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Quality of Decision-Making Processes in Teams: An Analysis of the Effects of Supportive Organizational Culture, Perceived Decision Relevance and a Potential Use of AI

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Abstract
This study investigates the quality of decision-making processes in corporate teams – a construct that is often overlooked or insufficiently operationalized in existing research. Based on the comprehensive framework by Spetzler et al. (2016), this research systematically assesses process quality, examines its influence on perceived decision-making success and identifies key factors that shape the decision-making processes quality in the context of team decision-making. A quantitative survey was conducted among 461 employees in Germany who regularly participate in team decision-making. Structural equation modeling was used to analyze the impact of a supportive organizational culture and the perceived relevance of the team decision on decision process quality, and subsequently the impact of this quality on the perceived success. Results show that both factors significantly enhance process quality, which in turn strongly predicts the perceived success. Additionally, the study explores how artificial intelligence (AI) as decision support influences process quality. A group comparison between employees with and without experience in AI-supported team decision-making and regression analyses reveal that actual use of AI is associated with higher trust in intelligent systems and a more favorable assessment of process quality. Trust in AI significantly predicts process quality across both groups. These findings contribute to the understanding of the determinants of decision-making quality and the emerging role of AI in organizational decision contexts. From a practical perspective, organizations can improve decision-making processes by providing sufficient resources and communicating the relevance of decisions. AI should be explored by users beforehand and fears addressed at an early stage to enhance trust and thus process quality.

Keywords Team decision · Decision-making process · Process quality · Artificial intelligence

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1 Introduction

Today's working environment is increasingly shaped by volatility, uncertainty, complexity and ambiguity (Nandram and Bindlish 2017), also known as VUCA world, driven by disruptive technologies such as AI, changing market demands and geopolitical instabilities (e.g., Mack and Khare 2016), among others. More recently, the BANI phenomenon further defines this environment as "brittle, anxious, nonlinear, and incomprehensible" (Adzhienko et al. 2023, p. 54), especially regarding the use of digital applications (Evseeva et al. 2021). These developments contribute to a growing complexity in organizational decision-making (cf. Evseeva et al. 2021). Given this complexity, corporate decisions are increasingly being made by teams, as collaborative problem solving enables more effective management of complex challenges (Chen and Linn 2012; Zhu et al. 2021).

Group decision-making (GDM) describes the process in which a group of individuals collectively makes a choice between several alternatives (Pérez et al. 2018; Wang 2015). The aim is to identify the alternative that, according to established criteria, represents the best possible solution and is supported by all group members (Alonso et al. 2009; see also literature review by Pajasmaa et al. 2025). The positive characteristics of GDM are particularly evident in complex decision situations: groups possess a broader collection of knowledge and information, are able to evaluate alternatives from different perspectives, and, through consensus building, achieve greater acceptance and satisfaction with the decisions made (Shih and Olson 2022). Thus, GDM is regarded as an approach that can significantly contribute to enhancing the quality of decision-making processes.

Due to its subjective nature, the concept of quality tends to be defined in terms of different aspects of the decision-making process (Bujar et al. 2017). According to Spetzler et al. (2016), the quality of decision-making processes is characterized by finding the best alternative for the given situation among all alternatives that are considered as good enough, despite uncertainties and the complexity of a decision, thereby generating the greatest possible value. In addition, quality is determined by avoiding biases and dysfunctional habits within a decision-making process and focusing purely on the aspects that are relevant to the current decision (Spetzler et al. 2016).

For organizations, high-quality decision-making processes are of central importance for maintaining responsiveness in complex, fast-moving environments and securing long-term competitiveness. Beyond enabling successful decision outcomes (Goll and Rasheed 2005; Ji and Dimitratos 2013; Samba et al. 2021), high-quality decision-making processes support sound reasoning and sustainable outcomes (e.g., Gong et al. 2018; Voorberg et al. 2021), help to manage risks and uncertainties (e.g., Houhamdi and Athamena 2024; Oger et al. 2019), foster operational efficiency and adoption capabilities (e.g., Reeves and Deimler 2012; Văcărescu Hobeanu 2018), and thereby support organizational resilience within those BANI-shaped environments.

To overcome different challenges and reduce uncertainties in decision-making processes, Spetzler et al. (2016) developed a framework, which postulates six different quality criteria for decision-making processes, including, among others, the narrowing and definition of the decision frame, the generation of creative courses of action, and the willingness to implement the chosen decision. Although this approach represents a comprehensive instrument for assessing decision process quality, it has so far not been commonly operationalized and tested in empirical research on a merely procedural level, especially not for GDM in corporate contexts.

