

Chatbots and team-based working dynamics: Management decision implications

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Abstract

Purpose - This study investigates the relationship between Artificial Intelligence (AI)-related system characteristics and two interpersonal states commonly associated with effective teamwork, namely employee well-being and mutual trust. While generative AI has shown potential to improve organizational performance, [its specific effects on internal team-based working relationships remain underexplored](#).

Design/Methodology/Approach - A theoretical model is developed to [explore](#) the influence of three antecedent variables, Quality of Information, System Quality, and Generative AI Use, on collaboration within teams. Collaboration is operationalized using two key constructs: Employee Well-Being and Mutual Trust. The model is empirically tested using data from a large-scale survey of 208 professionals working in team-based environments. Data analysis is conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Findings - The results confirm that all three antecedent variables positively influence team-based collaboration dynamics. Specifically, the use of generative AI chatbots, such as ChatGPT, is shown to enhance employee well-being and foster mutual trust within teams, both of which act as interpersonal enablers of team collaboration. These outcomes suggest that the integration of high-quality AI tools can meaningfully support collaborative processes in professional settings.

Originality - This study contributes to the emerging field of generative AI research by shifting the focus from performance outcomes to collaboration mechanisms within teams. It offers practical implications for managers seeking to optimize teamwork in AI-enabled environments, including investing in system quality, redesigning workflows to integrate AI effectively and promoting a culture of trust and transparency around AI adoption.

Keywords Artificial Intelligence, Collaboration, Generative AI Chatbots, Structural Equation Modeling, Working Dynamics.

1. Introduction

The last few years have been marked by the rapid advent of new technologies, which are profoundly reshaping organizations and impacting business performance. In this challenging context, Artificial Intelligence (AI) represents one of the most relevant innovations (Zhang *et al.*, 2025). AI is a general-purpose technology, which can improve organizational processes and contribute to positive societal outcomes (Basu *et al.*, 2023; Golgeci *et al.*,

2025; Fraile-Rojas *et al.*, 2025). The potential impact of AI on global markets in the coming years is immense. According to the McKinsey Global Institute, AI could contribute an additional \$13 trillion annually to the global economy by 2030 (Bughin *et al.*, 2018). Goldman Sachs (2023) highlights a significant surge in market interest in AI, noting that investments could reach \$100 billion in the United States and \$200 billion globally by the end of 2025. Specifically, Generative Artificial Intelligence (Gen AI) has been attracting substantial investments, with funding reaching approximately \$100 billion in 2023 (Aranca, 2024). Gen AI is a sub-case of AI, aimed at generating novel contents (i.e., texts, images, videos, etc.) (wael AL-khatib, 2023). It can reveal hidden patterns and stimulate breakthroughs, through the imitation and extension of human creativity in knowledge-intensive context (Dwivedi *et al.*, 2023). Recently, its adoption in organizations has been widely accelerated through the introduction of user-friendly conversational chatbots (e.g., ChatGPT), which are emerging in many contexts such as education (Hashmi and Bal, 2024), marketing (Cui *et al.*, 2024), manufacturing (Savastano *et al.*, 2024) and innovation management (Sedkaoui and Benaichouba, 2024; Sundberg and Holmström, 2024; Cimino *et al.*, 2025).

Several studies have recently highlighted the positive outcomes related to the adoption of generative AI-based tools in organizations. Singh *et al.* (2024) affirm that generative AI contributes to the adaptability of the organization and promotes both exploratory and exploitative innovation in dynamic settings. Other research works focus more on sustainability aspects. Olan *et al.* (2022), which apply a fuzzy set-theoretic approach, state that the combination of AI and knowledge sharing provides a more sustainable organizational performance strategy for business operations. Research on human-AI interaction in collaborative contexts has primarily examined how AI systems support human decision-making (Bao *et al.*, 2023), task coordination (Hemmer *et al.*, 2023), and knowledge processing (Jarrahi *et al.*, 2023) within organizational settings. Existing studies show that AI-enabled tools can enhance collaboration by facilitating information sharing, reducing cognitive load, and supporting joint problem-solving activities (Aslan *et al.*, 2025; Raisch and Fomina, 2025). However, this stream of research has scarcely focused on team-based dynamics.

Although the adoption of AI is helping to improve business performance, the achievement of Key Performance Indicators (KPIs) target values also significantly depends on the quality of the relationships in working groups and collaboration (Mattessich and Johnson, 2018). Morrissette and Kisamore (2020) reveal a positive link between team trust and team performance in real business teams. This positive association has been consistently supported by decades of research in the scientific literature (Jones and George, 1998; Braun *et al.*, 2013; De Jong and Elfring, 2016). However, the strength and nature of this relationship may vary depending on contextual factors, such as the type and size of the team. Innovative behavior of team members, quality and synergy of teamwork are listed as fundamental variables for positive teamwork performance (Berber *et al.*, 2020). Other studies focus on emotions of individuals. Dionne (2023) remarks that positive (negative) emotions of individuals impact positively (negatively) on team cohesion, then performance. Basically, when two or more individuals collaborate, they develop a mutual understanding and share resources, with the aim to reach together common goals (Marion and Fixson, 2021).

To the best of the authors' knowledge, there are no studies that analyze the connection between Generative AI and work-based relationships within teams. To address this relevant research gap, the authors propose a theoretical model aimed at studying the influence of generative AI Chatbots on team-based working relationships, providing

a foundation for future empirical research in this emerging area. Basically, the current research work answers the following three Research Questions (RQs):

RQ-1: How does the use of generative AI chatbots influence collaboration within team-based working relationships?

RQ-2: What is the role of information quality and system quality of generative AI chatbots in shaping employee well-being and mutual trust within teams?

RQ-3: To what extent does the intensity of generative AI use influence team-based working relationships, such as team collaboration, through its effects on employee well-being and mutual trust?

The need to analyze well-being and trust arises from the fact that these two concepts have significantly evolved within organizational sciences. The concept of trust in organizational research has developed from an initial view centered on individual behavior (Rousseau, 1998; 2011) toward a more complex and contextual perspective (Pinjani and Palvia, 2013). Early studies on trust focused on long-term interpersonal relationships, emphasizing how trust is gradually built through experience and repeated interactions between individuals and organizations. With increasing uncertainty in work contexts and the growing adoption of temporary and virtual teams, theories such as “swift trust” have emerged (Barrett, 2025), suggesting that trust can also be established in groups with limited interaction time, thereby shifting attention toward cognitive and perceptual mechanisms of immediate trust (Pinjani and Palvia, 2013). Traditionally, well-being was considered as the absence of psychological distress and work-related stress (Van der Doef and Maes, 1999; Demerouti *et al.*, 2001); however, it has progressively been redefined according to a broader perspective that includes positive emotions, job satisfaction, personal fulfillment, and the development of individual potential (Pradhan and Hati, 2022).

The proposed model identifies three antecedent variables with the intent of exploring the impact of generative AI chatbots on team working relationships, which refer to all the relational dynamics among team members that support coordinated collaboration. These antecedents are Quality of Information (QI), System Quality (SQ) and Generative AI Use (GAI). QI captures how accurate, relevant, and clear the content generated by a generative AI chatbot is, influencing its effectiveness in work-related activities (Magno and Dossena, 2023). SQ refers to the technical characteristics of generative AI chatbots that determine their usability, reliability, and overall effectiveness in supporting work activities (Magno and Dossena, 2023; Al-Emran *et al.*, 2024). GAI refers to the extent to which individuals interact with generative AI chatbots, in terms of both frequency and duration of use (Al-Emran *et al.*, 2024). These variables collectively provide a robust framework for evaluating both the technical (QI, SQ) and experiential (GAI) dimensions of generative AI, highlighting its multifaceted effects on interpersonal dynamics within teams. As concern team-based working relationships, the study focuses on the mechanism of collaboration, which represents a core team dynamic in professional settings (Schneider *et al.*, 2014). This study is theoretically relevant because it extends existing theories on team collaboration (Schneider *et al.*, 2014) and technology adoption by explicitly integrating Gen AI as an active agent in team dynamics. Moreover, while prior research has extensively examined the impact of AI on performance, innovation, and efficiency (Bansal *et al.*, 2021; Ali *et al.*, 2024), limited attention has been paid to its role in shaping relational and collaborative dynamics within teams.

