesis Test Result 3

H3	TTF **moderates** the relationship between AI usage and psychological safety	**Not Supported**

5.5 Supplementary Analysis: Polynomial Regression and RSA

Given the H1 rejection (5.2), strong UTAUT moderation (5.3), direct TTF role (5.4), and the logic in 4.2.7, polynomial regressions and RSA complement linear regressions to assess whether there is a congruence effect between AI usage, the contextual conditions (UTAUT & TTF), and PS, thereby adding more depth than linear effects alone (Edwards & Parry, 1993; Humberg et al., 2019).

5.5.1 AI usage and UTAUT (H2)

Since the exploratory higher-level UTAUT specification was justified in section 5.3, component-level polynomial and RSA analyses are reported as robustness checks (Appendices 14.2–14.4). Their highly similar patterns support the parsimonious aggregate specification used below.

Firstly, the underlying polynomial model (Appendix 12.1) shows that UTAUT constructs are the dominant linear predictor of PS (β=0.382***), while AI usage is not significant on its own (β=0.077). The strong positive interaction term (β=0.537***) indicates that PS is higher when AI usage and UTAUT constructs increase together, whereas the negative AI usage squared term (β=-0.193***) suggests that usage without corresponding adoption climate alignment is less favorable.

Surface Parameter	Coefficient	Std. Error	t-value	Significance
a1: Line of Congruence (slope)	0.455***	0.052	8.75	p < 0.01
a2: Line of Congruence (curvature)	0.331***	0.048	6.83	p < 0.01
a3: Line of Incongruence (slope)	-0.311***	0.076	-4.09	p < 0.01
a4: Line of Incongruence (curvature)	-0.730***	0.038	-19.25	p < 0.01
Observations	198			
Controls	Age, Workgroup size, Org. Size			

Cluster-robust standard errors reported
*** p<0.01, ** p<0.05, * p<0.1

Table 7: RSA Surface Test - AI Usage and UTAUT

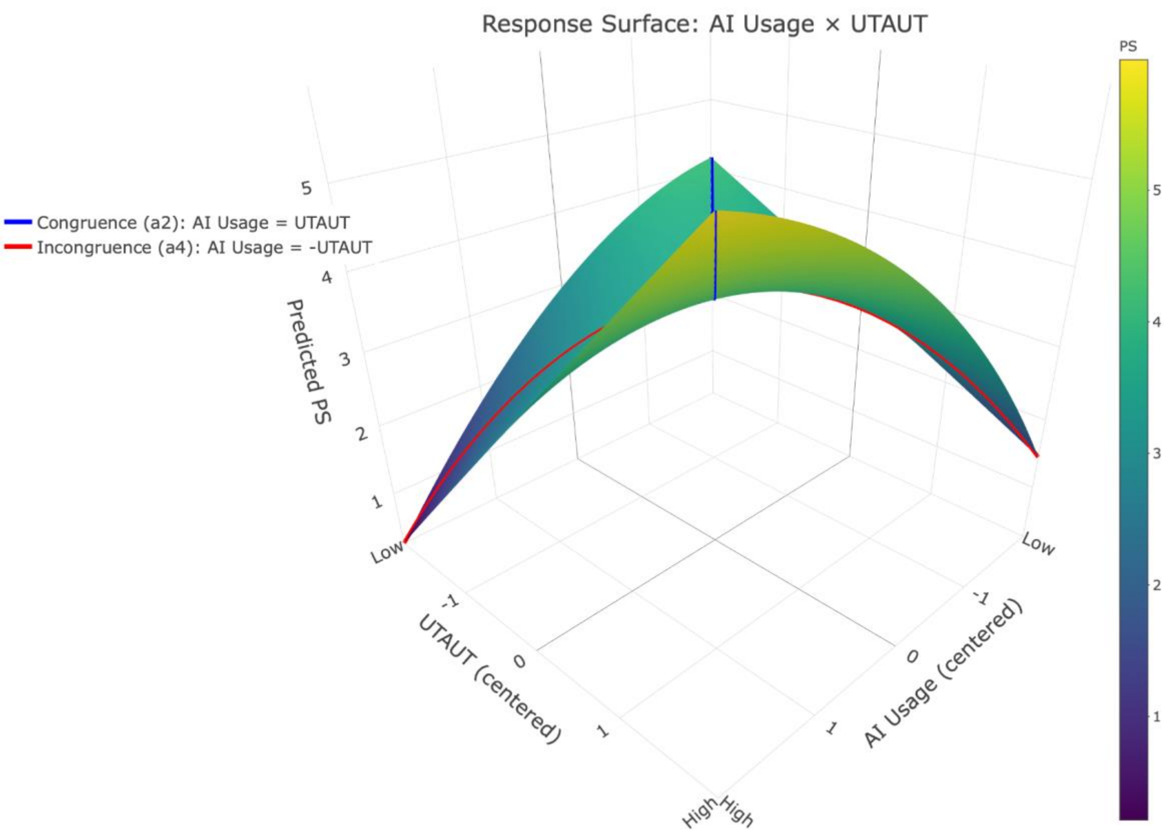

Figure 4: 3D Model of RSA Surface Test - AI Usage & UTAUT

The RSA results support the polynomial model (Appendix 12.1) with the positive congruence slope (a1=0.455***) indicating that PS increases as AI usage and UTAUT rise jointly. The positive congruence curvature (a2=0.331***) indicates that higher joint alignment between AI usage and UTAUT is associated with disproportionately higher PS. In practical terms this means that teams where AI usage is matched by a supportive adoption environment reported higher levels of PS. Furthermore, as illustrated by Figure 4, increases in PS become more pronounced when both AI usage and UTAUT constructs are high, whereas low-low (i.e. both low usage and UTAUT) combinations are associated with moderately increased levels of PS (see Appendix 13.1 for interactive model).

Along the line of incongruence, the negative slope (a3=-0.311***) and curvature (a4=-0.730***) indicate that mismatches between AI usage and UTAUT are associated with lower PS. The noticeable curvature suggests that these negative effects become stronger as the gap between the two variables increases.

5.5.2 AI usage & TTF

Surface Parameter	Coefficient	Std. Error	t-value	Significance
a1: Line of Congruence (slope)	0.785***	0.122	6.43	$p < 0.01$
a2: Line of Congruence (curvature)	-0.236***	0.050	-4.71	$p < 0.01$
a3: Line of Incongruence (slope)	-1.061***	0.107	-9.94	$p < 0.01$
a4: Line of Incongruence (curvature)	-0.516***	0.106	-4.89	$p < 0.01$
Observations	198			
Controls	Age, Workgroup size, Org. Size			

Cluster-robust standard errors reported
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: RSA Surface Test - AI Usage & TTF

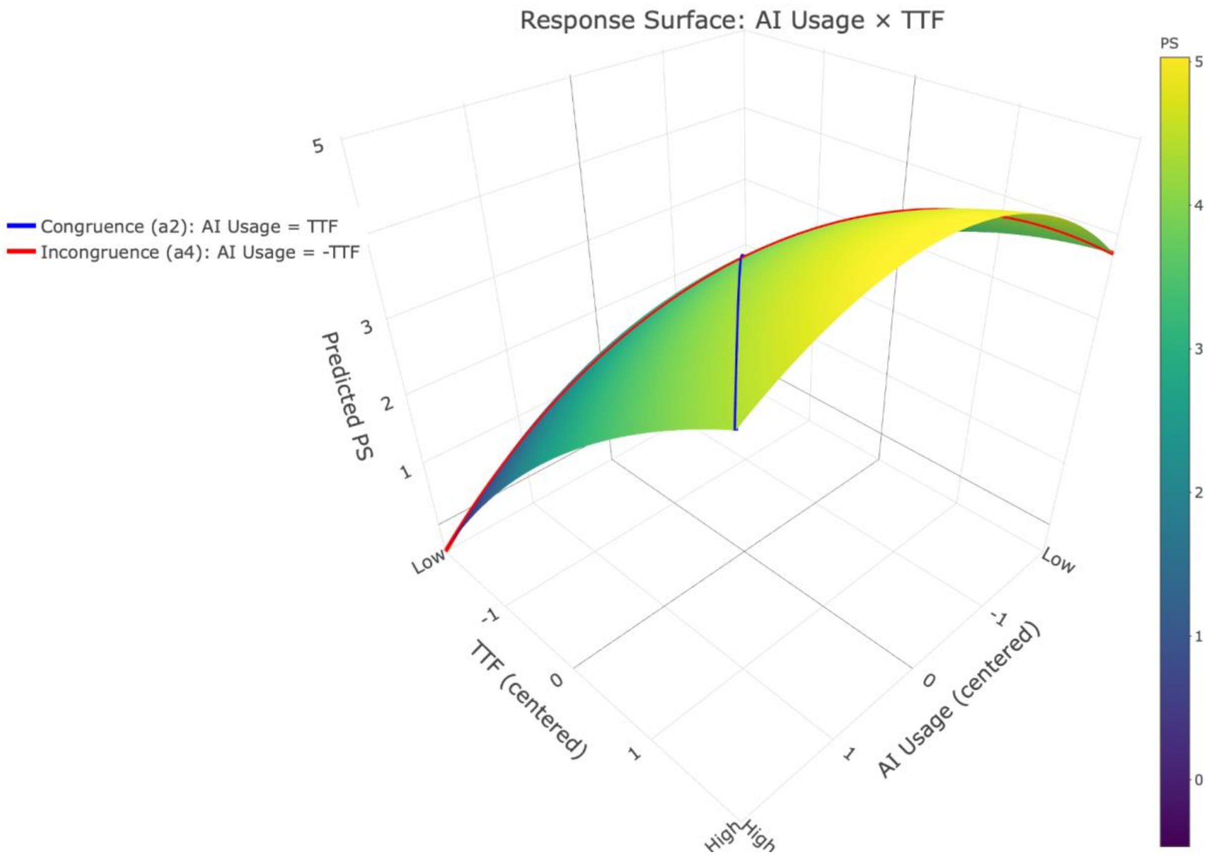

Figure 5: 3D Model of RSA Surface Test - AI Usage & TTF

For TTF, the positive congruence slope (a1=0.785***) indicates that PS improves when AI usage and TTF increase together. However, the curvature along the line of congruence is significantly negative (a2=-0.236***), resulting in a flatter and slightly concave surface. This suggests that alignment between AI usage and TTF is beneficial up to a point, but that the relationship is not continuously increasing. Instead, predicted PS appears to peak around high TTF and medium AI usage, with indications of negative marginal returns when AI usage continues increasing under already high-TTF conditions.

The negative incongruence slope (a3=-1.061***) and curvature (a4=-0.516***) indicate that AI usage-TTF discrepancies are associated with lower PS. The relatively steep negative slope suggests that even moderate mismatches, such as high usage with low TTF, are linked to notable decreases in PS (see Appendix 13.2 for interactive model).

Lastly, as shown in Appendix 12.2, the polynomial model is mainly driven by TTF, which has a strong positive coefficient (β=0.961***), while AI usage itself remains non-significant (β=-

0.118). The weakly significant interaction term (β=0.123*) points to some benefit when usage and fit move together, but the negative quadratic effects for AI usage (β=-0.221***) and TTF (β=-0.137*) suggest that this relationship is not continuously increasing; instead, PS appears to improve up to a point before additional usage under high-TTF conditions yields negative marginal returns.

6. Discussion

6.1 Direct Relationship: AI Usage and Psychological Safety (H1)

Contrary to H1, AI usage was positively rather than negatively associated with PS. This finding challenges the theoretical expectation in section 3.4.1, where AI usage was expected to weaken PS by increasing opacity and trust ambiguity (Seth & Edmondson, 2026; Glikson & Woolley, 2020), reducing perceived discretion and agency through algorithmic control mechanisms (Kellogg et al., 2020; Raisch & Krakowski, 2021), and making team members less willing to openly challenge AI-supported outputs (Webber, 2025). One possible explanation lies in the specific TMT strategic decision-making context.

As mentioned, strategic decision-making within TMTs involves uncertainty and complexity, where effective outcomes depend on optimal information processing (Papadakis et al., 1998), as well as knowledge distribution and integration (Rau, 2005). Since the AI tools attributed to the survey items (Appendix 1.5) were conceptualized in line with DSS literature, AI usage may therefore contribute to structuring decision conditions that support PS. DSS supports knowledge processing, evaluation, and structured reasoning (Keen & Scott Morton, 1978), which is further enhanced by AI (Phillips-Wren, 2013; Onwujekwe & Weistroffer, 2025). Similarly, PS research suggests that uncertain and ambiguous decision contexts make interpersonal risk-taking especially important, as team members must be willing to express uncertainty, challenge assumptions, and raise concerns (Edmondson, 2018; Edmondson & Bransby, 2023; O'Donovan et al., 2020).

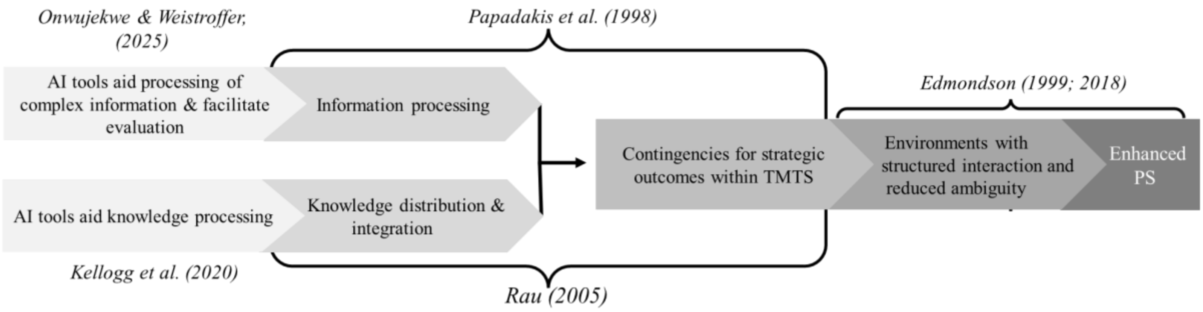

Figure 6: Literature Discussion on Direct Weak Positive Effect

Despite the positive relationship, the model's modest explanatory power (R^2=0.102) matters. Prior methodological research emphasizes that low R^2 values should not be interpreted diagnostically, as they do not reveal the underlying causes of unexplained variance (Figueiredo Filho et al., 2011). Low R^2 may reflect model incompleteness, unobserved heterogeneity, and omitted variables (Wooldridge, 2020), especially in social sciences where behavior is difficult to fully model (Ozili, 2022). Lastly, while peripheral to H1, the negative organizational size coefficient (β =-0.208*) may reflect that larger, more differentiated firms face greater difficulty sustaining local PS conditions (Guadalupe et al., 2012; Edmondson & Lei, 2014).

Taken together, AI-supported DSS may increase PS by structuring TMT decision processes and reducing ambiguity (Onwujekwe & Weistroffer, 2025; Bevilacqua et al., 2025). However, due to the weak coefficient and low R^2, AI usage alone provides limited insights into variation in PS. This also aligns with Edmondson's (1999; 2018) broader acknowledgement of PS as a socially embedded construct shaped by interaction patterns rather than isolated inputs. The key question is therefore not whether AI is used, but under which social and technological conditions. This shifts attention to UTAUT and TTF as contextual alignment factors.