Despite the wide range of empirical theories and research findings that provide a foundation for recognizing process-based aspects as influencing the decision quality (e.g., Arvai and Froschauer 2010), significant gaps remain in the empirical investigation of decision-making process quality. These gaps primarily stem from the fact that the construct of process quality is often only fragmented conceptualized and measured on the basis of isolated, selective aspects rather than systematically (cf. Bujar et al. 2017). A systematic assessment of process quality in team decision-making based on the quality criteria according to Spetzler et al. (2016) is largely missing. The present study addresses this gap by comprehensively examining the quality of decision-making processes in teams using the six criteria proposed by Spetzler et al. (2016). While partial aspects of these criteria, such as an appropriate decision-making framework, clarity about values, and the consideration of creative alternatives, have already been part of empirical studies (e.g., Bujar et al. 2017; Donelan et al. 2016; Garbuio et al. 2015), process quality is neither examined as a distinct, procedural construct, but rather as a broad combination of approaches, culture, competencies, and decision-making styles (cf. e.g., Donelan et al. 2016).

Furthermore, in terms of evaluating the effectiveness and perceived value of a decision, recent studies point to the advantages of subjective evaluations over traditional economic indicators, especially when focusing on the quality of a decision-making process itself (Ji and Dimitratos 2013; Samba et al. 2021). Against this background, the present study aims to address two research gaps by (1) offering a systematic and structured assessment of the quality of decision-making processes based on the criteria according to Spetzler et al. (2016) within GDM structures and (2) investigating the relationship with decision-making success using subjective, perception-based indicators. The following research question is answered by applying a structural equation modeling (SEM) approach:

RQ1 *What influence does the quality of a group decision-making process have on the perceived success of the decision as an outcome?*

Since many corporate team decisions are embedded within broader organizational and contextual dynamics (cf. e.g., Akyürek et al. 2015; Kozioł-Nadolna and Beyer 2021), decision-making processes are shaped by a range of external influences, including economic (Alkaraan and Northcott 2013), technological (e.g., Duan et al. 2019) or social and cultural (Apolo-Vivanco et al. 2019; Mador 2000) factors. Such factors may, depending on the presence and kind of characteristics, enhance or impair process quality and thus potentially affect the decision-making success (cf. Akyürek et al. 2015; Elbanna and Child 2007; Kozioł-Nadolna and Beyer 2021; Rodrigues and Hickson 1995). Specific examples that promote quality include the availability of resources and information as well as an appropriate organizational culture (Kozioł-Nadolna and Beyer 2021).

Building on these considerations, the present study examines which external (organizational and perceptual) factors are overarching associated with the quality of decision-making processes in teams:

RQ2 *Which external influencing factors are directly related to the quality of a decision-making process?*

Even though GDM is considered as a means to improve the quality of decision-making processes, its boundaries and limitations also need to be taken into account. Although teams combine more knowledge, experience, and perspectives, thereby creating a more stable and comprehensive foundation for decisions, choices are still made in uncertain and unpredictable environments. Factors such as incomplete or contradictory information, vast amounts of data, market volatility, and time pressure further complicate reaching high decision quality (Evseeva et al. 2021; Palomares et al. 2014; Rodríguez and Martínez 2015). Against this backdrop, the use and integration of AI as digital decision support in decision-making processes tends to become increasingly relevant for companies (cf. Trunk et al. 2020). One key reason for this is that AI can optimize and automate processes, save time as well as costs and improve the result quality (see literature review by Merkel-Kiss and von Garrel 2023), thus providing support in complex and uncertain work environments (Evseeva et al. 2021; Trunk et al. 2020).

According to Berente et al. (2021), AI can be defined as "the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems" (p. 1438); a definition that suggests that AI is primarily a phenomenon of the respective time in which it is considered (a more technical definition of AI can be found in the European Commission's AI Act). The types of AI can be broadly divided into three categories: weak AI with limited problem-solving abilities (e.g., actual voice assistants), strong AI with human-like intelligence, and super intelligent AI as theoretical concept outperforming other AI categories in every aspect (Kalota 2024). The trend is towards autonomous systems taking over tasks and roles from humans (O'Neill et al. 2022).