The remainder of the paper is organized as follows: Section 2 presents the theoretical framework of the study, including a description of the theoretical background, a literature review, the proposed theoretical model, and the

formulation of hypotheses to guide the research. Section 3 presents the employed methodology along with the description of the empirical analysis conducted. In Section 4, the authors present the main results of the study, while Section 5 reports the discussion of the main findings. Section 6 describes the main implications of the research work along with the main limitations and the potential avenues for future research. Finally, in Section 7, the conclusions drawn from the study are outlined.

2. Theory

2.1 Theoretical background

This study draws on three complementary theoretical perspectives to frame the analysis of Generative AI chatbots in team-based working environments: the Resource-Based View (RBV) (Madhani, 2010), sociotechnical systems theory (Appelbaum, 1997), and social exchange theory (Cook *et al.*, 2013). Together, these perspectives provide a coherent yet flexible foundation for understanding how Generative AI influences relational and collaborative dynamics within organizations. From a Resource-Based View (Madhani, 2010) perspective, organizations achieve sustained competitive advantage by leveraging valuable, rare, and difficult-to-imitate internal resources. While Generative AI technologies are increasingly accessible, their strategic value does not reside in the technology itself, but in the organizational capabilities that emerge from their effective integration into work processes. Sociotechnical systems theory provides a second, closely aligned lens by emphasizing the interdependence between technical and social subsystems within organizations. According to this perspective, organizational outcomes are shaped not only by technological features, but also by how technologies interact with human actors, work practices, and social relationships (Appelbaum, 1997). Generative AI chatbots represent a particularly relevant sociotechnical artifact, as they are embedded in daily work activities and actively interact with users through conversational and generative capabilities. Finally, social exchange theory offers a micro-level explanation for the relational outcomes observed in this study. This theory posits that social relationships develop through repeated exchanges of benefits, leading to trust, reciprocity, and cooperative behavior (Cook *et al.*, 2013). More recently, additional managerial perspectives based on technological advances have emerged, emphasizing the relational and organizational implications of AI. According to the dynamic capability perspective (Chatterjee *et al.*, 2024; Gao *et al.*, 2025), the use of AI enhances firms' innovation capabilities by strengthening digital adaptability and by improving their ability to reconfigure resources and respond effectively and efficiently to dynamic environments. Research on human–AI collaboration highlights how Gen AI systems act as collaborative partners shaping team interactions and improving trust (McGrath *et al.*, 2025). Moreover, recent research on AI-enabled knowledge management suggests that the adoption of AI may positively affect creativity in team and organizational levels (Grilli and Pedota, 2024). By integrating all these theoretical perspectives, the study wants to provide a multidimensional foundation for analyzing the relational impact of Generative AI in team-based work, combining strategic, sociotechnical, and relational explanations into a coherent theoretical background.

2.2 Literature review

The concept of Gen AI is quite novel and currently of great interest to the scientific community (AL-Khatib, 2024). By using the keyword “Generative Artificial Intelligence” in the “Article title, Abstract, Keywords” field of Scopus, one of the most recognized scientific databases, it is possible to notice that in the last few years the publications have been growing strongly, with a peak in 2024. Only to give an idea of the phenomenon, about 300 documents were published in 2019 against over 6,000 in 2024. Gen AI represents today one of the most advanced and revolutionary applications of AI. Based on the use of machine learning and self-training, such technology can improve creativity, by generating effectively and efficiently novel texts, images, and videos (wael AL-khatib, 2023), as well as influencing organizational management decisions (Wang *et al.*, 2025). Several studies are trying to understand the impact that the use of Gen AI, and more in general AI, is having on organizations. The most relevant ones are schematized in Table 1.

Table 1. Survey-based documents exploring the impact of AI on organizations’ performance

Reference	Research Methodology	Survey Respondents	Impacts on organizations
Malik <i>et al.</i> (2021)	Qualitative data analysis	32 professionals with average work experience of 7.6 years in 9 companies	AI has a positive impact on work-related flexibility and autonomy, creativity and innovation. Job performance is enhanced
Nayal <i>et al.</i> (2022)	SEM	297 respondents from agro-industries in India	Positive influence of adoption of AI-based tools on supply chain risk mitigation
Wamba (2022)	PLS-SEM	205 supply chain executives in USA	AI assimilation leads to improved organizational outcomes such as agility and firm performance
Wael AL-khatib (2023)	Covariance-Based-Structural Equation Modelling (CB-SEM)	260 managers and administrative employees in the Jordanian retailing industry	Positive impact of Gen AI on both exploratory and exploitable innovation
Khan <i>et al.</i> (2025)	Smart-PLS analysis	302 manufacturing companies	Gen AI facilitates explorative and exploitable innovation
Abrokwah-Larbi and Awuku-Larbi (2024)	SEM	225 small and medium enterprises in Ghana	Significance of AI in marketing for achieving financial performance, internal business process performance, learning performance, growth performance
Xu <i>et al.</i> (2024)	SEM	446 people in three Chinese cities (Shanghai, Guangzhou, Taiyuan)	The activation of enterprise innovation behavior is positively

			influenced by: AI-generated content quality, AI experience, supportive AI
Lozie <i>et al.</i> (2024)	Qualitative data analysis	3 participants in Canada with different age range, job experience and working sector	Generative AI has a positive impact on work dynamics in terms of enhanced job satisfaction, increased efficiency, improved work-life balance
Necula <i>et al.</i> (2024)	Logistic regression, random forest, XGBoost	233 employees across several industries	High levels of AI-based tools usage and their integration within organizational workflow enhance productivity (especially among young people)
Belhadi <i>et al.</i> (2024)	SEM	279 firms of different sizes, sectors and countries	AI techniques have the potential to improve supply chain performance
This paper	PLS-SEM	208 Italian professionals	Positive impact of Gen AI on team-based work relationships, focusing on collaboration mechanism

It is important to specify that such a table aims to represent a selective and illustrative overview of studies that examine the impact of AI in organizational contexts. The studies were selected based on their relevance to the objectives of this research, with particular attention to (i) empirical contributions published in established peer-reviewed journals, (ii) a clear organizational or managerial focus, and (iii) conceptual proximity to themes such as performance, innovation, work dynamics, or technology use at work. Overall, several research branches can be detected. Some studies investigate the impact of Generative AI on innovation management. Wael AL-Khatib (2023) and Khan *et al.* (2025) conclude that Gen AI has a positive influence on both exploitable and exploratory innovation. Indeed, the capacity of Gen AI to quickly create new content is completely in line with the concept of exploratory innovation, which focuses on experimenting with new ideas, technologies, and markets to create disruptive advancements. On the other side, its ability to analyze data patterns and generate tailored solutions can support exploitable innovation, which emphasizes refining and optimizing existing processes, products, or services to maximize efficiency and profitability (Jansen *et al.*, 2006). Moreover, Xu *et al.* (2024) identify the quality of AI-generated content as one of the factors activating enterprise innovation behavior. In an era where sustainability and resilience in supply chains are increasingly prioritized (Cimino *et al.*, 2024), there are also studies highlighting the positive impact of AI on supply chain management and risk mitigation (Nayal *et al.*, 2022; Belhadi *et al.*, 2024). A very relevant research branch explores the impact of AI on work dynamics. Lozie *et al.* (2024) have recently found that Gen AI can improve job satisfaction, work-life balance and efficiency, but involving only 3 respondents at the survey. Necula *et al.* (2024) also highlight the positive link between AI and efficiency (i.e., productivity). Summarizing, this body of research collectively underscores AI's transformative potential in improving organizational processes, driving innovation, and enhancing performance across different business contexts.