6.2 UTAUT: Moderation and Congruence Effect (H2)

The H2 findings shift the discussion from whether AI usage matters to the conditions under which it matters. While H1 showed that AI usage alone offers limited explanatory power (5.2), the significant UTAUT moderation indicates that the surrounding adoption environment is central to how AI usage relates to PS (5.3). The RSA results strengthen this interpretation by showing that PS is not only affected by higher AI usage or stronger UTAUT conditions separately, but by their alignment, especially when both are high (5.5.1). This broadly supports the logic developed in section 3.4.2, where UTAUT conditions were expected to influence the behavioral consequences of AI usage (Venkatesh et al., 2003; Cao et al., 2021; Jain et al., 2022). Yet, the result goes further than expected: favorable UTAUT conditions intensify, rather than merely buffer, the AI-PS relationship. Socio-technical theory (STT) offers a useful explanation for this pattern by showing why technological inputs depend on their alignment with social and organizational conditions (Trist & Bamforth, 1951; Trist, 1981).

STT argues that organizational outcomes emerge not from technological inputs in isolation, but from joint optimization of social and technical subsystems (Trist, 1981). While AI-enabled DSS may improve information processing and reduce ambiguity (Shrestha et al., 2019; Onwujekwe & Weistroffer, 2025), STT suggests that such technical gains translate into PS only when socially aligned (Trist, 1981). Contemporary studies similarly suggest that digital environments shape outcomes through perceived support structures, social dynamics, and the legitimacy of tools within teams (Viskova-Robertson, 2024). This is particularly relevant to UTAUT, as social influence captures how important others' support helps legitimize technology use in a given context (Venkatesh et al., 2003).

On the other hand, one possible concern is that performance expectancy, effort expectancy, and facilitating conditions mainly capture technical alignment, while social influence captures the social subsystem of STT, which would imply different component-level RSA patterns (Appendix 14.3). However, this concern is mitigated since the UTAUT components can still be interpreted through a socio-technical lens: each dimension connects the technical use of AI to the social context in which it is embedded. Performance expectancy and effort expectancy capture whether AI is perceived as useful and manageable in the team's decision work, facilitating conditions link technical resources to organizational support, and social influence reflects the social legitimization of AI use within the team (Venkatesh et al., 2003; Venkatesh et al., 2012). Thus, the similar component-level RSA patterns do not imply theoretical homogeneity, but more cautiously suggest that the UTAUT constructs behaved as closely aligned expressions of the same local AI adoption climate, with all constructs involving both technical and social aspects.

Extending this structural perspective, *social cognitive theory* (SCT) refines how socio-technical conditions translate into PS. Bandura (1986; 2001) conceptualizes individuals as agents who interpret, evaluate, and act upon environmental inputs. Individuals therefore interpret environmental inputs before acting (Rottschaefer & Knowlton, 1979). This is particularly prevalent in TMTs as they operate under bounded rationality (Hambrick & Mason, 1984) involving complex and interdependent cognitive load (Rau, 2005). SCT therefore offers an explanation for why AI usage does not uniformly raise PS, but depends on the team's AI adoption environment. As Zhong & Wang (2025) suggest, AI-related behavior does not follow mechanically from AI use itself, but depends on how employees interpret AI's usefulness and the surrounding social context. In this study, this logic helps explain why TMT members may read AI usage either as enabling voice and interpersonal risk-taking, or as increasing judgment dependency and exposure, with opposite implications for PS (Edmondson, 1999; 2018).

Finally, *Technology Affordances & Constraints Theory* (TACT) complements STT and SCT by explaining how socio-technical conditions and cognitive interpretations become behaviorally consequential through perceived affordances and constraints (Majchrzak & Markus, 2012). TACT posits that technology outcomes depend on the relationship between users, goals, and technology features. This builds on older affordance tradition (Gibson, 1986) where a technological affordance *"refers to the attributes of both the object [AI tools] and the actor"* (Gaver, 1991, p. 79).

As such, AI tools may enable transparency and control, but also surveillance. Whether these features are perceived as enabling or constraining depends on users' cognitive interpretations (Bandura, 1986, 2001) and the context in which the actor encounters the technology (Gibson, 1986). TACT does not conceptualize technology in terms of effort, but rather the action potentials that may or may not be perceived and enacted upon. Thus, AI tools may be interpreted as either enabling or constraining interpersonal risk-taking, depending on actor perceptions and team context (Edmondson, 1999; 2018). This is particularly relevant in TMT contexts, where strategic choices *"reflect the idiosyncrasies of decision makers"* and are filtered through cognitive lenses that shape interpretation (Hambrick & Mason, 1984, p. 195). As such, AI tools are unlikely to be interpreted uniformly within TMTs, but through cognitively bounded and opinion-laden perspectives shaped by the interaction between technical capabilities and social team conditions.

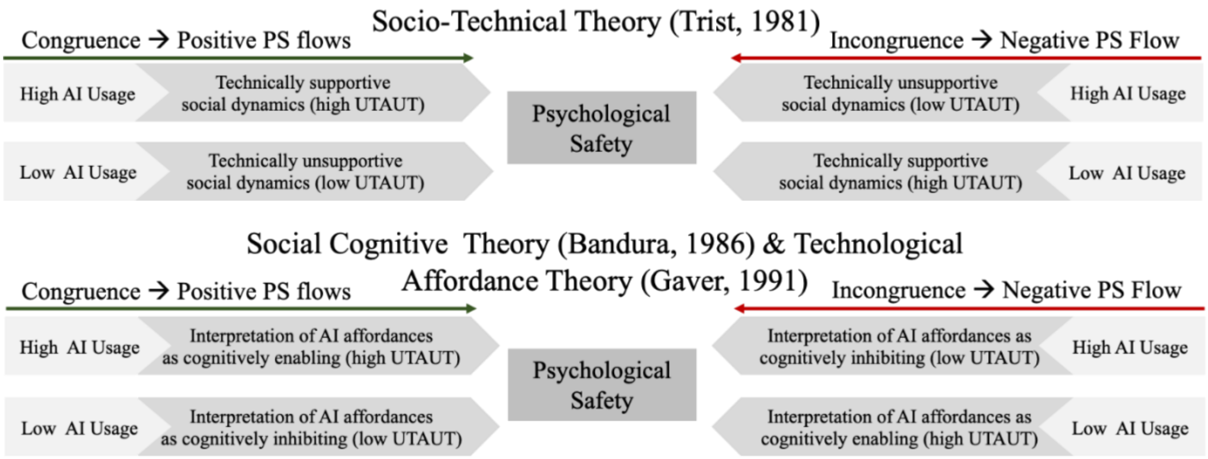

Figure 7: UTAUT as an Alignment Factor

Together, these perspectives suggest that the H2 moderation (5.3) and RSA results (5.5.1) depend on three mechanisms:

1. Congruent configurations of socio-technical alignment (STT)
2. Cognitive interpretation (SCT)
3. Technology affordance realization (TACT)

Although H2 is consistent with these mechanisms, TTF follows a different pattern. Rather than contradicting the above discussion, it suggests that functional task alignment may operate through a distinct pathway, warranting closer examination of why the TTF and UTAUT components differ, in relation to AI usage and PS.

6.3 TTF: Moderation and Congruence Effects (H3)

Before comparing H3 with H2, H3 must be interpreted in isolation. The findings do not support the expected moderating role of TTF, but they show that TTF is directly associated with PS **(5.4)**. The RSA results add nuance by showing that usage-fit alignment is beneficial up to a point, with predicted PS peaking around high TTF and medium AI usage before additional usage under high TTF produces diminishing returns **(5.5.2)**. This partly departs from the hypothesis developed in section **3.4.3**, where fit was expected to condition how AI usage relates to PS **(Goodhue & Thompson, 1995; Fuller & Dennis, 2009)**. However, the result does not necessarily contradict TTF logic. Rather, it suggests that functional fit may matter as an independent assessment of AI’s appropriateness for strategic decision tasks, while usage-fit alignment appears beneficial only up to a point.

The above interpretation fits the original logic of TTF, but shifts attention from TTF as an amplifier of AI usage to TTF as an independent enabling condition for PS. Goodhue and Thompson’s (1995) technology-to-performance-chain logic suggests that fit matters because technology supports outcomes when its capabilities match task requirements. However, fit alone does not necessarily predict usage, since perceiving a tool as suitable is not equivalent to using it. Prior research therefore integrates TTF with the Technology Acceptance Model (TAM) because fit alone does not explain whether users experience a technology as acceptable in practice. Davis’s (1989) TAM highlights two central mechanisms: perceived usefulness (whether the technology is expected to improve performance) and perceived ease of use (whether it is expected to be manageable and low-effort). This matters for PS because even task-fitting AI may feel burdensome, risky, or difficult to challenge if it is not perceived as useful and manageable. In AI-supported decision-making, managers’ willingness to use AI therefore depends not only on functional fit, but also on acceptance- and avoidance-related perceptions such as expected usefulness, effort, perceived risk, and anxiety (Cao et al., 2021). Wang et al. (2026) similarly show that TTF only affects AI usage indirectly through perceived usefulness, reinforcing that fit may operate through how technology is interpreted and accepted, not only through fit itself.

Thus, the insignificant moderation results (5.4) do not undermine TTF logic; instead, they support a socio-technical interpretation in which technical fit appears to support PS directly, whereas broader social and organizational conditions appear more important for making AI usage itself beneficial for PS (Trist, 1981). Rather than shaping how AI usage translates into outcomes, TTF appears to operate as an independent enabling condition for PS, reflecting whether AI is perceived as appropriate and workable for strategic decision tasks. Thus, in the linear moderation model, respondents who perceived stronger task-technology fit reported higher PS regardless of AI usage intensity. However, Wang et al. (2026, p. 11) simultaneously reveal monotonic patterns in which *“more frequent users reported higher TTF, PU [perceived usefulness], RGU [responsible AI usage] outcome”*, which contrasts with the RSA results where predicted PS peaks around high TTF and medium AI usage rather than increasing monotonically toward the high-high corner (Figure 5). Thus, they support the general alignment logic, but not the bounded high-TTF/high-usage pattern suggested by the RSA.

To explain this bounded usage-fit pattern, the closest support comes from technology usage intensity literature rather than from TTF literature alone. Ahearne et al. (2004) challenge the assumption that more technology usage is always better, showing that technology usage initially improves outcomes, but eventually produces diminishing and disabling effects beyond an optimal point. This provides the clearest parallel to the RSA interpretation that additional AI usage under already high-TTF conditions may not continue to increase PS proportionally. Fuller and Dennis (2009) add that initial TTF may lose explanatory power as teams appropriate technology over repeated tasks, suggesting that outcomes depend not only on fit, but also on how technology becomes embedded in use. Howard and Hair (2023) further show that TTF and “too little” fit relate to perceived usefulness and ease of use, whereas “too much” fit does not, suggesting that insufficient fit is more clearly problematic than excess fit is beneficial. However, these TTF studies should be interpreted cautiously, as they do not directly predict the present high-TTF/moderate-usage optimum and could, taken alone, suggest that fit mainly prevents poor technology experiences. Combined with Ahearne et al.’s (2004) usage-intensity findings, they nevertheless support a more nuanced interpretation: TTF appears to provide an important enabling condition for PS, while increasingly intensive AI usage under high-fit conditions may generate diminishing, and at very high levels marginally negative, returns.

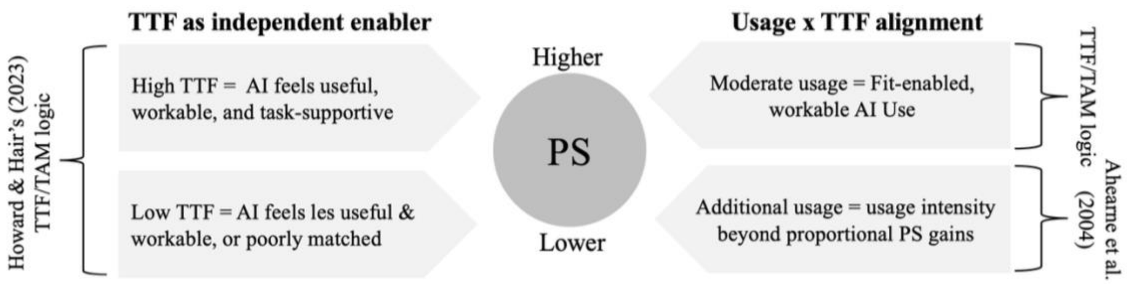

Figure 8: TTF as an Independent Enabler and Partial Alignment Factor

Although these studies examine technology usage rather than psychosocial outcomes, they help explain why high TTF may not make increasingly intensive AI usage continuously more beneficial for PS. This sets up the central contrast with UTAUT, which showed a stronger and more reinforcing alignment pattern.

6.4 Comparative Insight: UTAUT vs TTF

The contrast between UTAUT and TTF suggests that contextual conditions do not shape the AI usage–PS relationship in the same way. TTF appears directly important for PS, whereas UTAUT more clearly conditions how AI usage relates to PS. A broader explanatory lens is therefore needed to clarify why UTAUT, but not TTF, produced the stronger moderation and alignment pattern. Section 6.2 established that AI tools must be socially embedded (STT), cognitively interpreted (SCT), and enacted through perceived affordances (TACT), which helps explain why UTAUT functions as a broader alignment factor. However, to understand why this broader alignment matters specifically for PS, Self-Determination Theory (SDT) provides a useful supplementary lens (Ryan & Deci, 2000).

SDT shifts attention from task fit to whether surrounding conditions support the needs of autonomy, competence, and relatedness (Ryan & Deci, 2000). These needs are relevant to PS because interpersonal risk-taking becomes more plausible when team members feel able to act volitionally, capable of engaging with AI-supported decisions, and socially supported by others (Edmondson, 1999; 2018; Seth & Edmondson, 2026; Ryan & Deci, 2000). In this way, SDT links the socio-technical alignment logic in section 6.2 to the empirical divergence between UTAUT and TTF: the key distinction is not only whether AI fits the task, but whether the broader AI-use environment supports the psychological conditions under which PS can emerge.

As TTF concerns whether technology capabilities match task requirements, it maps most closely onto SDT's competence dimension, while UTAUT captures the full SDT cycle (Figure 9). Goodhue and Thompson's (1995) logic, as used by Khan et al. (2018), defines TTF through task characteristics, while Tao et al. (2023) find that TTF significantly predicts perceived usefulness, with SDT variables modelled separately. Thus, TTF predicts functional adequacy and may increase perceived competence in AI-supported decisions. However, SDT requires competence, relatedness, and autonomy for sustained motivation and psychosocial outcomes (Ryan & Deci, 2000). Prior studies integrating TTF and SDT suggest that the two perspectives can explain different parts of technology acceptance processes, with TTF often linked to functional usefulness and SDT capturing motivational needs (Khan et al., 2018; Tao et al., 2023; Alturki et al., 2023). From an SDT perspective, TTF captures whether AI tools are functionally appropriate, but not whether usage feels self-endorsed, socially supported, or interpersonally safe; thus, it only partially captures the conditions needed for psychosocial outcomes (Goodhue & Thompson, 1995; Ryan & Deci, 2000; Figure 9).