As the future of work and consequently changes in corporate decision-making are increasingly discussed due to the growing use of AI (cf. Chowdhury et al. 2022; Solberg et al. 2022) and the idea of regarding them as autonomous actors in socio-technical teams (Chowdhury et al. 2022; Seeber et al. 2020), the deployment of AI as decision support (cf. Baabdullah 2024; Dear 2019; El Khatib and Al Falasi 2021) in particular raises new questions about how such tools affect the quality of decision-making processes. This study additionally explores the impact of AI deployment within group decision-making processes on the quality of these:

RQ3 *To what extent does the use of AI have an impact on the quality of a decision-making process in a team?*

In the following, this paper consists of two parts: in the first part, the research questions *RQ1* and *RQ2* are discussed and examined, followed by an additional analysis of the research question *RQ3* in the second part.

2 Part I: Quality of a Decision-Making Process

2.1 Quality of a Decision-Making Process as Predictor for Perceived Decision Success

Numerous empirical studies demonstrate that rational, well-structured, informed and participatory processes are key drivers of decision success (e.g., Carmeli et al. 2009; Dean and Sharfman 1996; Nutt 2008; Samba et al. 2018). Traditionally, decision success has often been assessed using objective economic indicators such as profitability, cost efficiency or market share (e.g., Goll and Rasheed 2005; Samba et al. 2021; Szanto 2022), with these studies constantly linking formal and rational decision-making approaches to better corporate performance (Goll and Rasheed 2005; Samba et al. 2018). However, this impact of the decision-making process on decision success is not only evidenced by research relying on objective, performance-based measures of decision success, but also by studies using subjective, perception-based indicators such as perceived decision effectiveness or strategic appropriateness, which similarly benefit from rational, comprehensive, and goal-oriented processes (Elbanna and Child 2007; Ji and Dimitratos 2013; Samba et al. 2021; Thanos 2023). Although these findings highlight the impact of the quality of the decision-making process on decision success in both objective and subjective terms, most studies, as previously mentioned, capture process quality only in a limited way, often focusing only on individual aspects such as risk management (Arvai and Froschauer 2010) or comprehensiveness (e.g., Samba et al. 2021), rather than providing a comprehensive framework. Spetzler et al. (2016) address this gap by proposing six distinct factors that define high-quality decision-making in corporate contexts and enable decisions to be evaluated at the time they are made – based on the quality of the process rather than the eventual outcome. These six criteria are: narrowing down the decision-making framework, the definition of clear values and tradeoffs, the formulation of creative courses of action, the use of reliable information, the comprehensibility of the selection and the willingness to implement the decision. According to this approach, all criteria must be fulfilled simultaneously to ensure a high-quality decision-making process. This study adopts the approach by Spetzler et al. (2016) to operationalize and systematically assess the quality of decision-making processes. In line with the current shift in research, decision success is measured subjectively, thus as perceived success, capturing the retrospective evaluation of the respective decision, including aspects such as content validity, team satisfaction and realization of expected benefits. Based on the literature reviewed, which consistently demonstrates a strong link between high-quality decision-making processes, particularly those that reflect formal, structured and rational elements (now more comprehensively captured through the criteria by Spetzler et al. (2016)), and positive subjective evaluations of decision success, the following hypothesis is proposed as part of *RQ1*:

H1 *The perceived quality of a team decision-making process causes an increase in the perceived success of the respective decision.*

2.2 Factors Influencing the Decision-Making Process Quality

A variety of external factors influencing decision-making processes and their quality have already been identified in the literature (e.g., procedural structures within organizations according to Piezunka and Schilke 2023; different types of decision support according to Lilien et al. 2004).

One key factor is a supportive organizational culture, particularly the availability of resources for decision-making (cf. e.g., Miller 1997). According to Kozioł-Nadolna and Beyer (2021), sufficient resources in terms of financial, time, material and human resources enable decision-makers to thoroughly evaluate and compare courses of action, thereby enhancing the quality of decision-making processes and the likelihood of better outcomes, while resource shortages, especially financial limitations, hinder effective decision-making. The use of digital tools as part of the available resources can further support process quality by improving information access and analysis (e.g., Bajwa et al. 2005; Kowalczyk and Gerlach 2015). In line with Spetzler et al. (2016), sufficient time and human resources can support a systematic analysis of the decision framework and identification of feasible courses of action. Financial resources can enable the use of technical tools that improve the access to reliable data sources (Abu-AISondos 2023) and aid the development as well as assessment of potential courses of action. Overall, the availability of sufficient resources enhances the decision-making process both qualitatively and quantitatively, enabling well-founded and justifiable decisions.