However, so far there are no studies investigating the impact of AI on team-based working relationships and particularly on [the collaboration mechanism](#). Collaboration in the workplace improves organizational performance by enabling teams to merge their skills, knowledge, and perspectives, resulting in more innovative and effective solutions (Al-Hakim and Lu, 2017). It fosters clear communication, reduces redundancy, and enhances efficiency by promoting shared responsibility and accountability. Additionally, collaboration builds stronger relationships among employees, increasing engagement and motivation, which promotes better business results and sustained growth (Mattessich and Johnson, 2018). The probability of success increases when firms adopt collaboration to support innovation efforts (González-Benito *et al.*, 2016). Despite the rapid growth of studies on AI ([Cimino *et al.*, 2025](#); [Gao *et al.*, 2025](#); [McGrath *et al.*, 2025](#)), the existing literature reveals that none of the studies reviewed explicitly the use of AI by jointly considering information quality, system quality, and the frequency and duration of AI use. Basically, prior research has not integrated into a unified framework all these concepts. As a result, the combined influence of these technological and experiential dimensions on collaboration within teams remains largely unexplored. Both AI adoption and collaboration can have a significant impact on business performance. Therefore, the main aim of this paper is to analyze the impact of Generative AI (specifically chatbots) on collaboration in team-based working. To achieve this aim, the study develops a theoretical model and formulates hypotheses concerning the relationships between the model's constructs, which are subsequently tested empirically.

2.3 Theoretical framework

This study aims to develop a theoretical model with the intent of exploring the relationship between AI-related system characteristics and two interpersonal states that are central to effective teamwork: Employee Well-Being (WB) and Mutual Trust (MT). The model identifies three antecedent variables that explore the impact of generative AI chatbots on team-based working relationships. These antecedents are Quality of Information (QI), System Quality (SQ) and Generative AI Use (GAI). The variables collectively provide a robust framework for evaluating both the technical (QI, SQ) and experiential (GAI) dimensions of generative AI, highlighting its multifaceted effects on interpersonal dynamics within teams. As concern team-based working relationships, the study focuses on the mechanism of collaboration, which represents a core team dynamic in professional settings (Schneider *et al.*, 2014). Collaboration is defined as the extent to which individuals actively engage together to accomplish common goals (Schneider *et al.*, 2014). In this research, collaboration is operationalized using the constructs of Employee Well-Being (WB) and Mutual Trust (MT), which represents two interpersonal enablers commonly associated with collaborative work (Patel *et al.*, 2012). In this regard, Patel *et al.* (2012) developed a framework for collaborative work that identifies both employee well-being and mutual trust as key factors enabling collaboration. In addition, a substantial body of literature has established clear links between employee well-being and mutual trust and collaborative work processes and outcomes (Hockey, 1996; Bergman and Baker, 2000; De Jonge *et al.*, 2000; Carroll *et al.*, 2003; Zolin *et al.*, 2004; Van Fenema, 2005; Cordery and Soo, 2008). Employee well-being refers to the perceptions and emotional states that reflect employees' overall satisfaction with their work environment (Pradhan and Hati, 2022). Employees who experience higher levels of well-being are more inclined to engage in collaborative efforts with colleagues (Patel *et al.*, 2012). Similarly, trust plays a fundamental role in enhancing

collaborative relationships. Trust in a team has been defined as the degree of confidence of team members in one another (Pinjani and Palvia, 2013). A climate of mutual trust encourages individuals to engage confidently with one another, facilitating collaboration and delivering significant value to organizations and broader economic systems (Patel *et al.*, 2012). Finally, it is important to note that, to the best of the authors' knowledge, although employee well-being and mutual trust have been widely associated with collaboration and collaborative work in the existing literature, the proposed conceptualization of "collaboration" represents a novel contribution, as no prior studies have empirically tested these constructs as framed within the context and theoretical model of this research.

Figure 1 depict the proposed theoretical model.

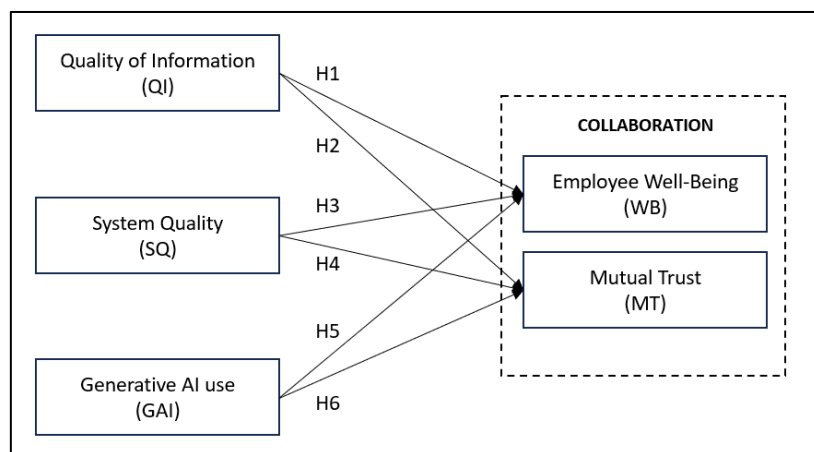


Figure 1. Theoretical framework

2.4 Hypotheses development

In this section, the authors detail the hypotheses that explore the relationships between the antecedents' variables (QI, SQ, GAI) and their impact on team-based working relationships (WB, MT).

Quality of Information

Quality of information refers to the accuracy, relevance, and clarity of the information produced by generative AI Chatbot, which directly influences its utility and reliability in work settings (Magno and Dossena, 2023). Higher quality of information can enhance job satisfaction. Specifically, Joshi and Rai (2000) conducted a field study involving 368 users and confirmed a positive relationship between information quality and job satisfaction. Similarly, Zamir (2023) distributed a structured survey to 300 employees across eight commercial banks at different managerial levels, and the findings also supported the positive impact of information quality on employee satisfaction.

Moreover, numerous studies have demonstrated a strong correlation between job satisfaction and employee well-being (Parker and Hyett, 2011; Slemp *et al.*, 2015; Sen and Khandelwal, 2017). Using an instrumental variable approach, Cannas *et al.* (2019) further confirmed the causal positive effect of job satisfaction on subjective well-being. Similarly, Yang *et al.* (2024), drawing on data from a cross-sectional survey of 2,480 physicians, found a significant positive association between job satisfaction and employee well-being.

Although prior research has extensively documented the direct and indirect links between information quality and employee well-being, no studies have yet examined the effect of information quality on employee well-being in the context of teams using generative AI. Extending the established findings identified within the scientific literature, the present study seeks to investigate this relationship within teams using generative AI. Therefore, it is assumed that the quality of information provided by generative AI chatbots positively affects employee well-being.

H1. Quality of Information has a positive influence on employee well-being.

In addition, high-quality information plays a crucial role in enhancing transparency (Hosseini *et al.*, 2018). Increased transparency, in turn, generates outcomes that are beneficial for strengthening working relationships (Jahansoozi, 2006). As transparency increases, it enhances trust among team members, leading to higher levels of collaboration and cooperation. Using a qualitative phenomenological approach, Jahansoozi (2006) studied members of the Sindre Petroleum Operators Group in Canada and found that transparency is essential for building trust, particularly in post-crisis contexts. Furthermore, Normann *et al.* (2010) further confirmed the positive effects of transparency by demonstrating that leader transparency significantly enhances followers' perceived trust. In teams using generative AI, this study conceptualizes transparency as the clarity, consistency, and accessibility of AI-generated outputs. Specifically, the authors assume that higher transparency implies AI outputs which are easier to understand, more reliable, and equally available to all team members. Such shared visibility reduces information asymmetries within the team and limits perceptions that certain individuals possess superior or hidden knowledge. As a result, team members should be more likely to perceive one another as reliable and trustworthy, thereby strengthening mutual trust. Therefore, the authors hypothesize that the quality of information, by enhancing transparency, positively influences mutual trust.

H2. Quality of Information has a positive influence on mutual trust.

System Quality

System quality refers to the technical attributes of generative AI Chatbot (Magno and Dossena, 2023), that directly influence their usability and effectiveness (Al-Emran *et al.*, 2024). Key attributes of system quality are ease of use and reliability (Al-Emran *et al.*, 2024). Ease of use refers to how user-friendly and intuitive the system's interface is (Al-Emran *et al.*, 2024), often reflecting the overall complexity of the system. Reliability, on the other hand, captures the system's consistency in performance and availability (Al-Emran *et al.*, 2024). Deficiencies in ease of use or reliability, and consequently in system quality, can lead to technostress, a form of stress associated with the use of technology (Ayyagari *et al.*, 2011). Elevated levels of stress can negatively affect an individual's well-being and lead to reduced attention and diminished collaboration with colleagues (Patel *et al.*, 2012). Based on these insights, the authors assume that system quality positively influences employee well-being.