By contrast, UTAUT components more closely resemble a need-supportive environment linked to all SDT needs. Osei et al. (2022) indicate that performance expectancy, effort expectancy, and facilitating conditions are directly related to competence, autonomy, and relatedness. Furthermore, while social influence is not explicitly linked to one SDT pillar in UTAUT, Ryan and Deci's (2000, p. 73) definition of relatedness as *"the need to feel belongingness and connectedness with others"* closely resembles social influence, where technology adoption depends on whether important others support the technology (Venkatesh et al., 2003). Recent AI adoption research similarly finds that performance expectancy, social influence, and AI learning self-efficacy significantly predict AI adoption, suggesting that AI uptake depends on practical benefits, social context, and confidence rather than functionality alone (Acosta-Enriquez et al., 2025). Chiu's (2022) SDT-based study further shows that digital support can satisfy autonomy, competence, and relatedness, with relatedness being especially important for behavioral, emotional, and agentic engagement.

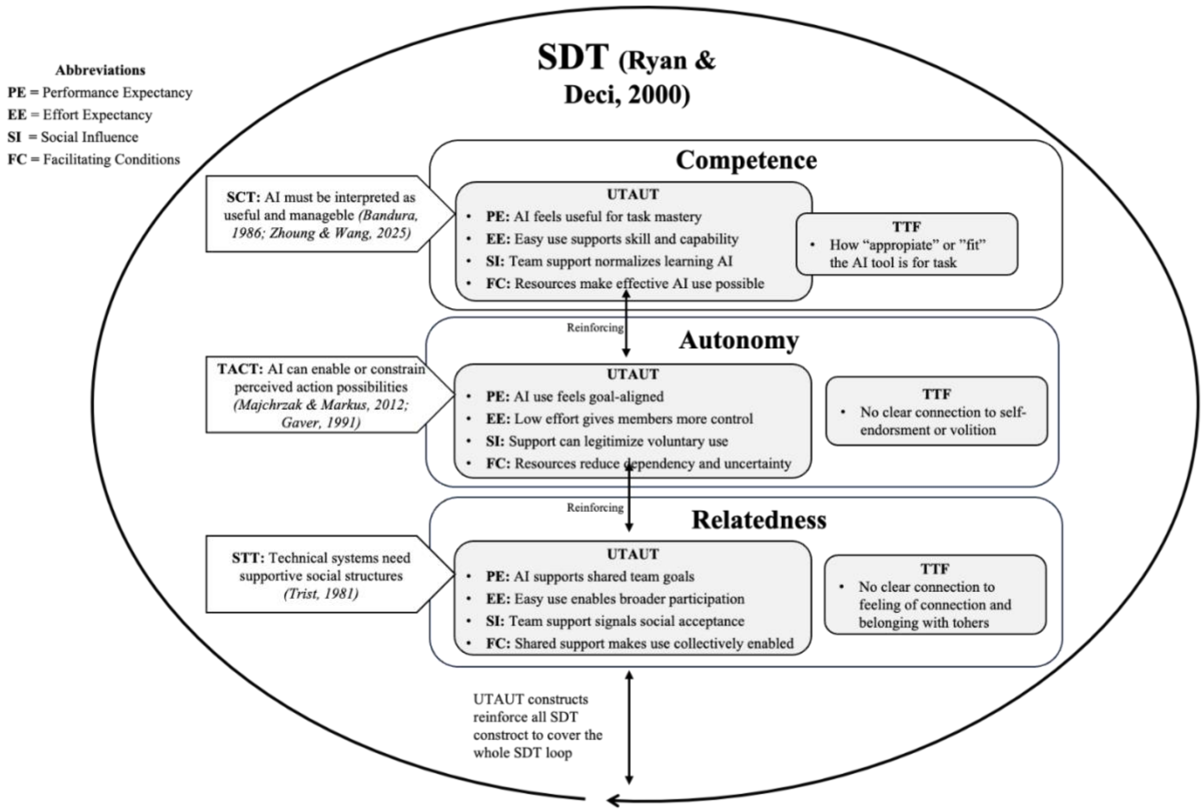

Figure 9: SDT as an Explanatory Tool for UTAUT & TTF Empirical Divergence

Taken together, one possible interpretation is therefore that TTF reflects an independent competence-related enabling condition, centered on whether AI is perceived as appropriate and workable for the task. UTAUT, by contrast, captures broader adoption conditions linked to competence, autonomy, and relatedness (Figure 9). As such, the initial framework is revised in Figure 10 by reframing the moderators as alignment factors.

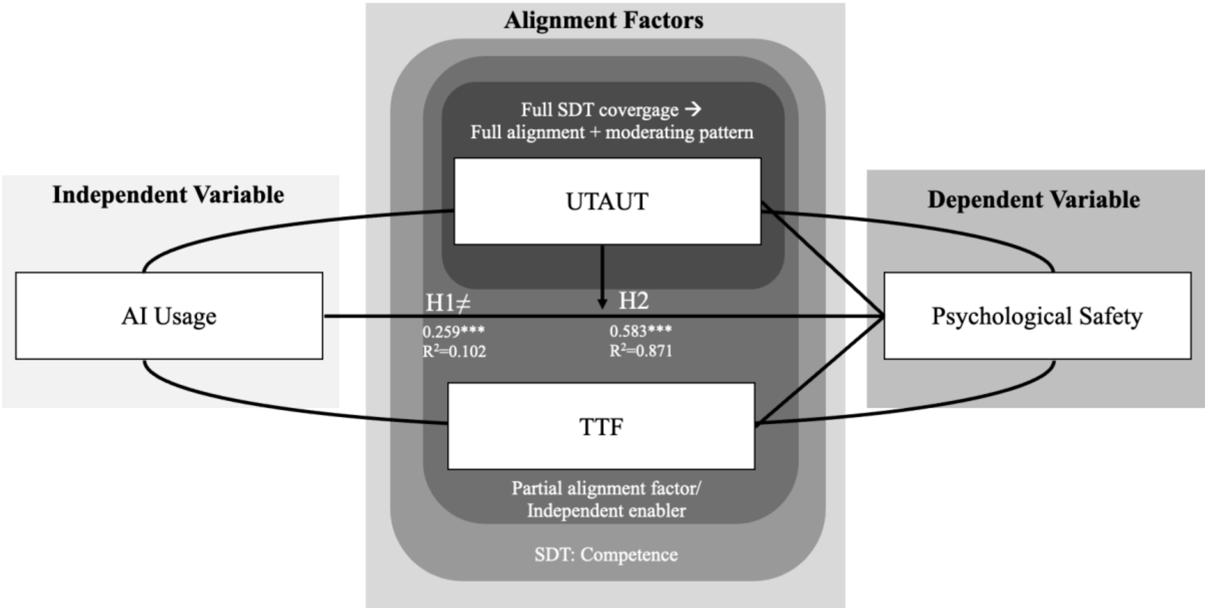

Figure 10: Final Theoretical Framework

7. Conclusion

7.1 Answering the Research Question

This thesis set out to answer the research question: *How does the use of AI tools relate to the perceived level of psychological safety within top management teams?* Survey data from 198 respondents across 50 TMTs show that AI usage is positively associated with PS. This contradicts the initial hypothesis that AI usage would undermine PS by increasing uncertainty, dependency, or reduced willingness to speak up. Instead, AI usage may improve PS by reducing ambiguity, supporting information processing, and making strategic reasoning more transparent.

However, the weak direct relationship and low explanatory power indicate that AI usage alone does not explain PS variation. Instead, the findings suggest that the relationship depends on the surrounding technological and social context. Most importantly, UTAUT constructs significantly moderated the relationship such that when AI usage was accompanied by perceptions that AI tools were useful, easy to use, socially supported, and institutionally enabled, PS increased to a greater extent. The RSA further supported this interpretation, showing that PS was highest when AI usage and UTAUT constructs were aligned, particularly at high levels.

Moreover, TTF also mattered, but differently from UTAUT. While TTF did not significantly moderate the AI usage-PS relationship, it had strong direct associations with PS. The supplementary RSA also showed that alignment between AI usage and TTF was linked to more favorable outcomes. The RSA suggested that predicted PS was highest around high TTF and medium AI usage, rather than at the high-high corner. This cautiously suggests that once AI tools are perceived as highly task-appropriate, additional AI usage may not increase PS proportionally, unlike the more continuously reinforcing alignment pattern observed for UTAUT.

Overall, the findings suggest that AI tools are not necessarily associated with lower PS in TMTs. Rather, AI usage may support PS when it helps structure strategic decision-making and is embedded in favorable contextual conditions, both social (UTAUT) and technical (UTAUT and TTF). Among these, the UTAUT constructs appear to play the more decisive alignment role, as they capture the broader social, motivational, and support conditions surrounding AI use. While TTF remains important, it appears to operate as an independent enabling condition for PS rather than as a continuously reinforcing social climate.

7.2 Theoretical Contributions

7.2.1 Contribution to TMT Literature

First, this thesis contributes to TMT literature by moving beyond observable executive attributes toward internal strategic decision processes (Carpenter et al., 2004; Wiersema & Hernsberger, 2021). Traditionally, UET has treated organizational outcomes as reflections of top managers' cognitions, values, and perceptions (Hambrick & Mason, 1984), while later TMT research has relied heavily on demographic and structural proxies to infer underlying cognitive and social dynamics (Carpenter et al., 2004; Wiersema & Hernsberger, 2021). Although studies examine social integration (Smith et al., 1994), trust and conflict (Simons &

Peterson, 2000; Rau, 2005), as well as behavioral integration (Simsek et al., 2005), direct investigation of psychosocial team states remains limited.

By examining PS directly within AI-supported TMT decision-making, this thesis contributes to a contextual understanding of strategic leadership. It complements Vandekerkhof et al.'s (2018) framing of PS as an emergent TMT state by indicating that such states may not only reflect internal team interaction patterns but may also be related to external technosocial conditions surrounding strategic decision-making. Thus, rather than positioning AI solely as a strategic capability or executive competence, as emphasized in prior research (e.g., Bevilacqua et al., 2025; Li et al., 2021; Pinski et al., 2024), this thesis suggests that AI may also be relevant for understanding the psychosocial conditions under which TMTs make strategic decisions.

7.2.2 Contribution to Psychological Safety Literature

This thesis further contributes to PS literature by applying Edmondson's (1999; 2018) team-level conceptualization in an AI-supported strategic decision-making context. Established PS research links interpersonal risk-taking to learning, voice, communication, and decision quality (Edmondson & Lei, 2014; Frazier et al., 2017). Contemporary AI-related work has instead suggested new risks for PS through trust ambiguity (Seth & Edmondson, 2026), weakened voice and openness (Webber, 2025), as well as reduced autonomy, discretion, and agency through algorithmic control (Kellogg et al., 2020).

However, the findings of this thesis suggest that AI usage alone is not necessarily negatively associated with PS as parts of the emerging AI–PS literature imply. Instead, AI usage appears more consistent with DSS-based arguments that AI can support information processing, problem structuring, and evaluation of alternatives (Keen & Scott Morton, 1978; Shrestha et al., 2019; Onwujekwe & Weistroffer, 2025). Thus, the issue is not AI usage per se, but the technosocial conditions under which AI is interpreted and used within TMTs.

7.2.3 Contribution to AI Adoption & Decision-Making Literature

Lastly, the thesis broadens AI and decision-making literature from adoption, usage, and performance toward psychosocial team outcomes. For DSS literature, this thesis extends both traditional (Keen & Scott Morton, 1978; Phillips-Wren, 2013) and contemporary literature (Shrestha et al., 2019; Onwujekwe & Weistroffer, 2025) by suggesting that AI-enabled DSS may not only influence decision quality, efficiency, and information processing, but also the social conditions under which strategic decisions are discussed and challenged. Specifically, by linking AI-supported decision-making to PS in TMTs, the thesis adds a team-level psychosocial perspective to the otherwise task- and performance-oriented literature.

Moreover, by incorporating UTAUT and TTF, the study further contributes to adoption and fit literature. UTAUT has mainly explained technology acceptance through performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2016; Dwivedi et al., 2019), while TTF has focused on outcomes through alignment between technological capabilities and task requirements (Goodhue & Thompson, 1995; Zigurs & Buckland, 1998). This thesis suggests that these frameworks may also explain when AI usage relates to psychosocial outcomes such as PS. However, the contribution is not symmetrical. The UTAUT constructs appear to capture a broader set of conditions: whether AI use feels useful and manageable, socially legitimized, and supported by the team environment. TTF, by contrast, mainly captures whether AI tools are functionally adequate for the tasks at hand. This distinction contributes to AI literature by showing that psychosocial consequences of AI use may depend less on usage alone than on the conditions surrounding that usage. More specifically, functional task fit appears to matter directly for PS, while social adoption conditions determine whether AI usage itself becomes more positively associated with PS.

7.3 Managerial Implications

7.3.1 Build a Supportive AI Adoption Climate, Not Only Technically Fit AI Tools

The main managerial implication is that TMTs should not treat AI implementation only as a question of technical fit. AI tools should be appropriate for the strategic tasks they are meant to support, but technical fit alone does not appear to make more intensive AI usage more beneficial for PS. Managers should therefore pair task-fitting AI tools with an adoption climate that makes AI use feel useful, understandable, supported, and legitimate within the team. In particular, AI usage appears more beneficial when TMT members perceive AI tools as useful, easy to engage with, socially supported, and institutionally enabled.

Instead of simply introducing AI tools, managers should actively build an AI adoption climate. To do so, leaders can clarify AI's role in strategic decisions; create shared routines and training; legitimize use through influential team members; and provide access, technical support, data literacy, and governance. Such an environment may support not only competence, but also autonomy and relatedness, which technical fit alone may not fully capture. Thus, AI should be managed as a socio-technical team condition, not merely as a functional tool.

7.3.2 Preserve Human Deliberation Around AI-Supported Decisions

A second managerial implication is that AI usage alone is not enough to strengthen team dynamics or decision-making. The weak direct relationship between AI usage and PS, together with the RSA results showing that alignment matters more than usage intensity alone, suggests that AI must be actively embedded in how TMTs discuss, challenge, and interpret strategic issues.

Managers should therefore position AI as a decision-support input rather than as a replacement for executive judgment. This is especially important in TMTs, where uncertainty, ethics, and contextual knowledge often matter. TMTs should create routines for questioning AI outputs, such as asking what assumptions are embedded, what the AI may miss, and which alternative interpretations should be considered. Leaders should also explicitly invite dissent around AI-supported recommendations, so that AI becomes a prompt for critical dialogue rather than a source of unquestioned authority.

7.4 Limitations

7.4.1 Research Design, Causality, and Self-Reported Perceptions

Firstly, the cross-sectional design limits causal conclusions. Since PS is dynamic (Edmondson, 2018), but was captured at one point in time, the findings should be interpreted as associations rather than evidence of causal effects. It is therefore possible that AI usage influences PS, but also that psychologically safe TMTs are more willing to experiment with and openly discuss AI tools. Moreover, the study relies on self-reported survey data. While this is appropriate because PS is inherently perceptual, collecting predictors and outcomes from the same respondents at the same point in time may introduce common-method bias, including consistency, social desirability, and same-source effects (Podsakoff et al., 2003). This matters because TMT dynamics and AI usage may be sensitive or reputationally consequential. Although anonymity can improve disclosure, it does not fully eliminate response bias in sensitive-question contexts (Ong & Weiss, 2000).