Furthermore, dealing with mistakes and wrong decisions as a cultural issue plays a crucial role in decision-making processes. By viewing mistakes as a natural part of human behavior as well as learning-oriented, thereby creating a positive error culture (Westphal 2022), organizations promote psychological safety (see Fischer et al. 2018; Westphal 2022) as well as organizational learning (e.g., Provera et al. 2010; Weinzimmer and Esken 2017) and enhance performance (van Dyck et al. 2005; Weinzimmer and Esken 2017), communication (Hetzner et al. 2011), and autonomy (Huettermann et al. 2024), which fosters high-quality decision-making processes. In line with Spetzler et al. (2016), a positive error culture could help to address uncertainties and knowledge gaps among decision-makers at an early stage, as it increases psychological safety, which in turn helps to clarify the decision framework and generate as well as evaluate alternatives more effectively. Open communication about mistakes can encourage more unconventional approaches and more informed discussions about potential consequences within the decision-making team.

In addition, organizational trust in decision-makers can significantly impact the decision-making process and its quality (e.g., Elbanna et al. 2015). According to Parayitam and Dooley (2009), trust operates on two levels: cognitively (trust in the competence of others) and affectively (based on interpersonal relationships). Trust can enhance the quality of decision-making processes by facilitating the flow of information, encouraging employees to share ideas and express concerns or criticism, and fostering openness and innovation (Parayitam and Dooley 2009). Referring to Spetzler et al.'s (2016) quality criteria, trust can support a clearer definition of the decision framework by enabling open discussion about conflicting objectives and boundaries. It can also promote honest dialogue on risks and benefits, improving evaluation of courses of action. Cognitive trust can help to ensure that all perspectives are recognized and integrated, leading to a broader range of courses of action. The open exchange of information in general can provide a better basis for justifying the final decision.

The outlined factors are collectively referred to as supportive organizational culture. Based on the above considerations, which suggest a positive influence on the quality of the decision-making process, the following hypothesis is formulated as part of *RQ2*:

H2 *A supportive organizational culture has a positive association with the decision-making process quality.*

Also, the perceived relevance of a corporate decision is strongly linked to the quality of the decision-making process. Research shows that decisions perceived as more impactful and consequential, especially in terms of profits, costs or productivity, are more likely to be approached with increased rationality (Hickson et al. 1986; Nooraie 2008; Papadakis et al. 1998) and comprehensiveness (Meissner and Wulf 2014), which in turn enhances the overall quality of the decision-making process (Nooraie 2008). Thus, a higher perceived relevance of a decision is likely to lead to a more thorough and structured process (Meissner and Wulf 2014; Nooraie 2008). Since Spetzler et al. (2016) particularly emphasize a rational and well-structured approach to decision-making, such as clearly defining the framework and providing sound justification for the chosen solution, it can be assumed, based on the mentioned research findings, that there is a direct (positive) correlation between the perceived relevance of a team decision and the quality of the decision-making process. Accordingly, the following hypothesis is proposed as part of *RQ2*:

H3 *Perceived relevance of the team decision has a positive impact on the decision-making process quality.*

The methodological approach of this study to empirically investigate the proposed hypotheses and address the outlined research questions will be explained in the following.

3 Part I: Method

3.1 Sample and Procedure

The present study was conducted at the end of November 2023 as a one-week online survey with the Unipark tool. As part of this study, individuals were surveyed who were employed by companies in Germany at the time of the research and who regularly make team decisions as part of their professional responsibilities. The participants were recruited through a survey provider in order to obtain cross-industry results with the largest possible sample size. Before participating, they received a data protection declaration and were only admitted to the survey if they agreed to the anonymous processing of their data. Attendees received monetary compensation for their participation in the survey.

Before responding to the statements about decision-making processes, participants were asked to think about a single specific decision they had made in the past together with their team, group, or department. This decision should be work-related, require a certain degree of coordination and interaction, and serve as a reference for all statements about decision-making processes within the questionnaire.

During the survey period, 825 data sets were generated. Of these, 120 data sets were excluded due to incorrect answers to screening questions, and 147 were removed using an instructed response item (see e.g., Kung et al. 2018). The basis for data cleansing were therefore 558 raw data sets. Following Leiner's criteria (2019), 31 data sets were excluded due to missing data and doubtful open-ended responses. Calculations of the speed index based on completion time per questionnaire page and the exceeding of the threshold of 2.0 for the elimination of data sets (Leiner 2019) led to a reduction of further 60 data sets. Six additional data sets were removed due to visually recognizable response patterns. After data cleansing, 461 data sets remained for analysis.