H3. System Quality has a positive influence on employee well-being.

Moreover, the response time of a system, defined as the time it takes for technology to process an input and deliver an output, is also a key indicator of its quality (Trivedi, 2019). Efficient response times are critical for enabling effective information sharing (Jermittiparsert and Pithuk, 2019). Information sharing is a basic enabler of mutual trust (Lee and Whang, 2000). Empirical evidence supports this relationship across various contexts. For

instance, Kulangara *et al.* (2016) demonstrated a positive effect of information sharing on trust in a study of 357 executives in the United States. Similarly, Susanty *et al.* (2018) further confirmed that information sharing significantly enhances trust between batik small and medium-sized enterprise (SME) owners and their suppliers. Lee and Kim (2023), based on data from 214 supply chain employees in Korea, found that information sharing positively influences mutual trust. Therefore, a system with higher quality, evidenced by faster response times, can positively influence mutual trust among team members.

H4. System Quality has a positive influence on mutual trust.

Generative AI use

Generative AI use can be defined as the level of interaction (frequency and duration) individuals have with generative AI Chatbots (Al-Emran *et al.*, 2024). Although Lozie *et al.* (2024) provided insights into the potential impact of generative AI on employee well-being, they noted that the existing literature remains limited in examining the combined effects of generative AI use and employee well-being. Prior research nonetheless suggests a positive relationship between artificial intelligence and well-being outcomes. For example, Guan *et al.* (2022, p. 1) argued that “artificial intelligence technology can enhance social well-being”. Similarly, Sison *et al.* (2024) emphasize that generative AI contributes to social well-being when implemented ethically. Orji *et al.* (2024) further demonstrated that generative AI use enhances well-being and social connectivity while reducing stress, thereby providing users with a sense of companionship. More recently, Filippelli *et al.* (2026), using survey data from 130 knowledge workers, found that generative AI adoption has a significant positive effect on employee well-being. Based on this growing body of research, it is reasonable to assume that generative AI Chatbots positively influences employee well-being.

H5. Generative AI use has a positive influence on employee well-being.

With regard to the impact of generative AI use on mutual trust, the existing literature remains limited. Nevertheless, several studies suggest that advanced technologies can play an important role in enhancing trust among team members (Kauffmann & Carmi, 2014; Kipkosgei *et al.*, 2020). Owens and Khazanchi (2018) further highlight that technological capabilities can positively influence trust in virtual teams. More recently, Paparić and Bodea (2024) emphasized the link between the use of generative AI in project settings and the development of trust among project team members. Based on these findings, the authors hypothesize that generative AI use positively influences mutual trust.

H6. Generative AI use has a positive influence on mutual trust.

3. Materials & Methods

3.1 Research context

This research study has been conducted in Italy, a country where interest in the AI paradigm is extremely high today for several reasons. The Agency for Digital Italy (AgID), an entity of the Italian government, has recently outlined a very structured strategy for the diffusion of Artificial Intelligence in Italy in the two-year period 2024-2026 (AgID, 2023). The development and adoption of AI solutions in businesses is listed among the main objectives. A recent report states that Italian economy could increase by up to 18 % through the adoption of Gen

AI (Microsoft and The European House-Ambrosetti, 2023). Moreover, the study claims that 50 % of Italian companies have already tried to use AI-based solutions, and 70 % of them have obtained benefits in terms of productivity. Although the potential benefits of large-scale diffusion of AI in Italy seem clear, several challenges or barriers are still present, such as lack of skills, resistance to technology, lack of AI culture, resource limitations (Garlatti Costa *et al.*, 2024). Studies on the influence that AI has on business performance therefore become essential to overcome resistance and bring benefits. This research promises to explore the impact that AI has on collaboration in the context of team-based working. The knowledge generated could be fundamental to improve organizational performance in a geographical context, where enhancing teamwork is crucial, given the large presence of Small and Medium Enterprises (SMEs), often characterized by limited financial resources (European Investment Bank, 2021).

3.2 Measurement instruments

To achieve the research objectives, the authors conducted a questionnaire-based survey among a sample of Italian professionals between October and December 2024. The questionnaire is structured into two distinct sections. The first section collects general information and demographic details about the participants, including gender, age and educational level. It also includes a question to identify participants' working arrangements, distinguishing between fully in-person (at an office or workplace), fully remote (smart working), or hybrid models, where more than 30% of work is conducted remotely. The second section focuses on measuring the variables outlined in the proposed research model. To ensure accuracy, the authors conducted a thorough literature review to identify previously validated questions used to measure these variables. Where necessary, the items were adapted to align with the specific context of this study. Information quality and system quality was measured using four and five items, respectively (Magno and Dossena, 2023). Generative AI use was evaluated through three items (Al-Emran *et al.*, 2024). Employee well-being and mutual trust were assessed selecting and adapting five and four items, respectively (Pradhan and Hati, 2022; Pinjani and Palvia, 2013). Moreover, the measurement scales adopted in this study are consistent with those used in prior empirical research. Specifically, similar items have been employed to assess QI (Trivedi, 2019), SQ (Trivedi, 2019), GAI (Albanna *et al.*, 2022), WB (Slemp *et al.*, 2015; Zheng *et al.*, 2025) and MT (Costa and Anderson, 2011).

The final instrument comprises 21 items, measured on a 5-point Likert scale ranging from “strongly disagree” to “strongly agree”. This scale was chosen as it has already been scientifically validated in the literature from which the items were derived. The developed questionnaire is reported in Appendix A.

3.3 Data collection

Data has been collected through an online survey by using on-line Microsoft forms. The sample selection was designed to include participants with practical experience using Generative AI Chatbots and a background in team-based work. Prior to the survey's official launch, a pilot study was conducted to refine the questionnaire items in terms of wording and conveying the overall meaning. Eight professionals participated in the pilot study under the guidance of the authors. Specifically, respondents were invited to assess whether the number of questions per construct was sufficient for a reliable evaluation, whether the questions were coherent and aligned with the

constructs being measured, and whether each question was clear and easily understandable. The feedback and recommendations obtained during this phase were reviewed, and any necessary adjustments to the questionnaire were implemented to enhance its clarity, coherence, and overall effectiveness. For example, items related to employee well-being were revised to more explicitly emphasize the team-based context (e.g., “I enjoy meaningful activities in the work I do” was refined to “I enjoy meaningful activities in the work I do within the team”). Similarly, several mutual trust items were adjusted to improve readability and interpersonal focus (e.g., “My colleagues can rely on me” was refined to “My team colleagues can rely on me”). Following this phase, the final questionnaire was distributed. Completing the questionnaire required approximately 5 min. Participants were recruited using convenience sampling approach. The online questionnaire was disseminated through multiple channels, including LinkedIn, email, and WhatsApp, to maximize reach among Italian professionals with experience in generative AI and teamwork. Participation was voluntary and self-selected. To reduce social desirability bias, respondents were guaranteed full anonymity. In addition, to mitigate potential common method bias, participants were informed of the academic purpose of the study, the order of the survey items was randomized, and constructs were intentionally interwoven throughout the questionnaire (Kline, Sulsky, and Rever-Moriyama, 2000; Podsakoff et al., 2003).

A total of 246 questionnaires were received. However, 29 were excluded from the analysis because the respondents either lacked experience with generative AI chatbots or did not have a background in team-based work. The remaining 217 questionnaires were further cleaned to identify and remove any repetitive or incoherent entries. Following this rigorous review, 208 valid questionnaires were kept, forming the base for the research analysis.