7.4.2 Sample, Generalizability, and TMT-Level Assumptions

As the thesis focuses on TMT strategic decision-making, findings should not be generalized directly to operational, middle-management, or project teams. Moreover, the industry-diverse sample increases heterogeneity, as industry characteristics may shape organizational culture (Chatman & Jehn, 1994) and AI adoption conditions (Bankins et al., 2024). Thus, the findings should be interpreted as cross-industry patterns rather than industry-specific effects.

In addition, TMTs should not automatically be treated as regular teams, since TMT research often risks inferring internal dynamics that may not be directly observable (Wiersema & Hernsberger, 2021). Some TMTs may function more as senior individuals than integrated teams, meaning that the "team" label should not be assumed uncritically (Hambrick, 1994), which is reinforced by research on structural interdependence within TMTs (Hambrick et al., 2015). This creates limitations for team-level theorizing, even though the ICC results (Appendix 11) supported aggregation and TMTs as units hold high importance for strategic outcomes in an organization.

7.4.3 Measurement, Construct Adaptation, and Model Scope

Because AI usage was measured broadly, the study cannot identify which specific AI tools, use cases, or technical features drive the observed relationship with PS. The findings should therefore be interpreted as applying to general perceived AI usage for strategic decision-making. In addition, the UTAUT dimensions were shortened to one item per construct due to the time-constrained nature of executive respondents, which may reduce construct depth. Aggregating these dimensions was also an exploratory choice, supported empirically but still departing from standard UTAUT applications. Finally, omitted variables such as leadership style, prior AI experience, organizational culture, AI governance, and team tenure may also influence PS. Lastly, as individual capabilities were not included in the TTF items, this might have affected the general outcome of the TTF results (Howard & Rose, 2019).

7.5 Future Research

7.5.1 Longitudinal Studies of AI Usage and PS

Future research should examine AI usage and PS over time, especially given PS's dynamism (Edmondson, 2018). Since TMTs differ from operational teams in strategic responsibility, hierarchy, and team integration (Hambrick, 1994; Hambrick et al., 2015; Wiersema & Hernsberger, 2021), longitudinal research would be useful for examining how AI-supported team dynamics and PS evolve over time in executive contexts (Wang et al., 2017; O'Neill et al., 2019). Such studies could follow TMTs across different stages of AI implementation to assess whether AI usage shapes PS over time, or whether psychologically safe teams are more likely to adopt AI in the first place. Future research could also examine whether AI initially creates uncertainty or distrust, but becomes supportive as teams gain familiarity, routines, and confidence.

7.5.2 Qualitative Research on TMT-AI Interaction

Future qualitative research could clarify the mechanisms behind the findings. Existing qualitative work shows that interviews with senior managers and decision-makers are useful for examining AI adoption and AI-supported decision-making. For example, Bevilacqua et al. (2026) use interviews with senior executives to study how AI reshapes top managers' strategic leadership skills, while Booyse and Scheepers (2024) use interviews with senior managers to identify social, trust-related, transparency, and control-related barriers to AI-based organizational decision-making. Qualitative studies could examine how top managers discuss, question, and interpret AI outputs during strategic decision-making. This could clarify why TTF operates differently from UTAUT constructs, for instance whether executives perceive task-appropriate AI as sufficient for supporting PS, and why broader conditions such as legitimacy, support, and social acceptance may continue to matter more for translating AI usage into PS. Such research could reveal dissent, authority, trust, and overreliance dynamics beyond survey data.

7.5.3 Comparative & Theoretical Extensions

Future studies should test generalizability across teams, contexts, and AI conditions. Comparative research could examine whether the relationship differs between TMTs, middle-management, and operational teams. Future research could also compare countries, industries, and decision types to assess whether cultural context or decision stakes shape the AI usage–PS relationship.

Beyond contextual generalizability, future research should further examine whether established technology adoption constructs operate differently in AI-supported TMT contexts. The unexpectedly high intercorrelations between the UTAUT dimensions raise questions about whether these constructs function as distinct mechanisms in executive settings, or whether they instead reflect a broader shared AI adoption climate. Similarly, the findings suggest that TTF is important for PS, but may not be sufficient to explain how AI usage translates into psychosocial team outcomes. While TTF captures functional alignment between technology and task requirements, the results suggest that broader socio-technical and psychosocial conditions may also shape how AI usage influences team dynamics. Future research could therefore continue integrating TTF with complementary perspectives such as socio-technical theory, self-determination theory, and technology affordance perspectives.

Finally, although the direct relationship between AI usage and PS was relatively small, the findings still indicate that AI usage may support PS under certain conditions. Future research should therefore continue investigating when and how AI usage may foster PS within teams, particularly in relation to supportive social, organizational, and technological conditions. This also supports continued efforts within upper echelons research to move beyond demographic and structural proxies toward more direct examination of psychosocial and behavioral processes within TMTs.

7.6 Final Thoughts

As AI becomes embedded in strategic decision-making, its implications extend beyond efficiency and performance. This thesis suggests that AI does not inherently make executive teams psychologically safe. Rather, its role depends on the conditions under which it is used. When AI is supported by a favorable adoption climate, appropriate task fit, and space for human judgment, it may help structure decisions while preserving conditions for critical dialogue. Thus, the managerial challenge is not merely to introduce AI, but to shape the social and technological environment around it. As TMTs navigate increasingly AI-supported decisions, the human dynamics surrounding the technology may prove just as important as the technology itself. In the age of AI, the task is not to let algorithms take the helm, but to bring the right adoption climate on board while setting sail for safer shores.

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Appendices

Appendix 1: Survey (English & Swedish)

Appendix 1.1: GDPR Block

English	Swedish

Welcome We invite you to take part in this survey, which is a component of a research project conducted by Adam Hofvander and Edwin Hydén Karlsson, Master students at the Stockholm School of Economics. The research aims to examine employees' perceptions of psychological safety within their team in relation to the use of AI tools, and whether this relationship is influenced by the organization's climate toward AI and the extent to which AI tools fit the tasks performed by team members. The findings from this survey will contribute to our Master thesis in Business & Management and will be shared with the public upon its completion. The survey takes approximately 3–5 minutes to complete and consists of multiple-choice questions. Your participation is greatly appreciated. Information regarding data protection: All information shared in this survey is strictly anonymous and confidential. The thesis based on this survey will not contain any information that could lead to participants being identified. Your employer will not be able to identify you as a participant. Participation in this survey is voluntary and can be canceled at any time. At cancellation of participation, your data will be deleted permanently. All data is stored and managed in a secure way by the Stockholm School of	**Welcome** Vi bjuder in dig att delta i denna enkät, som är en del av ett forskningsprojekt genomfört av Adam Hofvander och Edwin Hydén Karlsson, masterstudenter vid Handelshögskolan i Stockholm. Syftet med studien är att undersöka medarbetares uppfattningar om psykologisk trygghet i sina team i relation till användningen av AI-verktyg, samt om detta samband påverkas av organisationens klimat kring AI och i vilken utsträckning AI-verktygen passar de arbetsuppgifter som teammedlemmarna utför. Resultaten från denna enkät kommer att bidra till vår masteruppsats inom Business & Management och kommer att göras offentliga när uppsatsen är färdigställd. Enkäten tar cirka 3–5 minuter att besvara och består av flervalsfrågor. Vi uppskattar ditt deltagande och din värdefulla input. Information om dataskydd: All information som delas i denna enkät är helt anonym och konfidentiell. Uppsatsen som baseras på enkäten kommer inte att innehålla någon information som kan identifiera deltagare. Din arbetsgivare kommer inte att kunna identifiera dig som deltagare. Deltagandet i enkäten är frivilligt och kan avbrytas när som helst. Om du väljer att avbryta ditt deltagande kommer dina uppgifter att raderas permanent. All data lagras och

Economics and will be permanently deleted after completion of the project. No personal data will be published. If you want to read more about how the Stockholm School of Economics enforces your rights according to GDPR, please visit: https://www.hhs.se/gdpr	hanteras på ett säkert sätt av Handelshögskolan i Stockholm och kommer att raderas permanent efter att projektet har avslutats. Ingen personlig data kommer att publiceras. Om du vill läsa mer om hur Handelshögskolan i Stockholm säkerställer dina rättigheter enligt GDPR, vänligen besök: https://www.hhs.se/gdpr

GDPR Consent

English	**Swedish**
I have read the information regarding data protection and agree to participate in the study.	Jag har tagit del av informationen om dataskydd och samtycker till att delta i studien.
• Yes, continue the study. • No thanks, I do not want to.	• Ja, jag vill fortsätta och delta i studien. • Nej tack, jag vill inte delta i studien.

Appendix 1.2: Screening Block

English	**Swedish**

This study examines employees' perceptions of psychological safety in their team in relation to AI tool usage, and whether this relationship is influenced by the organization's AI Climate and the fit between AI tools and team tasks. A strategic decision-making team refers to a formal leadership group responsible for major organizational decisions, such as decisions about strategy, investments, or long-term organizational direction.	Denna studie undersöker medarbetares uppfattningar om psykologisk trygghet i sina team i relation till användningen av AI-verktyg, samt om detta samband påverkas av organisationens klimat kring AI och hur väl AI-verktygen passar de arbetsuppgifter som teammedlemmarna utför. Ett strategiskt beslutsfattande team avser en formell ledningsgrupp som ansvarar för större organisatoriska beslut, till exempel beslut om strategi, investeringar eller organisationens långsiktiga inriktning.

Question

English	**Swedish**
Are you currently part of a strategic decision-making team?	Ingår du för närvarande i ett strategiskt beslutsfattande team?
• Yes • No	• Ja • Nej

Appendix 1.3: Control Block

Age

English	Swedish
What is your age?	Vad är din ålder?
• 18-29 • 30-39 • 40-49 • 50-59 • 60-69 • 70+	• 18-29 • 30-39 • 40-49 • 50-59 • 60-69 • 70+

Workgroup Size

English	Swedish
How big is your strategic decision-making team (including yourself)? If you work in several strategic decision-making teams, please choose the one you spend most time with.	Hur stort är ditt strategiska beslutsfattande team (inklusive dig själv)? Om du arbetar i flera strategiska beslutsfattande team, vänligen välj det team där du tillbringar mest tid.
• 2 people • 3-6 people • 7-9 people • 10+ people	• 2 personer • 3-6 personer • 7-9 personer • 10+ personer

Organizational size

English	Swedish
How big is your organization?	Hur stor är din organisation?
• Less than 20 people • 20-49 people • 50-199 people • 200-500 people • 500+ people	• Mindre än 20 personer • 20-49 personer • 50-199 personer • 200-500 personer • 500+ personer

Role

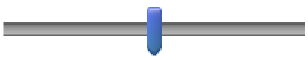
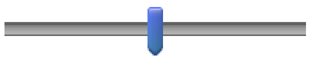
English	Swedish
What is your role? (If you have multiple please fill in the one which has the highest strategic importance in your organization)	Vilken är din roll? (Om du har flera roller, ange den som har störst strategisk betydelse i din organisation.)
• C-Suite • Executive Management Team • Strategy Team • Investment Team • Other senior position please fill in	• C-nivå (C-suite) • Ledningsgrupp • Strategiteam • Investeringsteam • Annan senior position, vänligen ange

Appendix 1.4: Individual AI Usage Control Items

Usage Control 1

English	Swedish
During a typical workday in your TMT, how frequently do you use AI-based tools in your work?	Under en typisk arbetsdag i ditt TMT, hur ofta använder du AI-baserade verktyg i ditt arbete?
• Never • Less than 1 h • 1-2 h • 3-4 h • 4+ h	• Aldrig • Mindre än 1 h • 1-2 h • 3-4 h • 4+ h

Usage Control 2

English	Swedish
During a typical workday in your TMT, what proportion of your work time do you use AI-based tools? 0 = not at all, 100 = used for all work tasks. Please indicate your answer by moving the slider. 	Under en typisk arbetsdag i ditt TMT, hur stor andel av din arbetstid använder du AI-baserade verktyg? 0 = inte alls, 100 = används för alla arbetsuppgifter. Ange ditt svar genom att flytta reglaget. 

Appendix 1.5: Team AI Tool Usage

(All items use the same Likert scale below)

English	Swedish
• Strongly Disagree	• Instämmer inte alls
• Disagree	• Instämmer inte
• Neutral	• Neutral
• Agree	• Instämmer
• Strongly Agree	• Instämmer helt

English	Swedish
AI-U1 Using AI tools has become a habit in my team.	**AI-U1** Att använda AI-verktyg har blivit en vana i mitt team.
AI-U2 When evaluating strategic options in my team, AI tools are used to support the evaluation.	**AI-U2** När strategiska alternativ utvärderas i mitt team används AI-verktyg för att stödja utvärderingen.
AI-U3 AI tools are often used to justify strategic decisions made in my team.	**AI-U3** AI-verktyg används ofta för att motivera strategiska beslut som fattas i mitt team.
AI-U4 AI tools are used to evaluate performance-relevant outcomes in my team.	**AI-U4** AI-verktyg används för att utvärdera resultat som är relevanta för prestation i mitt team.

Appendix 1.6: Team AI Adoption Climate (UTAUT)

(Likert scale same as above)

English	Swedish
AI-PE In my team, the use of AI tools improves strategic decision-making outcomes.	**AI-PE** I mitt team förbättrar användningen av AI-verktyg resultaten av strategiska beslut.
AI-EE In my team, it is easy to become skillful at using AI tools.	**AI-EE** I mitt team är det lätt att bli skicklig på att använda AI-verktyg.
AI-SI Senior members (including myself) and people who have influence in my team support the use of AI tools.	**AI-SI** Seniora medlemmar (inklusive jag själv) och personer med inflytande i mitt team stödjer användningen av AI-verktyg.
AI-FC In my team, we have the support and resources to adopt AI tools.	**AI-FC** I mitt team har vi stöd och resurser för att använda AI-verktyg.

Appendix 1.7: Task–Technology Fit (TTF)

(Likert scale same as above)

English	Swedish
TTF-1 In my team, the AI tools we use are appropriate for the tasks my team performs.	**TTF-1** I mitt team är de AI-verktyg vi använder lämpliga för de arbetsuppgifter som mitt team utför.

TTF-2 In my team, the functions of the AI tools are sufficient to support my team's work tasks.	**TTF-2** I mitt team är funktionerna i AI-verktygen tillräckliga för att stödja mitt teams arbetsuppgifter.
TTF-3 Overall, the capabilities of the AI tools meet the needs of my team's work.	**TTF-3** Överlag motsvarar AI-verktygens kapacitet behoven i mitt teams arbete.