Out of the 461 data sets, 214 participants identified as *female*, 246 as *male* and 1 as *non-binary*. The average age was 46.19 years (SD = 10.14 years). Various levels of education as their highest qualification were stated, including: *Master's degree or diploma* (n = 125), *Bachelor's degree or intermediate diploma* (n = 65), *high school graduation/general higher education entrance qualification* (n = 73), *Completed apprenticeship* (n = 59) and *lower secondary school certificate* (n = 31). The average length of professional experience was 18.14 years (SD = 10.56). The sample includes participants from different industries, with the most represented sectors being *pharmaceuticals and healthcare* (n = 52), *technology and IT* (n = 39), *industry and manufacturing* (n = 39) as well as *finance*, *insurance and law* (n = 39). Most respondents work for companies with more than 1,000 employees (n = 129). All participants stated that they regularly make team decisions in a corporate context. The average number of team members, including the respondent, was 22. The type of decision made by participants related to, among other things, *work organization*, *products and services*, *the company's people*, *technologies*, and *the strategy and culture of the company*. Specific examples included, among others, the handling of staff shortages, employee dismissals, the distribution of responsibilities, home office regulations, the organization of workflows, the streamlining of existing processes, the selection of service providers for individual process steps, and decisions relating to specific customers.

A SEM approach (Fig. 1) was applied to test the hypotheses and was evaluated using partial least square structural equation modeling (PLS-SEM) with assistance of the *SmartPLS* software (Smart PLS GmbH). A variance-based PLS-SEM is usually applied in exploratory research contexts, as it shows better predictive ability compared to the covariance-based method (Hair et al. 2022). According to Hair et al. (2022), the empirical analysis of a PLS-SEM follows two basic steps: (1) the analysis of the measurement models, and (2) the evaluation of the structural model.

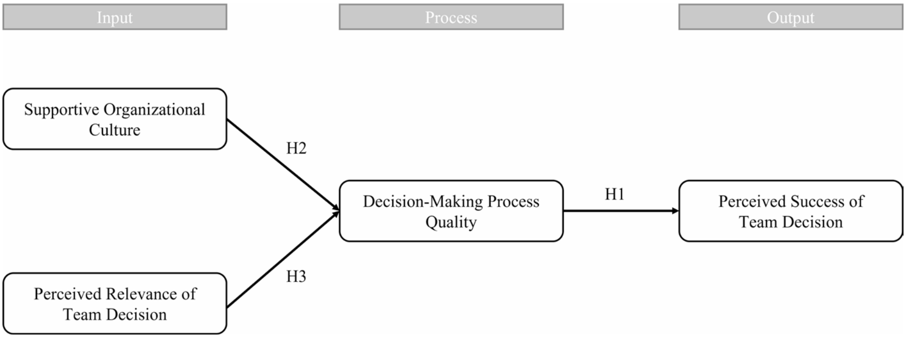

Fig. 1 Proposed model of corporate decision-making with input, process and output variable

3.2 Measures

A complete list of the items used in this study can be found in the Online Appendix. All items were measured using a six-point Likert scale (*1 = strongly disagree* to *6 = strongly agree*). The constructs are all considered to be reflective constructs.

3.2.1 Measurement of Supportive Organizational Culture (OC)

An organizational culture scale was developed based on insights from various authors to assess the corporate framework conditions influencing decision-making processes, particularly the cultural conditions (see Online Appendix 1). To address the company's approach to handling mistakes, an item was formulated based on the concept of error culture as described by Caldwell and O'Reilly III (2003) (OC_3). Since, following Miller (1997), the availability of resources, including human and financial resources, also plays a role in decision-making, one item was developed to reflect this aspect (OC_6). Drawing on Misra et al. (2009), an additional item was formulated to capture the level of organizational trust in the team's ability to successfully manage the decision-making process (OC_7).

3.2.2 Measurement of Perceived Relevance of Team Decision (REL)

The items on the perceived relevance of team decision were created according to Poethke et al. (2019). The original scale refers to the relevance of work and was adapted to the context of a past decision for the conducted study. As the five items do not capture the perceived relevance of the decision for people outside the company, an additional item (REL_3, Online Appendix 2) was initial added based on the German version of the Work Design Questionnaire (WDQ) (Stegmann et al. 2019). However, this item was excluded from further calculations due to statistical criteria.