3.4 Data analysis

The authors utilized the Partial Least Squares approach to Structural Equation Modeling (PLS-SEM) to test and validate the proposed research model and hypotheses (Dijkstra, 2014; Dijkstra and Henseler, 2015). PLS-SEM was chosen for its appropriateness in handling small sample sizes (Willaby *et al.*, 2015), and its recommendation for datasets with a limited number of indicators per latent variable (Hair *et al.*, 2023). *Moreover, given that the primary objective of this study is predictive and exploratory in nature (Rigdon, 2012)*, PLS-SEM was selected as the most appropriate analytical technique, rather than alternative statistical methods (Hair et al., 2017; Hair et al., 2019).

The analysis was conducted using SmartPLS4 software, developed by SmartPLS GmbH (further information about SmartPLS4 can be found at <https://www.smartpls.com>). Finally, the sample size for this study consisting of 208 valid questionnaires, adheres to the guideline of being at least ten times larger than the maximum number of arrowheads pointing to the latent variables (WB and MT) in the model (Hair Jr *et al.*, 2021).

4. Results

This section presents the empirical results of the study. Following established PLS-SEM reporting guidelines (Hair Jr. et al., 2021), the results are structured into three main parts. First, in Section 4.1, descriptive statistics are provided to summarize the demographic and work-related characteristics of the respondents. Second, the measurement model is assessed to evaluate indicator reliability, internal consistency, convergent validity, and

discriminant validity (see Section 4.2). Finally, the structural model is examined to test the proposed hypotheses and assess the explanatory power of the research model (see Section 4.3). Prior to conducting the analyses, univariate normality was assessed by examining skewness and kurtosis values for all indicators. Although PLS-SEM does not require normality assumptions, the results showed that all skewness and kurtosis values fell within the acceptable range of -2 to $+2$ (Hair et al., 2022; Vaithilingam et al., 2024). These results, reported in Table 2, indicate no severe deviations from normality and further support the robustness of the analysis, given the well-established resilience of PLS-SEM to non-normal data distributions (Hair et al., 2022).

Table 2. Skewness and Kurtosis values

Item	Kurtosis	Skewness
QI-1	0.041	-0.670
QI-2	1.264	-0.806
QI-3	0.788	-0.904
QI-4	0.390	-0.709
SQ-1	0.269	-0.627
SQ-2	-0.344	-0.446
SQ-3	-0.221	-0.491
SQ-4	0.285	-0.626
SQ-5	0.275	-0.567
GAI-1	0.794	-0.966
GAI-2	0.829	-1.023
GAI-3	0.750	-0.954
WB-1	-0.279	-0.269
WB-2	-0.573	-0.401
WB-3	0.147	-0.635
WB-4	-0.086	-0.645
WB-5	-0.236	-0.293
MT-1	-0.352	-0.309
MT-2	-0.348	-0.474
MT-3	-0.537	-0.414
MT-4	-0.590	-0.425

4.1 Descriptive statistics

Table 3 summarizes the general information and demographic details about the survey participants.

Table 3. Participants demographic and work arrangements

Demographic character		Frequency (n)	Percentage (%)
Gender	Men	140	67%
	Women	62	30%
	Prefer not to say	6	3%
Age	< 20 years	0	0%
	20 - 29 years	28	13%
	30 - 39 years	42	20%
	40 - 49 years	70	34%

	> 50 years	68	33%
Educational level	Middle School Degree	9	4%
	High School Degree	13	6%
	Bachelor/Master's Degree	95	46%
	Doctoral or other Postgraduate Degree	91	44%
Primary work arrangement	Full in person	118	57%
	Fully remote	12	6%
	Hybrid	78	38%

The sample is characterized by a relatively high level of professional maturity and educational attainment, with the majority of respondents aged 40 years or older and holding at least a bachelor's degree. This profile is consistent with the study's focus on professionals with experience in team-based work and the use of generative AI technologies, which are more likely to be adopted and integrated into complex organizational contexts. In addition, the prevalence of in-person and hybrid work arrangements suggests that respondents operate in environments where collaboration remains central. These characteristics indicate that the sample is well suited to examine the relationships proposed in the research model.

4.2 Measurement model results

The measurement model was assessed following the evaluation process proposed by Hair Jr *et al.* (2021). The initial step was to assess indicator reliability. This assessment was achieved by computing the indicator loadings. The results, as reported in Table 4, show that each indicator loading exceeds the recommended threshold of 0.708 (Hair Jr *et al.*, 2021), confirming the indicator reliability of the measurement model. The second step involved evaluating the internal consistency reliability. This assessment was conducted by calculating Cronbach's alpha values (Hair Jr *et al.*, 2021). As presented in Table 4, the computed values confirm the reliability of the constructs, exceeding the minimum threshold of 0.7 (Dijkstra and Henseler, 2015; Hair Jr *et al.*, 2023). Moving forward, the third step addressed the evaluation of convergent validity, measured using the Average Variance Extracted (AVE) for each construct. The results, reported in Table 4, confirm that the AVE values exceed the minimum acceptable threshold of 0.50 (Hair *et al.*, 2022). The fourth and final step in the assessment process was the evaluation of discriminant validity, which was assessed using three metrics: Cross-loadings (Hair Jr *et al.*, 2023) the Fornell-Larcker criterion (Fornell and Larcker, 1981), and the Heterotrait-Monotrait Ratio (HTMT) (Henseler *et al.*, 2015). Results, presented in Tables 5 to 7, confirm the discriminant validity of the measurement model (Hair Jr *et al.*, 2023; Hair Jr *et al.*, 2021; Fornell and Larcker, 1981; Henseler *et al.*, 2015). Specifically, the cross-loadings confirms that the values for each item related to its construct are higher than the values for that item related to other constructs, the Fornell-Larcker criterion is satisfied for all constructs, and none of the HTMT values exceed the conservative threshold of 0.90.

Table 4. Indicator Reliability, Internal Consistency Reliability, Convergent Validity Measures

Construct	Items #	Indicators loadings	Cronbach's alpha	AVE
QI	4	0.865 – 0.903	0.909	0.787
SQ	5	0.773 – 0.882	0.900	0.716

GAI	3	0.898 – 0.924	0.901	0.835
WB	5	0.789 – 0.891	0.903	0.722
MT	4	0.853 – 0.874	0.885	0.743

Table 5. Cross Loadings

	QI	SQ	GAI	WB	MT
QI-1	0.865	0.677	0.693	0.676	0.611
QI-2	0.901	0.705	0.709	0.640	0.637
QI-3	0.879	0.735	0.724	0.642	0.651
QI-4	0.903	0.717	0.741	0.642	0.670
SQ-1	0.692	0.876	0.675	0.651	0.631
SQ-2	0.681	0.882	0.713	0.681	0.674
SQ-3	0.637	0.831	0.621	0.572	0.570
SQ-4	0.706	0.865	0.674	0.641	0.674
SQ-5	0.665	0.773	0.638	0.582	0.548
GAI-1	0.759	0.728	0.918	0.717	0.665
GAI-2	0.741	0.731	0.924	0.684	0.679
GAI-3	0.714	0.696	0.898	0.670	0.639
WB-1	0.634	0.604	0.629	0.844	0.595
WB-2	0.616	0.614	0.644	0.870	0.691
WB-3	0.615	0.648	0.645	0.891	0.666
WB-4	0.614	0.609	0.627	0.850	0.691
WB-5	0.630	0.666	0.658	0.789	0.624
MT-1	0.593	0.639	0.590	0.640	0.854
MT-2	0.651	0.674	0.639	0.666	0.874
MT-3	0.650	0.596	0.629	0.671	0.866
MT-4	0.601	0.624	0.636	0.677	0.853

Table 6. Fornell-Larcker

	QI	SQ	GAI	WB	MT
QI	0.887				
SQ	0.799	0.846			
GAI	0.808	0.786	0.914		
WB	0.733	0.741	0.755	0.849	
MT	0.724	0.735	0.723	0.770	0.862

Table 7. Heterotrait-Monotrait Ratio (HTMT)

	QI	SQ	GAI	WB	MT
QI					
SQ	0.884				
GAI	0.892	0.872			
WB	0.808	0.819	0.837		
MT	0.807	0.820	0.810	0.861	

4.3 Structural model results

After successfully assessing the measurement model, the authors proceeded to evaluate the structural model. The first step involved examining potential collinearity issues by calculating the Variance Inflation Factor (VIF). The results showed VIF values of 3.163 for QI, 3.282 for SQ and 3.42 for GAI, all well below the threshold limit of 5 (Hair *et al.*, 2011), thereby confirming the absence of collinearity issues.