Appendix 1.8: Psychological Safety (PS)

(Likert scale same as above)

English	Swedish
PS_1 (R)[1] If you make a mistake on this team, it is often held against you.	**PS_1 (R)** Om du gör ett misstag i detta team hålls det ofta emot dig.
PS_2 Members of this team are able to bring up problems and tough issues.	**PS_2** Medlemmar i detta team kan ta upp problem och svåra frågor.
PS_3 (R) People on this team sometimes reject others for being different.	**PS_3 (R)** Personer i detta team avvisar ibland andra för att de är annorlunda.
PS_4 It is safe to take a risk on this team.	**PS_4** Det är tryggt att ta risker i detta team.
PS_5 (R) It is difficult to ask other members of this team for help.	**PS_5 (R)** Det är svårt att be andra medlemmar i detta team om hjälp.

[1] (R) indicates that the item is reverse-coded; see Appendix 2.6

PS_6 No one on this team would deliberately act in a way that undermines my efforts.	**PS_6** Ingen i detta team skulle medvetet agera på ett sätt som underminerar mina ansträngningar.
PS_7 Working with members of this team, my unique skills and talents are valued and utilized.	**PS_7** När jag arbetar med medlemmar i detta team värderas och används mina unika färdigheter och talanger.

Appendix 1.9: Attention Control Question

English	**Swedish**
What has the theme of this survey been?	Vad har den här enkäten handlat om?
• Remote work • AI usage and its effect on psychological safety • Affection for your work team	• Distansarbete • Användning av AI och dess påverkan på psykologisk trygghet • Känsla av tillhörighet till ditt arbetslag

Appendix 1.10 Logic Behind Survey Item Construction

Variable	**Logic behind item construction**
PS	All seven items were adopted directly from Edmondson's (1999) psychological safety scale, as this measure is widely used and theoretically aligned with PS as a team-level perception of interpersonal risk-taking.

AI-U1: Habitual use	Captures habitual use as introduced in UTAUT2, reflecting routine technology usage over time (Venkatesh et al., 2012).
AI-U2: Evaluation of strategic options	DSS literature links decision support to the evaluation of alternatives in semi-structured decision processes; this item therefore captures AI use for evaluating strategic options within TMTs (Simon, 1977; Phillips-Wren, 2013).
AI-U3: Justification of decisions	DSS outputs include forecasts, explanations, recommendations, and advice; this item therefore captures the extent to which AI-generated outputs are used as an analytical basis for explaining or supporting strategic decisions, rather than for social legitimacy (Phillips-Wren, 2013).
AI-U4: Evaluation of outcomes	DSS literature connects decision support to implementation review and outcome evaluation; this item therefore captures AI use for assessing performance-relevant consequences of strategic decisions (Simon, 1977; Phillips-Wren, 2013).
UTAUT Constructs	The four UTAUT items were adapted from Venkatesh et al. (2003) to capture performance expectancy, effort expectancy, social influence, and facilitating conditions in relation to AI-supported strategic decision-making. Each item represents one core UTAUT dimension, while being reformulated to fit the TMT and AI-use context.
TTF	The TTF items were adapted from Zhou et al. (2010) and reformulated for strategic decision-making in TMTs. The items capture whether AI tools are appropriate for the team's tasks, whether their functions sufficiently support those tasks, and whether their overall capabilities meet the team's work needs, reflecting task and technology characteristics as well as overall perceived fit (Goodhue & Thompson, 1995).

Appendix 2: Code Specifics

Appendix 2.1: Control Question Codes

Variable Name	Variable Type	Coding
Age	Ordinal	18–29 = 0 30–39 = 1 40–49 = 2 50–59 = 3 60–69 = 4 70+ = 5
Workgroup Size	Ordinal	2 people = 0 3–6 people = 1 7–9 people = 2 10+ people = 3
Organizational Size	Ordinal	<20 = 0 20–49 = 1 50–199 = 2 200–500 = 3 500+ = 4

Appendix 2.2: AI Usage (Individual-Level Control) Codes

Variable Name	Variable Type	Coding
AI usage Frequency	Ordinal	Never = 0 <1h = 1 1–2h = 2 3–4h = 3 4+h = 4
AI usage (Slider)	Continuous	0–100 scale

Appendix 2.3: Team AI Usage Codes

Variable Name	Variable Type	Coding
AI_U1 – AI_U4	Ordinal	Strongly Disagree = 1 Disagree = 2 Neutral = 3 Agree = 4 Strongly Agree = 5

AI usage (Aggregate Mean)	Continuous	(AI_U1 + AI_U2 + AI_U3 + AI_U4) / 4

Appendix 2.4: UTAUT Constructs Codes

Variable Name	Variable Type	Coding
AI_PE	Ordinal	1–5 Likert
AI_EE	Ordinal	1–5 Likert
AI_SI	Ordinal	1–5 Likert
AI_FC	Ordinal	1–5 Likert
UTAUT Constructs (aggregated)	Continuous	(AI_PE + AI_EE + AI_SI + AI_FC) / 4

Appendix 2.5: Task-Technology Fit (TTF) Codes

Variable Name	Variable Type	Coding
TTF_1 – TTF_3	Ordinal	Strongly Disagree = 1 Disagree = 2 Neutral = 3 Agree = 4 Strongly Agree = 5

TTF (Aggregate Mean)	Continuous	(TTF_1 + TTF_2 + TTF_3) / 3

Appendix 2.6 Psychological Safety (PS) Codes

Variable Name	Variable Type	Coding
PS_2, PS_4, PS_6, PS_7	Ordinal	Strongly Disagree = 1 → Strongly Agree = 5
PS_1(R), PS_3(R), PS_5(R)	Ordinal (Reversed)	Strongly Agree = 1 Agree = 2 Neutral = 3 Disagree = 4 Strongly Disagree = 5
Psychological Safety (Aggregate Mean)	Continuous	(PS_1(R) + PS_2 + PS_3(R) + PS_4 + PS_5(R) + PS_6 + PS_7) / 7

Appendix 3: Miscellaneous TMT Info

Team ID	TMT Size	Included Respondents	Response Rate
1	6	4	67%
2	8	3	38%
3	12	6	50%
4	7	4	57%
5	9	4	44%
6	11	3	27%
7	7	3	43%
8	9	4	44%
9	5	3	60%
10	8	5	63%
11	7	6	86%
12	4	3	75%
13	8	3	38%
14	7	4	57%
15	9	3	33%
16	10	4	40%
17	7	5	71%
18	6	4	67%
19	9	4	44%
20	5	3	60%
21	8	5	63%
22	9	8	89%
23	4	4	100%
24	8	6	75%
25	6	5	83%
26	7	3	43%

27	9	4	44%
28	5	4	80%
29	3	3	100%
30	6	3	50%
31	4	3	75%
32	5	3	60%
33	9	7	78%
34	5	5	100%
35	6	5	83%
36	5	4	80%
37	6	5	83%
38	7	3	43%
39	2	1	50%
40	8	3	38%
41	7	4	57%
42	9	3	33%
43	4	2	50%
44	6	5	83%
45	13	4	31%
46	3	2	67%
47	5	3	60%
48	6	3	50%
49	4	2	50%
50	8	8	100%
Total / Mean	**6.82**	**3.96**	**58%**

Appendix 4: VIF-Tests for Multicollinearity

Appendix 4.1 VIF - H1 Direct Model

VARIABLE	VIF	1/VIF
AI usage	1.090	.917
Age	1.140	.877
Workgroup Size	2.040	.490
Org. Size	1.980	.505
Mean VIF	1.563	.

Appendix 4.2 VIF - H2 UTAUT Moderation

VARIABLE	VIF	1/VIF
AI usage	1.270	.787
UTAUT Constructs	1.550	.645
Interaction	1.450	.690
Age	1.150	.870
Workgroup Size	2.200	.455
Org size	2.030	.493
Mean VIF	1.608	.

Appendix 4.3 VIF - H3 TTF Moderation

VARIABLE	VIF	1/VIF
AI usage	1.420	.704
TTF	1.290	.775

Interaction	1.340	.746
Age	1.140	.877
Workgroup Size	2.170	.461
Org. Size	2.110	.474
Mean VIF	1.578	.

Appendix 4.4 VIF - Polynomial H2 (UTAUT)

VARIABLE	VIF	1/VIF
AI_usage_c	4.20	.238
UTAUT_c	3.29	.304
AI_usage_sq	3.07	.326
AI_usage × UTAUT	1.53	.654
UTAUT_sq	4.36	.229
Age	1.08	.924
Workgroup Size	1.11	.899
Org. Size	1.18	.845
Mean VIF	2.48	.

Appendix 4.5 VIF - Polynomial H3 (TTF)

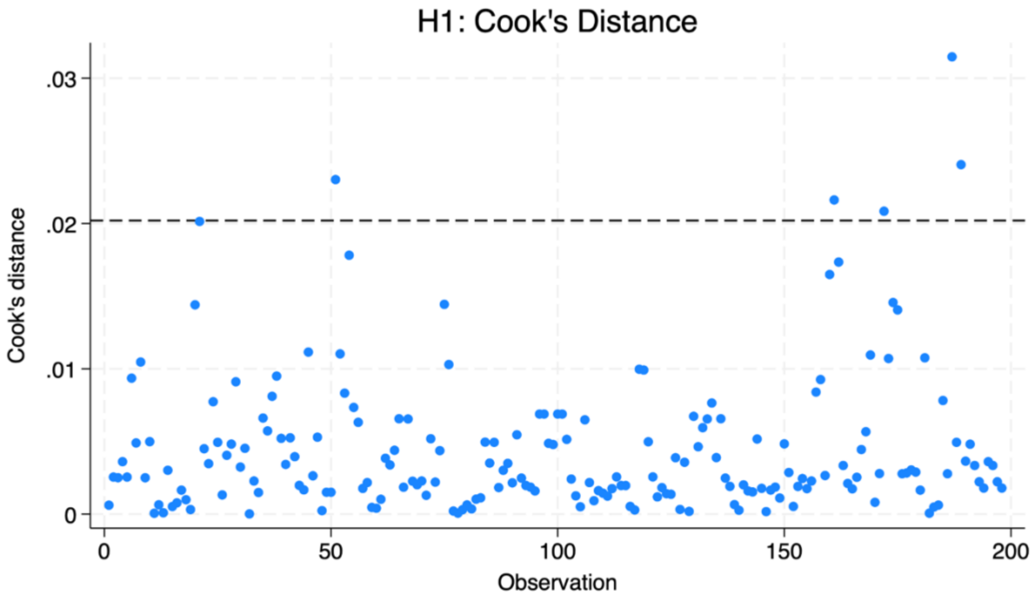
VARIABLE	VIF	1/VIF
AI_usage_c	2.51	.399
TTF_c	1.37	.729
AI_usage_sq	3.14	.318
AI_usage × TTF	1.69	.592

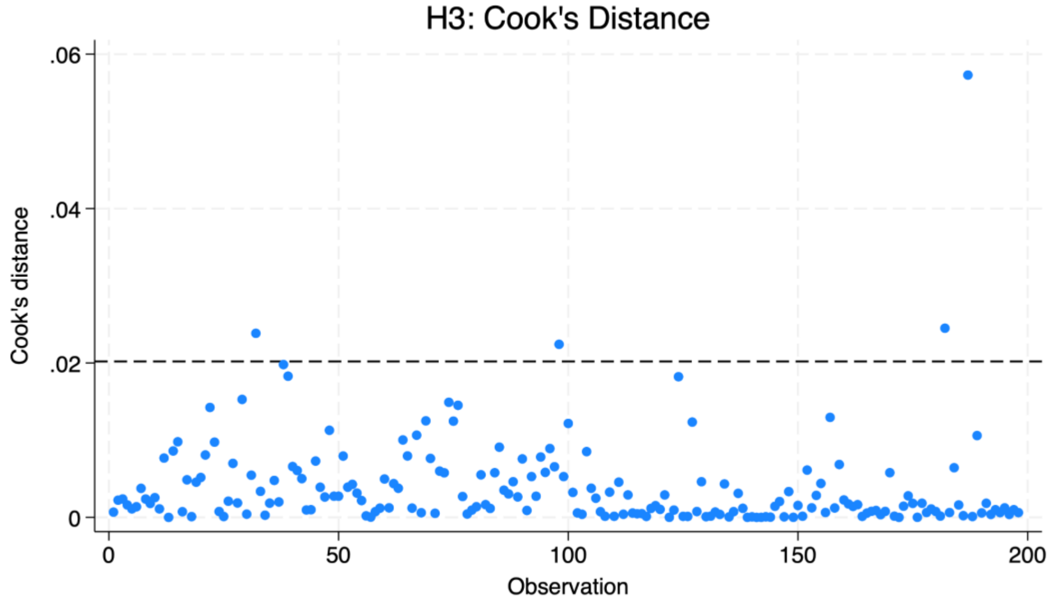
TTF_sq	1.30	.767
Age	1.09	.918
Workgroup Size	1.10	.908
Org. Size	1.16	.861
Mean VIF	1.67	.

Appendix 4.6 VIF - UTAUT Components (Aggregation Test)

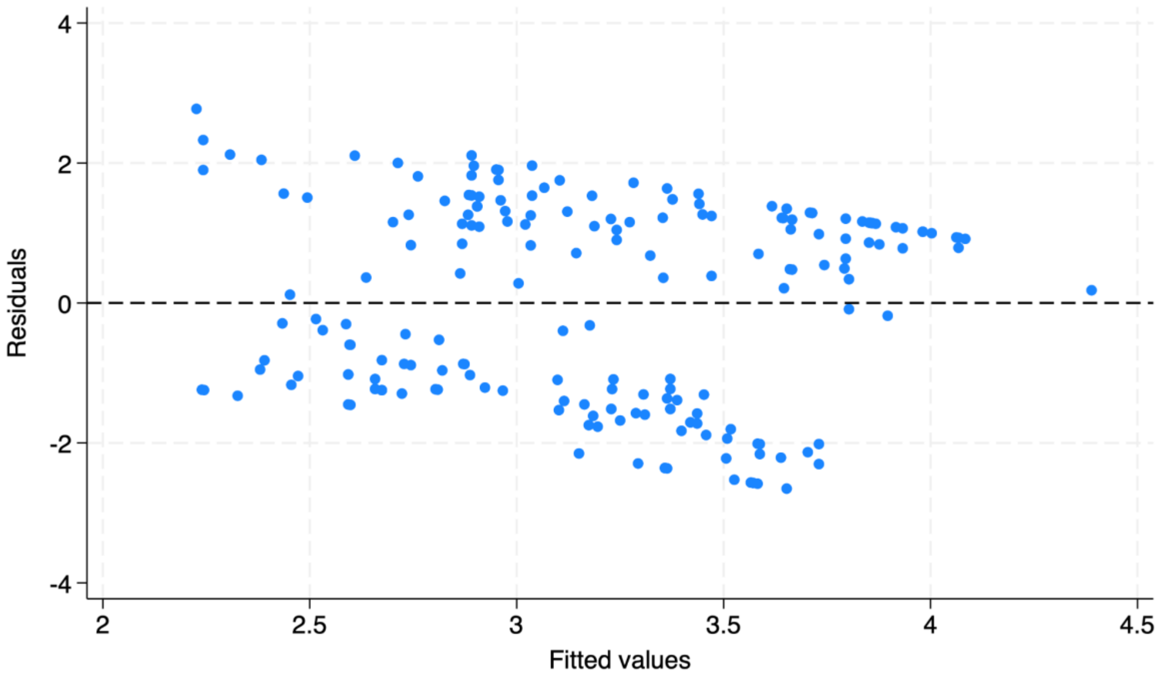
VARIABLE	VIF	1/VIF
AI usage	1.230	.813
AI_PE	9.330	.107
AI_EE	9.790	.102
AI_SI	8.310	.120
AI_FC	12.030	.083
Age	1.190	.840
Workgroup Size	2.270	.441
Org. Size	2.070	.483
Mean VIF	4.850	.