3.2.3 Measurement of Decision-Making Process Quality (QP)

Six items inspired by the decision quality criteria according to Spetzler et al. (2016) were formulated to assess the quality of the decision-making process (Online Appendix 3). These criteria include the consideration of an appropriate frame, relevant and reliable information, clear values and tradeoffs as well as creative alternatives. In addition, the quality of the decision-making process requires a sound reasoning process and a subsequent commitment to action. These six criteria according to Spetzler et al. (2016) were evaluated for their practical relevance in a previous qualitative interview study as preliminary study.

3.2.4 Measurement of Perceived Success of Team Decision (STD)

The scale for the retrospective evaluation of the perceived success of the taken decision was individually formulated and consists of a total of three concluding items. These cover the assessment of the team's satisfaction with the decision, the realization of the expected benefit and the content-related success of the decision (Online Appendix 4).

4 Part I: Results

The evaluation of the measurement models was carried out on the basis of the four criteria to be fulfilled according to Schloderer et al. (2009) and Hair et al. (2022), i.e., the reliability of the criteria indicator and the internal consistency as well as the convergent validity and discriminant validity. Several criteria were also examined in the evaluation of the path model, for example model fit, collinearity, predictive power and significance. These criteria serve as quality indicators and provide evidence for the robustness and explanatory strength of the structural relationships (Hair et al. 2022). In both the measurement model and the path model, all assessed criteria were fulfilled and thus indicate a good overall model quality. An overview of the results of both evaluations can be found in Online Appendix 5. The results of further statistical diagnostics such as, among others, cross-validated predictive ability test (CVPAT) and f^2 effects sizes, evaluating the robustness of the findings, are presented in Online Appendix 6.

The three research hypotheses were evaluated based on the results of the SEM (Fig. 2). Hypothesis *H1* proposed a positive relationship between the quality of the decision-making process (QP) and the perceived success of the team decision (STD). As indicated by a highly significant path coefficient ($\gamma = 0.753$, $t = 27.694$, $p < .001$), this hypothesis is strongly supported by the data. Furthermore, with $R^2 = 0.567$, over

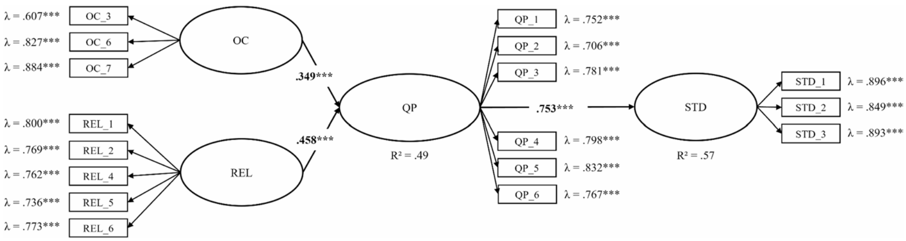

Fig. 2 Structural equation model (note: $\alpha = 0.05$)

56% of the variance in STD can be explained by QP solely. Additionally, the analysis reveals a significant and positive relationship between supportive organizational culture (OC) and QP ($\gamma = 0.349$, $t = 8.108$, $p < .001$), supporting Hypothesis *H2*. Hypothesis *H3* addressed the perceived relevance of a team decision (REL) as a predictor of QP. This relationship is also statistically significant and positive ($\gamma = 0.458$, $t = 11.510$, $p < .001$), indicating that process quality is higher for decisions that are perceived as more important. The combined explanatory power of OC and REL for QP is reflected in an R^2 value of 0.492, which lies between *moderate* and *substantial* levels (cf. Chin 1998). This suggests that while both variables can be seen as significant predictors, other factors not included in the current model may also contribute to variations in QP. In summary, all three hypotheses are supported by the results.