As the next step, the authors focused on the assessment of the significance and relevance of the structural model relationships based on the bootstrapping routine (5,000 subsamples, bias-corrected and accelerated bootstrap, two-tailed test). The findings, reported in Table 8, confirm that all the three antecedent constructs (QI, SQ, GA) positively influence both WB and MT. Specifically, SQ has the highest impact on MT with a coefficient of 0,329, followed by GAI and QI with 0,265 and 0,247 respectively. While GAI demonstrates the strongest influence on WB with a coefficient of 0,351, followed by SQ at 0,294 and QI at 0,214. The statistical significance of the path model was assessed (1) by employing bootstrapping standard errors to compute the t-values of path coefficients and (2) by calculating the confidence intervals. The t-values, as reported in the “T statistics” column of Table 8, exceed the threshold limit of 1.96, clearly indicating the statistical significance of the indicator weights (Hair Jr *et al.*, 2021). Furthermore, the confidence interval values, as presented in Table 8, further confirm the statistical significance of the path model, as none of the intervals include the value zero (Hair Jr *et al.*, 2021). These findings validate all proposed hypotheses in the theoretical model.

The evaluation of the structural model concluded with an assessment of the model’s explanatory power. This was conducted by calculating the coefficients of determination, R^2 (Shmueli and Koppius, 2011) and R^2_{adj} (Theil, 1961). The results, presented in Table 9, confirm a satisfactory level of explanatory power for the proposed model (Hair *et al.*, 2011).

To further support the presentation of the findings, Figure 2 visually depicts the main results of the structural model.

Table 8. Significance and relevance of the path coefficients

	β	Sample mean	Standard deviation	T values	P values	2.50 CI	97.50 CI	Results
QI -> WB (H1)	0.214	0.208	0.088	2.442	0.015	0.035	0.376	Supported
QI -> MT (H2)	0.247	0.247	0.085	2.906	0.004	0.080	0.413	Supported
SQ -> WB (H3)	0.294	0.297	0.083	3.526	0.000	0.137	0.461	Supported
SQ -> MT (H4)	0.329	0.332	0.071	4.662	0.000	0.194	0.471	Supported
GAI -> WB (H5)	0.351	0.354	0.079	4.425	0.000	0.208	0.522	Supported
GAI -> MT (H6)	0.265	0.263	0.080	3.292	0.001	0.111	0.427	Supported

Table 9. R^2 AND R^2_{ADJ}

	R^2	R^2_{adj}
MT	0.613	0.607
WB	0.640	0.635

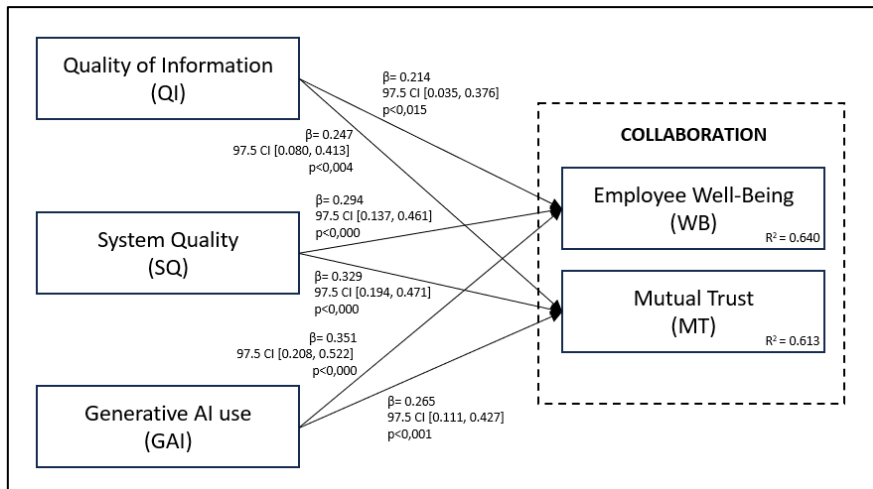


Figure 2. Results of structural model assessment

The structural model results provide strong empirical support for the proposed theoretical framework. Specifically, the findings confirm that QI, SQ and GAI act as key antecedents of collaboration outcomes in teams using generative AI, operationalized through employee well-being and mutual trust. The significant positive effects of QI on both WB and MT highlight the importance of accurate, clear, and reliable AI-generated information in enhancing positive individual and relational outcomes. Similarly, the strong effects of SQ, particularly on MT, underscore the critical role of system performance attributes, such as responsiveness, in shaping collaborative dynamics. These findings are consistent with prior research showing that higher SQ, especially in terms of responsiveness, facilitates effective information sharing (Jermisittiparsert & Pithuk, 2019), which in turn fosters mutual trust among team members (Kulangara et al., 2016; Susanty et al., 2018; Lee & Kim, 2023).

Furthermore, the results show that GAI exerts the strongest influence on employee WB, suggesting that frequent and sustained interaction with generative AI tools can enhance employees' psychological and emotional experiences at work.

5. Discussion

This study aims to explore the impact of Generative AI Chatbots on key interpersonal conditions supporting team-based working dynamics, namely employee well-being and mutual trust. Given the limited scientific literature on this topic, the authors address this gap by introducing a new theoretical model. This model consists of three antecedent variables - Quality of Information, System Quality, and Generative AI use - designed to measure the impact of Generative AI Chatbots on the collaboration mechanism within teams. Within this research framework, collaboration has been operationalized through the variables of employee well-being and mutual trust. The proposed model was empirically tested using a large-scale survey, with data analysis performed using Partial Least Squares - Structural Equation Modeling (PLS-SEM). Specifically, the results provide empirical evidence on how the use of generative AI chatbots influences collaboration within team-based working relationships (RQ1), clarify the role of information quality and system quality in shaping employee well-being and mutual trust (RQ2), and assess the extent to which the intensity of generative AI use affects key relational mechanisms underlying team-

collaboration (RQ3). Taken together, the findings offer a coherent and integrated response to the research questions and contribute to a deeper understanding of Generative AI-enabled team dynamics.

In the first set of findings, this study confirms a positive impact of QI on both WB (H1) and MT (H2), despite exhibiting the lowest effect size among all antecedents ($\beta_{H1} = 0.214$ and $\beta_{H2} = 0.247$, respectively). The influence of QI on WB can be attributed to several key factors. First, accurate, relevant, and clear information can effectively reduce common workplace stressors such as uncertainty and cognitive overload. Second, the quality of information provided by generative AI Chatbots can enhance task execution, support decision-making processes, and reduce ambiguity, which together enhances employees' overall satisfaction with their work environment. In this regard, several are also the studies in scientific literature demonstrating the strong correlation between overall job satisfaction and employee well-being (Parker and Hyett, 2011; Slemp *et al.*, 2015; Sen and Khandelwal, 2017; Cannas *et al.* (2019), Yang *et al.* (2024)). Third, precise and reliable information can increase employees' competence and confidence, which contributes to a greater sense of control over their work outcomes. This enhanced sense of control can help significantly to reduce feelings of helplessness and anxiety, leading to higher levels of well-being. In summary, employees who use generative AI Chatbots that provide high-quality information are less stressed and feel more competent, confident, and empowered in control. *As a result, they are more satisfied with their work environment and more inclined to engage positively with their peers, creating interpersonal conditions that are supportive of collaborative dynamics within the team. This chain of factors underscores the critical role that quality of information provided by generative AI Chatbots plays in supporting the interpersonal conditions that enable collaboration within team-based work environments.*

Quality of information significantly enhances also mutual trust within teams. By delivering accurate and clear information, these chatbots improve transparency in team interactions. Such transparency ensures that all actions and decisions are visible and understandable to every employee within a team, thereby reducing suspicions and clarifying potential misconceptions. When team members are assured that they are receiving the complete and accurate picture, their trust in one another naturally strengthens. *This increase in trust strengthens the interpersonal conditions that facilitate collaboration and cooperation, empowering team members to share ideas, take risks, and address challenges cooperatively, all while being supported by reliable and supportive colleagues.* The positive relationship between QI and MT is also confirmed by existing literature. Hosseini *et al.* (2018) confirm the connection between high-quality information and increased transparency, while Jahansoozi (2006) demonstrates how transparency significantly strengthens working relationships by also enhancing trust among team members.