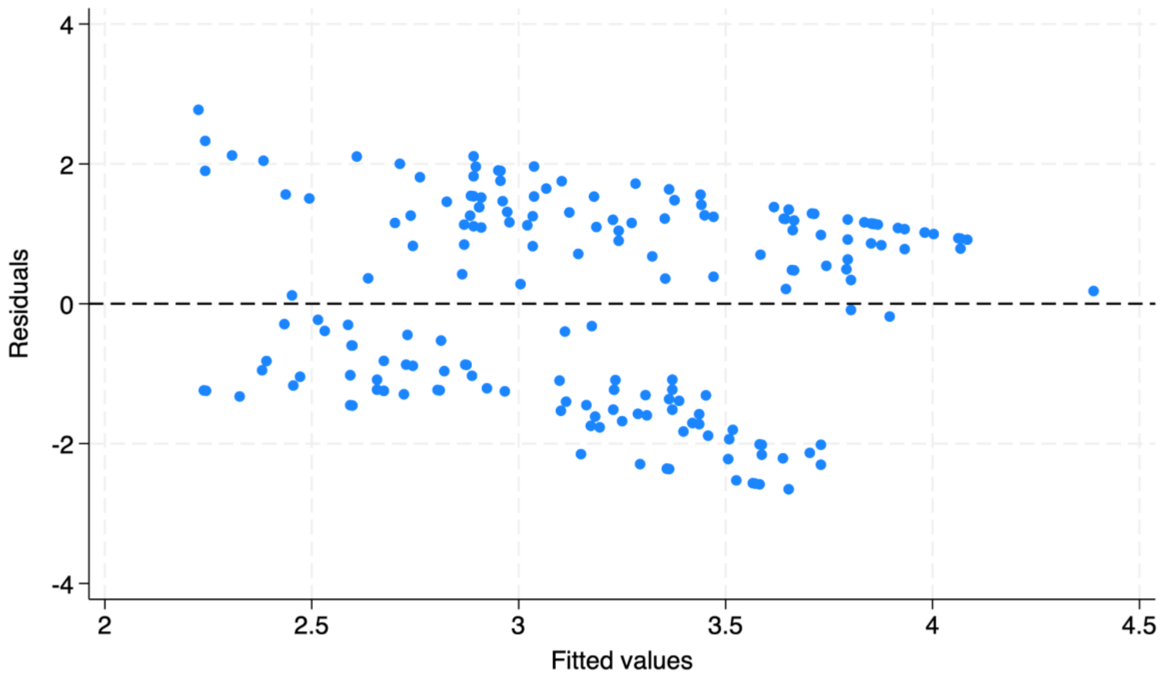
Appendix 5: Cook's Influence Diagnostics



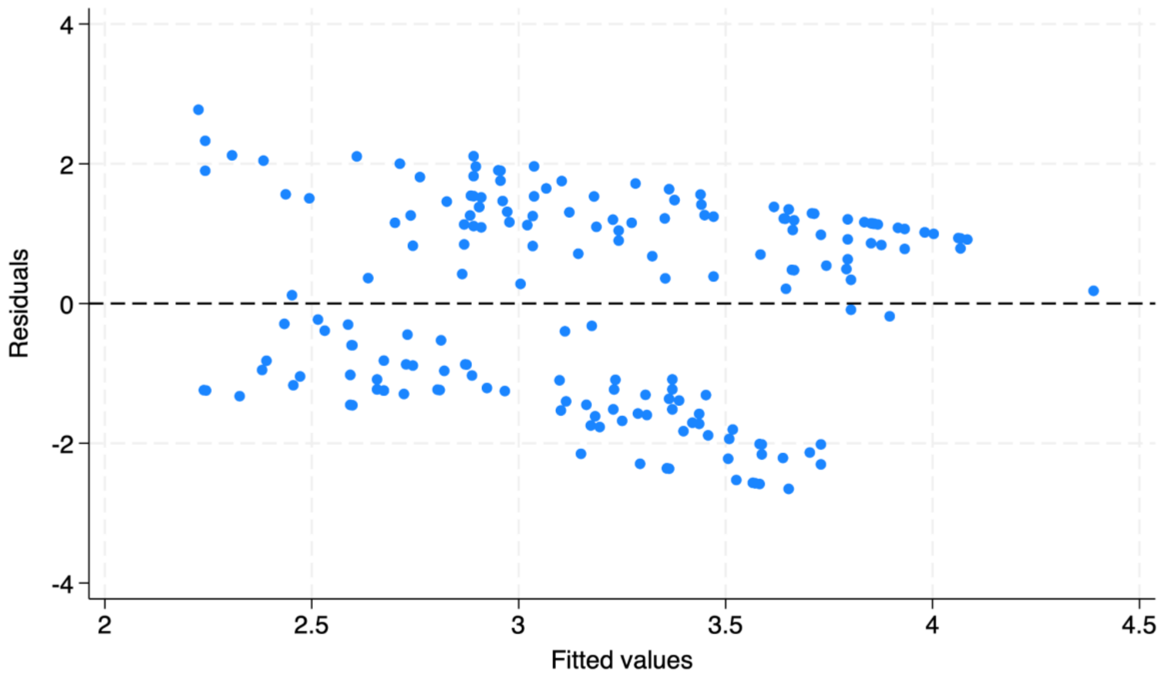


Appendix 6: Residual-Versus-Fitted Plots for Linearity and Model Specification





4
2
0
-2
-4
Residuals
2
2.5
3
3.5
4
4.5
Fitted values



4
2
0
-2
-4
Residuals
2
2.5
3
3.5
4
4.5
Fitted values

Appendix 7: Correlation Matrices

Appendix 7.1: Control Variable Correlations

Variables	(1)	(2)	(3)	(4)
(1) Usage Control 1	1.000			
(2) Usage Control 2	0.848***	1.000		
(3) AI Usage	0.679***	0.573***	1.000	
(4) Age	-0.097	-0.092	-0.069	1.000

Appendix 7.2: PS Items Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) PS_1	1.000						
(2) PS_2	0.888***	1.000					
(3) PS_3	0.901***	0.914***	1.000				
(4) PS_4	0.902***	0.936***	0.922***	1.000			
(5) PS_5	0.880***	0.902***	0.883***	0.908***	1.000		

(6) PS_6	0.914***	0.907***	0.917***	0.927***	0.904***	1.000	
(7) PS_7	0.902***	0.907***	0.911***	0.928***	0.875***	0.904***	1.000

Appendix 7.3: AI usage Items Correlations

Variables	(1)	(2)	(3)	(4)
(1) AI_U1	1.000			
(2) AI_U2	0.876***	1.000		
(3) AI_U3	0.858***	0.829***	1.000	
(4) AI_U4	0.883***	0.886***	0.860***	1.000

Appendix 7.4: UTAUT Components Correlations

Variables	(1)	(2)	(3)	(4)
(1) AI_PE	1.000			
(2) AI_EE	0.897***	1.000		
(3) AI_SI	0.914***	0.890***	1.000	
(4) AI_FC	0.913***	0.937***	0.904***	1.000

Appendix 7.5: TTF Components Correlations

Variables	(1)	(2)	(3)
(1) TTF_1	1.000		
(2) TTF_2	0.660	1.000	
(3) TTF_3	0.767	0.775	1.000

Appendix 7.6: Extensive Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) PS	1.000							
(2) AI usage	0.254***	1.000						
(3) AI_PE	0.558***	-0.186***	1.000					
(4) AI_EE	0.612***	-0.184***	0.897***	1.000				
(5) AI_SI	0.624***	-0.155**	0.914***	0.890***	1.000			

(6) AI_FC	0.574***	-0.218***	0.913***	0.937***	0.904***	1.000		
(7) UTAUT	0.612***	-0.193***	0.965***	0.965***	0.958***	0.973***	1.000	
(8) TTF	0.766***	0.303***	0.385***	0.447***	0.425***	0.418***	0.434***	1.000

Appendix 7.7: UTAUT (H2) Polynomial Correlations

Variable	(1)	(2)	(3)	(4)	(5)
(1) AI_usage_c	1.000				
(2) UTAUT_c	-0.193*	1.000			
(3) AI_usage_sq	-0.732*	0.152*	1.000		
(4) UTAUT_sq	0.475*	-0.743*	-0.145*	1.000	
(5) Interaction	0.167*	0.443*	-0.275*	-0.390*	1.000

Appendix 7.8: TTF (H3) Polynomial Correlations

Variable	(1)	(2)	(3)	(4)	(5)

(1) AI_usage_c	1.000				
(2) TTF_c	0.303*	1.000			
(3) AI_usage_sq	-0.732*	-0.350*	1.000		
(4) TTF_sq	0.135	0.154*	0.142*	1.000	
(5) Interaction	-0.343*	0.137	0.500*	0.305*	1.000

Appendix 8: Bootstrap Results for RSAs

Appendix 8.1: Bootstrap for UTAUT (H2) RSA

Parameter	Coefficient	SE	z	p-value	95% CI
a1	0.459***	0.055	8.34	0.000	[0.351, 0.567]
a2	0.334***	0.049	6.81	0.000	[0.238, 0.430]
a3	-0.305***	0.081	-3.77	0.000	[-0.463, -0.146]

a4	-0.739***	0.039	-19.16	0.000	[-0.815, -0.664]

*** p<0.01, ** p<0.05, * p<0.10

Replications = 1000

Appendix 8.2: Bootstrap for TTF (H3) RSA

Parameter	Coefficient	SE	z	p-value	95% CI
a1	0.844***	0.119	7.07	0.000	[0.610, 1.077]
a2	-0.235***	0.055	-4.25	0.000	[-0.344, -0.127]
a3	-1.079***	0.113	-9.56	0.000	[-1.301, -0.858]
a4	-0.482***	0.115	-4.20	0.000	[-0.706, -0.257]

*** p<0.01, ** p<0.05, * p<0.10

Replications = 1000

Appendix 9: Cronbach’s Alpha for Higher-Level Constructs

Appendix 9.1: Cronbach’s Alpha for PS

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average Interitem Covariance	Alpha
PS_1	198	+	0.9509	0.9335	2.2599	0.9835
PS_2	198	+	0.9621	0.9477	2.2074	0.9826
PS_3	198	+	0.9599	0.9458	2.2568	0.9828
PS_4	198	+	0.9724	0.9612	2.1631	0.9818
PS_5	198	+	0.9465	0.9268	2.2384	0.9839
PS_6	198	+	0.9639	0.9510	2.2424	0.9824
PS_7	198	+	0.9574	0.9420	2.2414	0.9830
Test Scale					2.2299	0.9853

Appendix 9.2: Cronbach's Alpha for AI Usage

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average Interitem Covariance	Alpha
AI_U1	198	+	0.9550	0.9166	1.6210	0.9475
AI_U2	198	+	0.9456	0.9054	1.7356	0.9510
AI_U3	198	+	0.9343	0.8853	1.7464	0.9563
AI_U4	198	+	0.9577	0.9220	1.6235	0.9457
Test Scale					1.6816	0.9622

Appendix 9.3: Cronbach's Alpha for UTAUT Constructs

Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average Interitem Covariance	Alpha

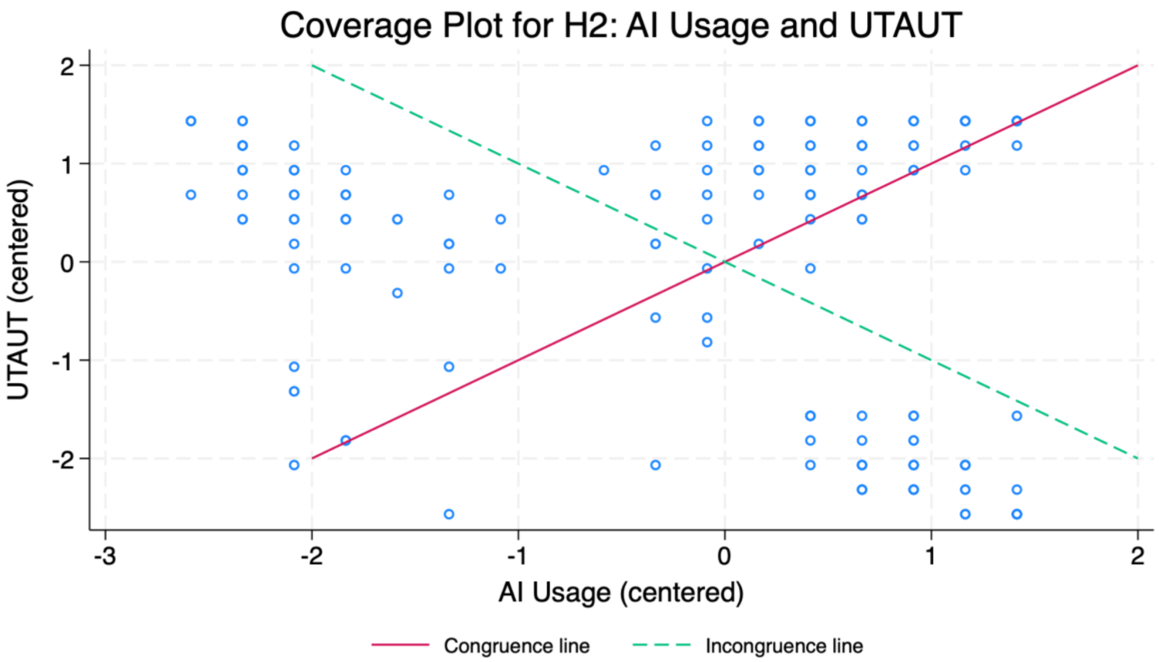
AI_PE	198	+	0.9652	0.9363	2.0844	0.9674
AI_EE	198	+	0.9651	0.9369	2.1094	0.9670
AI_SI	198	+	0.9583	0.9293	2.2591	0.9702
AI_FC	198	+	0.9726	0.9502	2.0835	0.9632
Test Scale					2.1341	0.9751