5 Part I: Discussion

5.1 Theoretical Implications

In contrast to the more traditional approach commonly used in many companies, this study evaluates the quality of the decision-making process not on the basis of economic factors or the outcome of the decision, but on content- and process-related factors in the decision-making process, as proposed by Spetzler et al. (2016). The intention was to separate the course of the decision (process) from the later end result (output) in the evaluation. The results indicate that the decision-making process and particularly its quality can be regarded as a central influencing factor for the perceived success of team decisions. This supports the suitability of the holistic approach by Spetzler et al. (2016) as a conceptual framework for assessing decision quality purely based on process-related characteristics. Building on this, previous model approaches and research results already emphasize the relationship between the quality of a decision-making process and its subsequent success, arguing that structured and high-quality processes increase the probability of favorable outcomes (cf. e.g., Goll and Rasheed 2005; Ji and Dimitratos 2013; Rodrigues and Hickson 1995). The results of this study provide further empirical evidence for this correlation and underline that companies should not focus solely on the decision outcomes, but must also invest in decision-making process optimization itself. However, it has to be mentioned that the strong correlation between QP and STD ($\gamma = 0.753$) could also be caused in part by characteristics of the cognitive processing during the evaluation of the specific constructs, i.e., people often struggle to assess a decision-making process independently of its final outcome (Arvai and Froschauer 2010).

Furthermore, the framework proposed by Spetzler et al. (2016) is considered suitable for application to all types of corporate decision-making processes (Spetzler et al. 2016). The present study applied the six quality criteria to the context of GDM and was able to demonstrate its suitability for this type of decision-making. However, because the context of GDM was considered rather implicitly in the present study, no explicit relationship between participatory decision-making processes, their characteristics and the resulting decision outcomes was examined, in contrast to, for example, Carmeli et al. (2009). According to Pajasmaa et al. (2025), for GDM, there are various process-related key factors that should be taken into account in order to optimize decision-making, including, among other things, the specification of the decision-makers and the assembled group, as well as the type of exchange and communication between them. Further studies should therefore place particular emphasis on analyzing how team dynamics and group characteristics influence the quality of decision-making process and, in turn, affect decision success. The same applies to individual factors of the decision makers, which were also not included in the present study. So, in contrast to other empirical studies, this structural equation model does not examine the influence of individual (e.g., cognitive) and team dynamical factors on the quality and perceived success of a team decision. Instead, it focuses on structural conditions of the company and characteristics of the decision itself (perceived relevance) as influencing factors. The significant correlation between organizational culture and quality confirms the previous assumption that companies can increase the quality of a decision by providing adequate resources (cf. Kozioł-Nadolna and Beyer 2021). Not only material resources are relevant in this context, but also intangible resources such as trust or tolerance for mistakes. Further studies could take a more differentiated approach to the type of resources that are most likely to support high decision quality. Previous research findings emphasize that a negative error culture, for example in the shape of blame and cover-up, can impede decision-making processes, while a positive error culture promotes learning processes (Westphal 2022). The results of this study support this assumption by indicating that companies that trust their employees and in which a positive error culture prevails promote a higher quality of decision-making processes. Finally, the evidence that the perceived relevance of a decision can be seen as a key driver of decision quality ($\gamma = 0.458$) confirms previous findings in the specialist literature (e.g., Nooraie 2008).

5.2 Practical Implications

As the quality of the process seems to have a significant influence on the perceived success of team decisions, companies should focus on promoting quality. According to the results of this study, at least half of the variance in the quality construct is explained by both the perceived relevance of the decision and the supportive organizational culture. This means that the quality of a decision-making process is shaped by the corporate framework conditions on which the company can exert a targeted influence, both on the availability of resources as well as on the communication and presentation of the decisions to be made. Trust in employees as well as the importance of upcoming decisions can also be consciously communicated and tolerance for mistakes can be emphasized so that a supportive organizational culture and the perceived relevance of the team decision increase the quality of the process and thus also influence the perceived success of the decision. In more detail, this means:

Firstly, due to the strong influence of perceived relevance, companies should not neglect the communication of the relevance of the decision. The importance of the decision for the company should be clearly emphasized in advance or at the latest during the decision-making process, e.g., by communicating possible short-term and long-term consequences or potential changes for individual employees, the team and the company itself (e.g., DuFrene and Lehman 2014). Clear and transparent communication of the decision-making context and objectives (e.g., Sakamoto et al. 2014) and the early participation of relevant stakeholders (e.g., Malets and Quack 2013) can also influence the perception of the team's decision. The link between perceived relevance and quality can also be attributed to the operationalization of the quality construct: a well-structured decision-making process, such as using a decision-making framework, considering multiple alternatives and evaluating them against predefined objectives, not only determines decision quality but also highlights its relevance for the company. A thorough and careful approach, which can be assumed to increase with the relevance of the decision to be made, can therefore be proactively promoted by emphasizing the importance of a decision.