A positive correlation between SQ and both WB (H3) and MT (H4) is also confirmed by the study. The influence of SQ on WB ($\beta_{H3} = 0.294$) can be attributed to several key factors. A user-friendly chatbot that is intuitive and easy to navigate reduces the cognitive effort required by employees, thereby alleviating stress and fatigue. Furthermore, employees utilizing intuitive generative AI Chatbots can enhance their efficiency, which enables them to manage their workloads more effectively. Such efficient task management directly improves employees' emotional states by directly improving their overall satisfaction with their work environment. Moreover, the reliability of generative AI chatbots plays a crucial role in reducing work-related anxiety. A chatbot that performs consistently and without failures helps mitigate concerns about potential technological disruptions, thereby contributing to the establishment of a more stable and stress-free work environment. Systems that are

always operational and seldom experience downtime also prevent disruptions in employees' work, eliminating the stress linked with waiting or operational delays. **These factors collectively enhance employee well-being and promote interpersonal conditions supportive of collaboration in the workplace.** These findings are consistent with existing literature, which highlights the negative effects of stress on individual well-being, which in turn leads to reduced attention and diminished collaboration with colleagues (Patel *et al.*, 2012).

In addition, SQ exhibits an even stronger influence on MT ($\beta_{H4} = 0.329$), highlighting the importance of reliable, responsive, and user-friendly AI systems in promoting trust-based team relationships. The influence of SQ on MT can be understood by examining the response times of generative AI chatbots, which serve also as a critical indicator of their effectiveness. A chatbot that delivers quick and simultaneously accurate responses enhances information sharing, which represents an essential component for enhancing mutual trust within an organization (Lee and Whang, 2000). When employees recognize that they have access to a reliable tool capable of promptly addressing their inquiries and concerns, they are more likely to collaborate and engage with one another. Moreover, an efficient and quicker chatbot can free up valuable time of team leaders and managers, allowing them to concentrate on strategic decision-making and relationship-building. This dynamic can contribute to a more trusting work environment, as employees experience their leaders being more available and involved.

The positive connection between GAI and both WB (H5) and MT (H6) highlights the importance of using advanced technology to support the interpersonal conditions associated with collaborative dynamics in professional settings. It should be noted that Generative AI Use has the strongest effect on WB ($\beta_{H5} = 0.351$), suggesting that frequent and sustained interaction with generative AI chatbots plays a central role in shaping employees' positive work experiences. Although the existing body of research (Lozie *et al.*, 2024) points to a gap in exploring the impact of generative AI on employee well-being, this study confirms such a strong and relevant connection. The rationale behind it can be understood by examining two key factors. Firstly, frequent use of generative AI chatbots enables employees to automate repetitive tasks regularly, enhancing efficiency beyond occasional use. Secondly, engaging regularly with generative AI chatbots can provide employees with more opportunities to increase their knowledge leading to a sense of accomplishment and personal growth. **These factors together contribute to improved employees' wellbeing, which is associated with workplace dynamics supportive of collaboration within teams.**

Finally, regarding the impact of generative AI on MT ($\beta_{H6} = 0.351$), frequent and regular use of generative AI chatbots ensures that team members receive consistent support for routine tasks as well as complex data analysis, thus reducing the potential for human error. Minimizing errors enhances the reliability of each employee. **As individual reliability improves, colleagues may perceive higher levels of trust, contributing to working conditions that support collaboration within the team.** This finding is also supported by scientific literature, which includes several studies highlighting that the use of advanced technologies can significantly enhance trust among team members (Kauffmann and Carmi, 2014; Kipkosgei *et al.*, 2020; Owens and Khazanchi, 2018).

Unlike traditional workplace technologies such as collaboration platforms, information systems, or decision-support tools, that mainly operate as passive or facilitative infrastructures, Generative AI chatbots introduce a different form of technological mediation in team-based work. Prior literature has largely conceptualized technology as an enabler of coordination (Den Hengst and Sol, 2001), information sharing (Davison *et al.*, 2013),

and efficiency (Cardona *et al.*, 2013), with relational outcomes such as trust and well-being emerging indirectly from improved task execution. Our findings confirm these established relationships but also extend them by showing that Generative AI modifies the underlying mechanisms through which technology influences team dynamics. Specifically, the generative, conversational, and adaptive nature of Generative AI chatbots allows them to actively participate in work processes by producing content, supporting sensemaking, and responding dynamically to users' needs. This shifts the role of technology from a static tool to a quasi-interactive agent embedded in daily team activities.

From a management theory perspective, the findings reconnect the theoretical concepts introduced in this study with empirical results. Consistent with the RBV, generative AI functions as a relational capability that strengthens valuable social resources such as employee well-being and mutual trust, rather than as a purely technical asset. From a sociotechnical systems perspective, the results show that information quality, system quality, and AI use jointly shape social and relational outcomes within teams. In line with social exchange and dynamic capability perspectives, sustained interaction with generative AI promotes recurring positive exchanges that enhance trust and well-being. Therefore, for management practice, the main insight is that value creation depends on strategic and continuous integration of AI into team workflows.

6. Implications

6.1 Theoretical contributions and implications

This study contributes to the growing body of literature on the intersection of Gen AI and team dynamics by empirically demonstrating how generative AI positively impacts collaboration within working teams.

First, by validating the positive influence of Gen AI on employee well-being and mutual trust, the research expands current theoretical frameworks on team collaboration and technology adoption (Neves, 2024). Basically, the notion that AI is a facilitator of social and relational dynamics within teams is strengthened in this study. Traditional theories on team dynamics mainly focus on human-only interactions, while the present research highlights AI as a significant tool in improving interpersonal relationships, thereby shifting the paradigm from human-human interaction to human-AI-human collaboration. Another theoretical implication concerns the advancement of scientific literature on "psychological safety", a topic of great relevance today. It is a "shared belief amongst individuals as to whether it is safe to engage in interpersonal risk-taking in the workplace" (Edmondson, 1999; Newman *et al.*, 2017). Psychologically safe work environments have a virtuous nature where employees respect each other's skills, have positive intentions towards each other and engage in constructive discussions (Edmondson, 1999). In this context, the use of relevant and accurate information provided by chatbots reduces misunderstandings, [improves team-based working relationships](#). Substantially, an AI tool can be seen as a neutral entity for communication, which reduces tension in working relationships. Furthermore, the empirical demonstration that [AI impacts team-based working relationship](#), which in turn impacts business performance, provides important theoretical insights into the RBV of competitive advantage (Madhani, 2010). RBV analyzes the organization's internal resources and emphasizes their strategic role in achieving sustainable competitive advantage. In this study, employee well-being and mutual trust are conceptualized as relational and social resources that

enhance collaboration and are difficult for competitors to replicate. By showing how Generative AI contributes to these relational mechanisms, the study aligns with the RBV by positioning AI-enabled collaboration as a strategic organizational capability rather than a purely technical asset.

Moreover, the proposed model has clear theoretical implications for both sociotechnical systems theory (Appelbaum, 1997) and social exchange theory (Cook et al., 2013). From a sociotechnical perspective, the findings demonstrate that Generative AI chatbots influence team outcomes through the joint interaction of technical attributes (information quality, system quality, and intensity of use) and social dynamics (employee well-being and mutual trust), thereby supporting the notion of joint optimization between social and technical subsystems. From a social exchange perspective, the results suggest that the benefits provided by Generative AI such as reliable information, reduced cognitive effort, and sustained support, act as positive inputs in workplace exchanges, promoting reciprocal relational outcomes in the form of enhanced well-being and trust, which ultimately strengthen collaboration within teams.

The results of the study show that AI can be a strategic resource for organizations, to differentiate themselves from the market competitors in the achievement of team performance and collaboration.