Appendix 9.4: Cronbach's Alpha for TTF

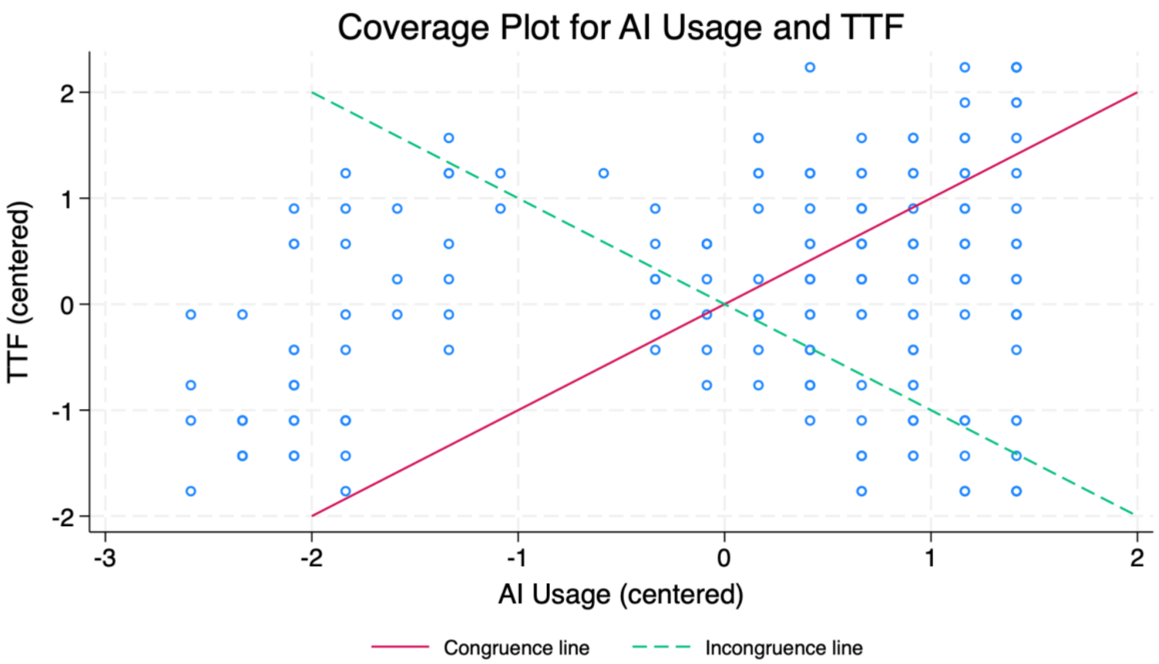
Item	Obs	Sign	Item-Test Correlation	Item-Rest Correlation	Average Interitem Covariance	Alpha
TTF_1	198	+	0.8946	0.7575	1.0826	0.8731
TTF_2	198	+	0.8925	0.7621	1.1144	0.8679
TTF_3	198	+	0.9336	0.8461	0.9493	0.7945
Test Scale					1.0487	0.8918

Appendix 10: Configuration Coverage Plots for RSA Validation

Appendix 10.1: Configuration Coverage Plot UTAUT (H2) RSA



Appendix 10.2: Configuration Coverage Plot TTF (H3) RSA



Appendix 11: ICC1 of Aggregate Items

Variable	ICC	95% CI	F	p-value
PS	0.245	[0.091, 0.399]	2.28	0.0001
AI usage	0.154	[0.010, 0.298]	1.72	0.0070
UTAUT	0.166	[0.020, 0.312]	1.79	0.0043
TTF	0.245	[0.092, 0.399]	2.28	0.0001
Observations	198			
Teams	50			

Appendix 12: Polynomial Regression Models

Appendix 12.1 Polynomial Regression UTAUT

VARIABLES	H2 Polynomial: AI usage × UTAUT → PS
AI_usage_c	0.077
	(0.053)
UTAUT_c	0.382***
	(0.054)
AI_usage_sq	-0.193***
	(0.040)

AI_usage_UTAUT	0.537***
	(0.021)
UTAUT_sq	-0.010
	(0.054)
Age	0.072
	(0.058)
WorkgroupSize	-0.005
	(0.072)
OrgSize	0.027
	(0.042)
Constant	3.530***
	(0.185)
Observations	198
R-squared	0.891
Clustered SE	Team_ID
Controls	Age, WorkgroupSize, OrgSize

Cluster-robust errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Appendix 12.2: Polynomial Regression TTF

VARIABLES	H3 Polynomial: AI usage × TTF
AI_usage_c	-0.118
	(0.105)
TTF_c	0.961***
	(0.062)
AI_usage_sq	-0.221***
	(0.079)
AI_usage_TTF	0.123*
	(0.064)
TTF_sq	-0.137*
	(0.074)
Age	-0.028
	(0.109)
WorkgroupSize	-0.088
	(0.107)
OrgSize	-0.101
	(0.075)
Constant	4.128***

	(0.306)
Observations	198
R-squared	0.636
Clustered SE	Team_ID
Controls	Age, WorkgroupSize, OrgSize

Cluster-robust errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Appendix 13: HTML for 3D of RSAs

Appendix 13.1: HTML 3D RSA for UTAUT (H2)

https://edwin1karlsson-creator.github.io/MSc-3D-RSA-Interactive/RSA_UTAUT_Interactive.html

Appendix 13.2: HTML 3D RSA for TTF (H3)

https://edwin1karlsson-creator.github.io/MSc-3D-RSA-Interactive/RSA_TTF_Interactive.html

Appendix 14: UTAUT Component Moderation, Polynomials & RSA

Appendix 14.1: Component Moderation UTAUT

VARIABLES	(1) H2a: PE	(2) H2b: EE	(3) H2c: SI	(4) H2d: FC
AI usage (centered)	0.276***	0.289***	0.302***	0.272***
	(0.045)	(0.047)	(0.057)	(0.046)

Performance Expectancy (PE, centered)	0.378***			
	(0.026)			
AI usage × PE	0.538***			
	(0.016)			
Effort Expectancy (EE, centered)		0.338***		
		(0.029)		
AI usage × EE		0.564***		
		(0.021)		
Social Influence (SI, centered)			0.449***	
			(0.037)	
AI usage × SI			0.533***	
			(0.025)	
Facilitating Conditions (FC, centered)				0.383***
				(0.037)
AI usage × FC				0.531***
				(0.024)
Age	0.028	0.027	0.061	0.085

	(0.073)	(0.061)	(0.075)	(0.072)
Workgroup Size	0.083	-0.054	0.035	0.049
	(0.078)	(0.092)	(0.090)	(0.098)
Org. Size	0.041	0.032	0.057	0.036
	(0.051)	(0.045)	(0.056)	(0.054)
Constant	3.110***	3.353***	3.019***	3.042***
	(0.194)	(0.199)	(0.244)	(0.231)
Observations	198	198	198	198
R^2	0.867	0.848	0.809	0.836
Clustered SE	Team_ID (50 teams)			
Controls	Age, Workgroup Size, Org. Size			

Cluster-robust errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Appendix 14.2: Component Polynomial UTAUT

VARIABLES	(1) H2a: PE	(2) H2b: EE	(3) H2c: SI	(4) H2d: FC
AI usage (centered)	0.089**	0.022	0.012	0.020
	(0.043)	(0.044)	(0.056)	(0.052)
Performance Expectancy (PE, centered)	0.398***			
	(0.039)			
AI usage × PE	0.509***			

	(0.015)			
PE^2	0.016			
	(0.030)			
Effort Expectancy (EE, centered)		0.370***		
		(0.037)		
AI usage × EE		0.511***		
		(0.033)		
EE^2		0.001		
		(0.037)		
Social Influence (SI, centered)			0.565***	
			(0.052)	
AI usage × SI			0.523***	
			(0.027)	
SI^2			0.144***	
			(0.049)	
Facilitating Conditions (FC, centered)				0.423***
				(0.044)

AI usage × FC				0.488***
				(0.025)
FC^2				0.020
				(0.036)
AI $usage^2$	-0.182***	-0.216***	-0.247***	-0.230***
	(0.041)	(0.040)	(0.038)	(0.037)
Age	0.041	0.047	0.085	0.100
	(0.065)	(0.055)	(0.067)	(0.065)
Workgroup Size	0.055	-0.065	-0.022	0.030
	(0.070)	(0.087)	(0.084)	(0.088)
Org. Size	0.024	0.014	0.041	0.023
	(0.045)	(0.038)	(0.054)	(0.049)
Constant	3.430***	3.723***	3.226***	3.405***
	(0.204)	(0.222)	(0.257)	(0.240)
Observations	198	198	198	198
R^2	0.884	0.872	0.846	0.863
Clustered SE	Team_ID	Team_ID	Team_ID	Team_ID
Controls	Age, Workgroup Size, Org. Size,	Age, Workgroup Size, Org. Size,	Age, Workgroup Size, Org. Size,	Age, Workgroup Size, Org. Size,

Cluster-robust errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix 14.3: Component RSA UTAUT

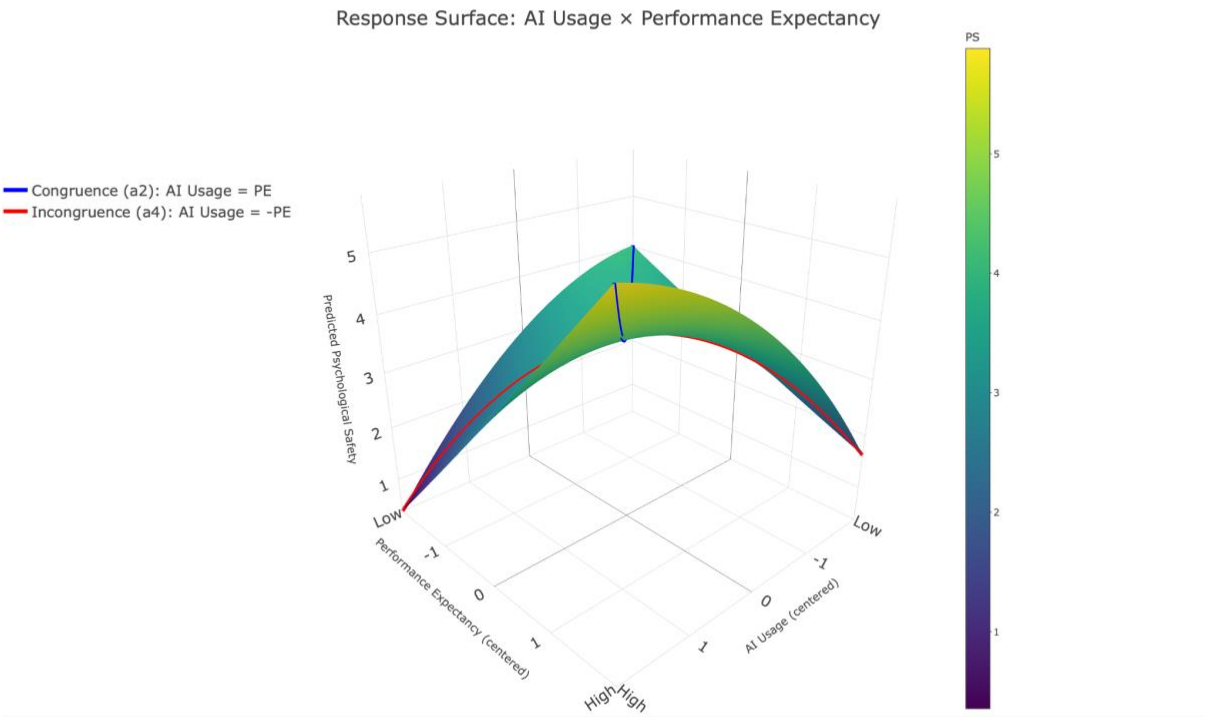
Component	Surface Parameter	Coefficient	Std. Error	t-value
PE	a1: Line of Congruence slope	0.479***	0.057	8.36
PE	a2: Line of Congruence curvature	0.313***	0.047	6.64
PE	a3: Line of Incongruence slope	-0.312***	0.062	-5.01
PE	a4: Line of Incongruence curvature	-0.681***	0.042	-16.39
EE	a1: Line of Congruence slope	0.379***	0.058	6.57
EE	a2: Line of Congruence curvature	0.283***	0.060	4.69
EE	a3: Line of Incongruence slope	-0.357***	0.061	-5.84
EE	a4: Line of Incongruence curvature	-0.732***	0.035	-20.86

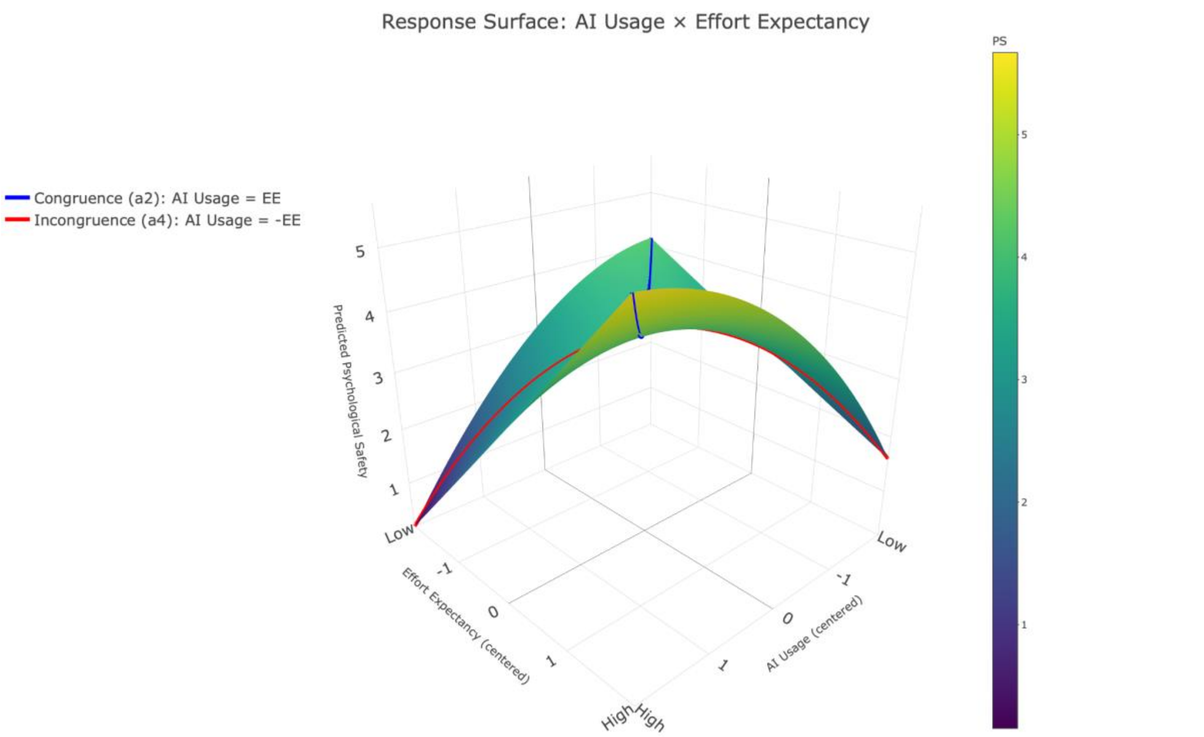
SI	a1: Line of Congruence slope	0.577***	0.065	8.94
SI	a2: Line of Congruence curvature	0.422***	0.056	7.49
SI	a3: Line of Incongruence slope	-0.549***	0.074	-7.39
SI	a4: Line of Incongruence curvature	-0.627***	0.043	-14.65
FC	a1: Line of Congruence slope	0.436***	0.057	7.66
FC	a2: Line of Congruence curvature	0.279***	0.051	5.46
FC	a3: Line of Incongruence slope	-0.387***	0.071	-5.45
FC	a4: Line of Incongruence curvature	-0.702***	0.039	-18.15
Observations	198			
Controls	Age, Workgroup size, Org. Size			