6.2 Implications for practice

From a practical point of view, the first main implication is that managers should invest more in Gen AI systems (Thomas *et al.*, 2024), able to produce accurate, relevant and clear information. In this context, frequent evaluations of such systems should be conducted to ensure that the “Quality of Information” remains high over time, considering that this factor directly impacts employee well-being and mutual trust. Moreover, top management should collaborate with IT teams to select Gen AI tools, which are intuitive and user-friendly; difficulty in using Gen AI, fear of failure, fear upgradation are in fact mentioned among the main barriers to the adoption of this technology (Cubric, 2020; Kar and Kushwaha, 2023). To this aim, technical support and training must be provided to employees, minimizing potential frustration or technical challenges, that could negatively affect collaboration, then organization performance. Overall, the adoption of Gen AI should be encouraged by adopting specific strategies. On the one hand, it would be necessary to redesign existing business processes, including Gen AI in the various workflows. For example, use of Chat GPT could support brainstorming sessions, draft communications, or provide real-time data analysis. Process redesign should be oriented toward shifting repetitive and alienating tasks from humans to AI, allowing workers to focus on more creative and collaborative work, to increase their satisfaction and well-being. Obviously, the spread of Gen AI in organizations is enabled especially by the creation of a culture of trust around chatbots: in this case, transparent information should be provided, during specific workshops or corporate events, on how the different systems work and protecting employee data privacy.

Overall, it is crucial that company management is constantly updated on the opportunities offered by the adoption of AI within the organization. Companies navigate increasingly competitive and dynamic environments, characterized by the daily release of new technologies and tools, which if properly exploited can determine a significant increase in company performance. Finally, the last key practical implications is the need for managers to stay continuously updated on the emergence of new technologies, as these innovations, when properly leveraged, can enable organizations to achieve significantly higher levels of performance. Generative AI (Corvello, 2025) is a clear example of how technological advancements can transform collaboration and efficiency.

6.3 Limitations and future research

This study, while offering valuable insights into the impact of Gen AI on team-based working relationship, is not without limitations. First, the questionnaire was conducted exclusively in Italy, limiting the geographical scope of the research. Cultural, economic, and organizational differences across countries may influence how Gen AI is perceived and utilized, and thus the findings may not be directly generalizable to other contexts. Second, the study did not focus on a specific industry or sector, which introduces the risk of the results being heterogeneous. Different industries have distinct dynamics, workflows, and levels of technology adoption, which may affect the impact of Gen AI on collaboration, trust, and well-being. Basically, the lack of industry-specific focus might limit the applicability of the findings to specific organizational contexts. Anyway, it is important to note that this is a preliminary, exploratory study, primarily aimed at opening new perspectives for understanding the relationship between generative AI and team dynamics, with a focus on collaborative aspects. As claimed by Lozie *et al.* (2024), there is indeed a lack of scientific literature that analyzes the relationship between Gen AI adoption and employee well-being. Future research is then planned to refine the analysis from a demographic point of view and propose other theoretical models characterized by further constructs, with the aim to discover new relationships, currently unexplored.

An additional limitation of this study concerns the operationalization of collaboration. While collaboration is a multifaceted construct encompassing behavioral, interactional, and network-based dimensions, the present study focuses on two psychological constructs (MT and WB). These variables should therefore be interpreted as interpersonal enablers of collaborative behavior within working teams. Future research should incorporate behavioral, interactional, and network-based dimensions to provide a complete assessment of collaboration in generative AI-enabled teams.

A further limitation of this study concerns the conceptual scope of the proposed framework. While the model focuses on core technological antecedents and relational outcomes to provide an exploratory explanation of Generative AI-enabled collaboration, it does not explicitly account for alternative conceptual models or competing explanations. For instance, trust formation within teams may also be influenced by leadership behaviors, organizational culture, or contextual factors, and employee well-being could act as a moderating or mediating variable rather than an outcome. Exploring such alternative configurations was beyond the scope of the present study but represents another promising direction for future research. Comparative and extended models could help identify boundary conditions and deepen understanding of the mechanisms through which Generative AI shapes team-based working dynamics. An additional limitation of this study is that the effects of generative AI may differ depending on team configuration, such as whether teams are co-located or virtual. Team structure can influence how generative AI tools are used, the extent to which they mediate interaction, and their relevance for relational outcomes. Exploring how different team configurations moderate the relationships observed in this study represents a promising avenue for future research and may help identify important boundary conditions of AI-enabled collaboration.

Finally, this study did not conduct subgroup analyses based on demographic and work-related characteristics of the surveyed participant, therefore future research could examine the potential differences across these subgroups

with the aim of identifying whether some groups benefit more from generative AI enabled collaboration and inform more tailored organizational implementation strategies.

7. Conclusions

This study aimed to explore the relationship between Gen AI and team-based working dynamics, addressing a relevant gap in the emerging literature on AI in organizational contexts. By empirically testing a theoretically grounded model, the study examined how selected AI-related system characteristics are associated with two interpersonal states commonly linked to effective teamwork, namely employee well-being and mutual trust.

Drawing on survey data from 208 professionals working in team-based environments and analyzed using PLS-SEM, the findings indicate that information quality, system quality, and the intensity of generative AI use are positively associated with both employee well-being and mutual trust. These results suggest that, within the scope of the present study, the quality of AI-generated content, the perceived technical reliability of generative AI systems, and sustained interaction with such tools are relevant factors shaping relational dynamics in teams. While all hypothesized relationships were supported, the magnitude of the effects varies across antecedents, underscoring the differentiated role of technological and usage-related dimensions.

This research provides an initial and exploratory empirical foundation for understanding how generative AI is embedded in team contexts and how its characteristics relate to key relational outcomes. Given the cross-sectional design, contextual focus, and limited set of constructs, the conclusions remain bounded to the empirical scope of the study. Nonetheless, the results contribute to ongoing scholarly conversations by highlighting the relevance of relational and sociotechnical considerations in the adoption of generative AI at work. Therefore, it promises to be the starting point for future studies, aimed at analyzing further constructs and discovering more relationships between technology and humans.

APPENDIX

Table A.1 summarizes all the research model constructs and items.

Table A.1. Research model constructs and items

Construct	Item	Nr.	Source
Quality of Information (QI)	<i>Generative AI provides me with the necessary information</i>	QI-1	Adopted from Magno and Dossena (2023)
	<i>Generative AI provides responses to queries as I expected</i>	QI-2	
	<i>Generative AI provides sufficient information</i>	QI-3	
	<i>The information provided by Generative AI is helpful regarding my questions or problems</i>	QI-4	
System Quality (SQ)	<i>I found it easy to become skillful at using Generative AI chatbot</i>	SQ-1	Adopted from Magno and Dossena (2023)
	<i>I believe that Generative AI chatbot is easy to use</i>	SQ-2	
	<i>Using Generative AI chatbot required minimal mental effort</i>	SQ-3	
	<i>Generative AI Chatbot was quick in response</i>	SQ-4	
	<i>Generative AI Chatbots I use are reliable</i>	SQ-5	
Generative AI use (GAI)	<i>I use Generative AI tools frequently</i>	GAI-1	Adopted from Al-Emran <i>et al.</i> (2024)
	<i>I spend a lot of time using Generative AI tools</i>	GAI-2	
	<i>I exert myself to use Generative AI tools</i>	GAI-3	

Well-Being (WB)	<i>I am quite satisfied with my work environment</i>	WB-1	Adapted from Pradhan and Hati (2022)
	<i>I enjoy meaningful activities in the work I do within the team</i>	WB-2	
	<i>I attach lots of value to the work I do with my colleagues within the team</i>	WB-3	
	<i>The colleagues of my team often motivate me by recognizing and celebrating my achievements</i>	WB-4	
	<i>My workplace is very supportive</i>	WB-5	
Mutual Trust (MT)	<i>I demonstrate thoughtfulness and respect toward the feelings of my team colleagues</i>	MT-1	Adapted from Pinjani and Palvia (2013)
	<i>I am friendly toward my team colleagues</i>	MT-2	
	<i>My team colleagues can rely on me</i>	MT-3	
	<i>Colleagues in my team think that I am trustworthy</i>	MT-4	

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