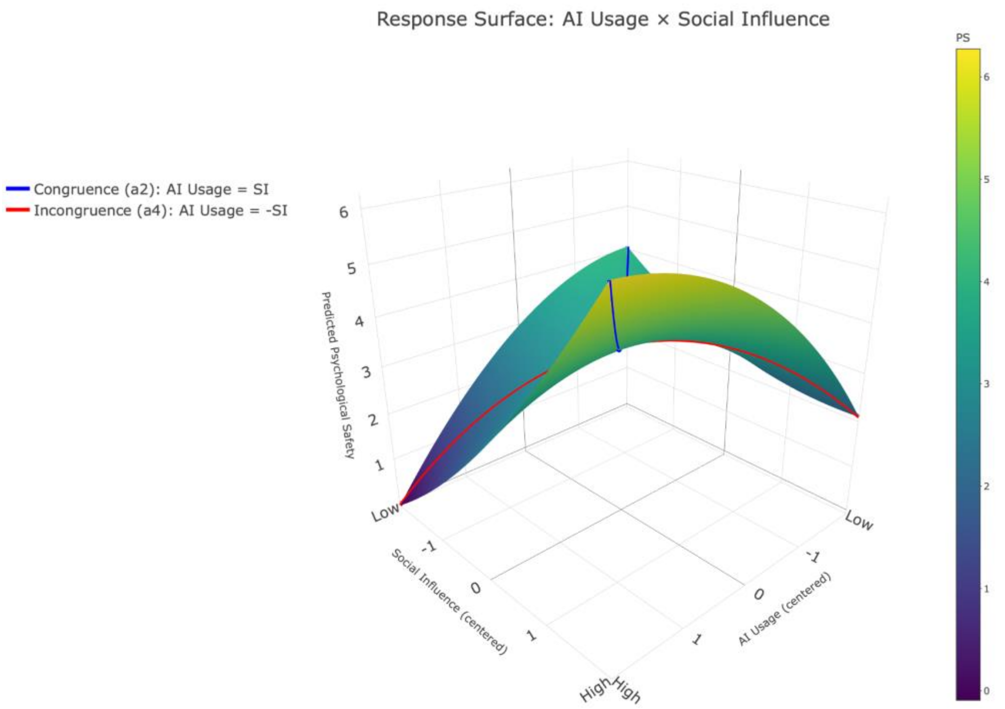
Cluster-robust standard errors reported

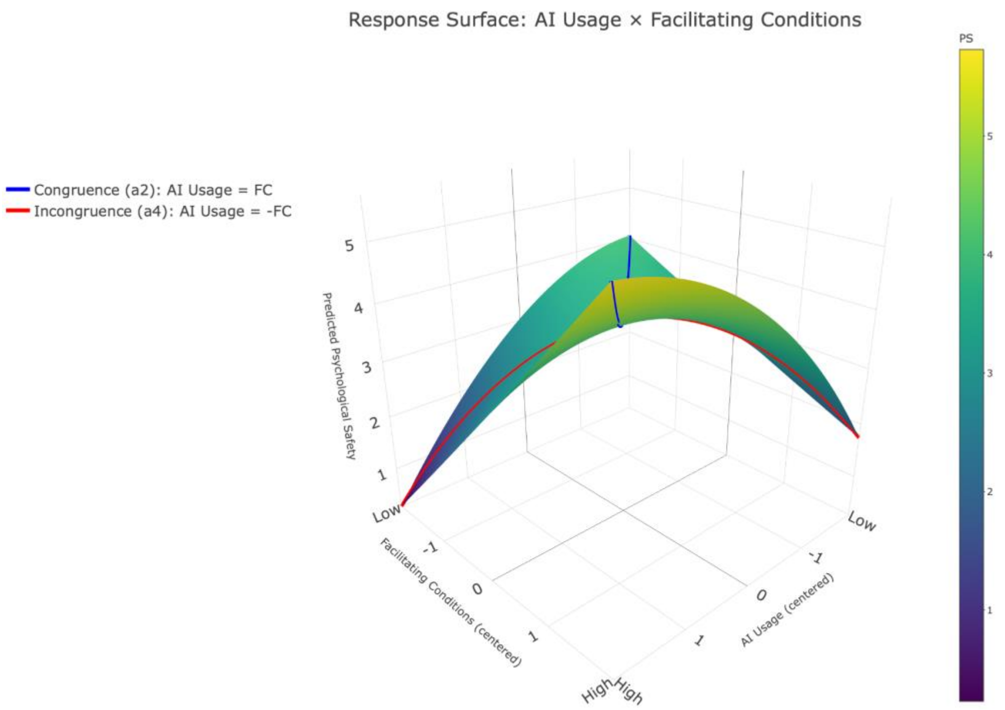
*** p<0.01, ** p<0.05, * p<0.1

Appendix 14.4: Component RSA 3D Models






Response Surface: AI Usage × Social Influence
Congruence (a2): AI Usage = SI
Incongruence (a4): AI Usage = -SI
Predicted Psychological Safety
Social Influence (centered)
AI Usage (centered)
Low
High
PS


Response Surface: AI Usage × Facilitating Conditions
Congruence (a2): AI Usage = FC
Incongruence (a4): AI Usage = -FC
Predicted Psychological Safety
Facilitating Conditions (centered)
AI Usage (centered)
Low
High
PS

Appendix 15: Robustness Check H2 Excluding N=12 Influential Observations

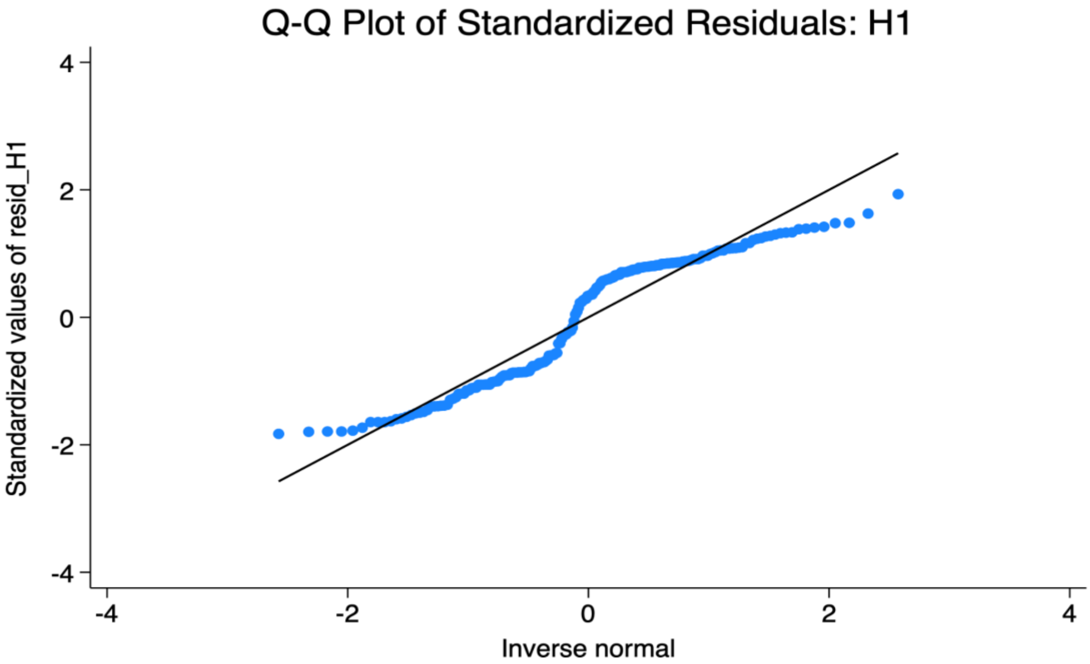
VARIABLES	H2: AI usage × UTAUT → PS
AI_usage_c	0.320***
	(0.033)
UTAUT_c	0.405***
	(0.028)
AI_usage × UTAUT	0.572***
	(0.016)
Age	0.082
	(0.050)
Workgroup Size	0.084
	(0.083)
Org. Size	0.090**
	(0.042)
Constant	2.832***
	(0.169)
Observations	186

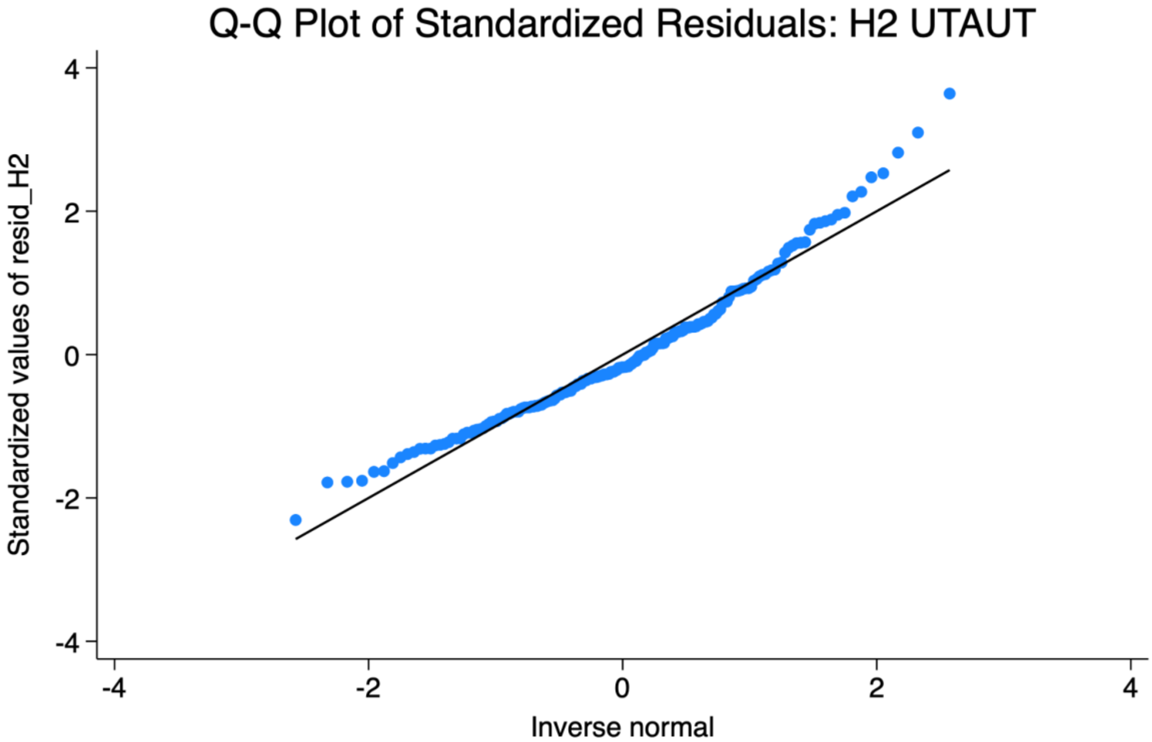
R-squared	0.909
Clustered SE	Team_ID, 50 teams
Controls	Age, Workgroup Size, Org. Size

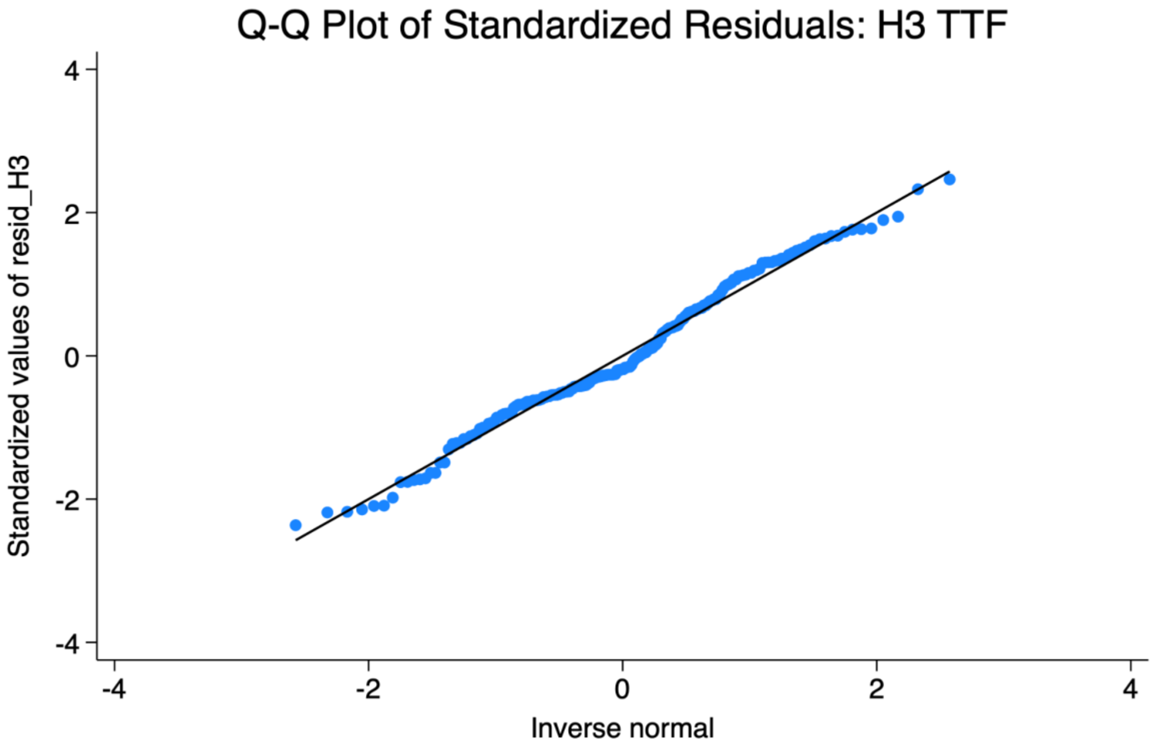
Cluster-robust errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

Appendix 16: QQ Plots for Normal Distribution of Residuals




Q-Q Plot of Standardized Residuals: H2 UTAUT
Standardized values of resid_H2
Inverse normal
4
2
0
-2
-4
-4
-2
0
2
4


Q-Q Plot of Standardized Residuals: H3 TTF
Standardized values of resid_H3
Inverse normal
4
2
0
-2
-4
-4
-2
0
2
4

Appendix 17: AI Disclosure

Generative AI tools were used during selected stages of this thesis process in accordance with the Stockholm School of Economics' guidelines on AI usage in academic work. Primarily, ChatGPT (OpenAI) was used as a supportive tool for language refinement, structural feedback, translation support, and discussions related to methodological and statistical concepts relevant to the study.

AI tools were also used to improve clarity, coherence, and academic formulation throughout the writing process, as well as to support discussions related to regression analysis, moderation analysis, and Response Surface Analysis (RSA). In addition, AI was occasionally used to assist with formatting consistency and to cross-check alignment between references and citations used in the thesis.

Particular attention was given to risks related to inaccurate information, fabricated references, oversimplified interpretations, and potential bias. To reduce these risks, all theoretical, methodological, and empirical discussions were continuously verified against original academic sources and independently assessed by the authors. The use of AI tools also provided insights into how generative AI can support academic work through increased efficiency, language refinement, and conceptual discussion, while reinforcing the importance of critical evaluation and independent scholarly judgement.