Secondly, the structured approach in decision-making processes, as required by the quality criteria according to Spetzler et al. (2016), can be established in companies at an early stage and made standard, e.g., through good documentation of decision-making processes, the introduction of checklists, clear time and personnel structures. According to Kowalczyk and Gerlach (2015) or Bajwa et al. (2005), the introduction and use of decision-making tools that support the organization of information, the analysis of data or the collaboration of team members, for example, could also promote a structured approach to decision-making processes – and thus higher quality.

Thirdly, since both material (financial, personnel, time) and immaterial resources (error culture, trust) promote the quality of the decision-making process, companies should ensure appropriate organizational support. This means that not only targeted resource management is important (cf. Westphal 2022), but also the provision of tools or further education and training for decision-making. The establishment of a positive error culture can also promote the psychological safety of employees (cf. Fischer et al. 2018) and thus strengthen performance, open communication as well as the reflection and handling of errors (e.g., Hetzner et al. 2011). In addition to decision-making processes, other business processes can also benefit from this.

Measures to establish a positive error culture could be, for example: encouraging employees to accept mistakes and consider them as learning opportunities, providing open communication and a supportive learning culture, for example, via best practices for decision-making processes (Provera et al. 2010; van Dyck et al. 2005; Weinzimmer and Esken 2017). The establishment of a management culture in which managers set a good example, show trust in their employees and do not question their decision-making authority without good reason can also contribute as a resource to promoting quality. Opportunities for this may lie in the decentralization of decision-making structures (more autonomy for teams) (Huettermann et al. 2024) or in the further development of coaching skills among managers so that employees can be supported in decision-making processes without conveying a lack of trust or patronizing them (see e.g., Koskinen and Anderson 2023).

5.3 Limitations and Future Directions

In general, the SEM constructs were measured using participants' self-assessments based on a retrospective consideration of a decision. This could have led to distortions, particularly in the case of QP and STD, for example due to dishonest assessments, social desirability or also positivity bias (Adler and Pansky 2020; Zimmerman and Walker 2022). The mean values of the two constructs (see Online Appendix 5) show that they were generally assessed as high; however, an additional evaluation by external reports, qualitative interviews or experimental studies could lead to further insights.

Another limitation is that the results are based on cross-sectional data and therefore on the evaluation of single decisions. Future studies could validate the findings and the correlations found using longitudinal studies across several decisions and points in time.

Furthermore, since the timing of the retrospective decision was not assessed in the present study, it was not possible to determine when the success of the respective decision occurred or how much time typically passed between the completion of the decision-making process and the visibility of its outcomes. As a consequence, no specific insights could be gained regarding the time frame of decisions, and the evaluation of success cannot be fully taken into account; for example, it may be the case that the participants who rated the success of the decision less favorably did not yet have the opportunity to assess its full scope, as the success had not yet materialized and the decision did not occur far enough in the past.

In addition, since the criteria according to Spetzler et al. (2016) have not yet been operationalized, no validated scale was available at the time of the survey. For this reason, the items were developed closely based on the wording used by Spetzler et al. (2016) (see Online Appendix 3). Further studies should determine a validated scale and refine the formulation of these items (e.g., with regard to the dimensions measured and the connection between related aspects within an item), as the approach of the decision quality criteria proved to be effective in this exploratory procedure (e.g., by enabling quality to be measured as a strong predictor of the decision success).

Another limitation is that the model examined here is limited in its scope to a few variables. Other factors may also influence the quality of the decision-making process (see R^2 value, Fig. 2). Given that decision quality has a strong influence on the perceived success of the decision, future studies should replicate these findings and investigate additional (direct and indirect) influencing factors, such as, as already mentioned, specific team characteristics, attributes of the decision-makers, or further organizational factors.

Despite the limitations outlined above, this study contributes to the investigation of the quality of corporate group decision-making processes in two ways: first, by empirically testing the holistic approach proposed by Spetzler et al. (2016), and second, by examining its process-related quality criteria in combination with corporate influencing variables. Moreover, the separate examination of quality and success provides additional insights and supports a more nuanced understanding of these two dimensions.

Since different forms of decision support can also have an influence on the evaluation of decision quality (Carneiro et al. 2019; Lilien et al. 2004) and as the use of AI as decision support is becoming increasingly relevant for companies (see e.g., Solberg et al. 2022), the impact of AI on the quality of the decision-making process in a team decision was also explored as part of the quantitative study to derive initial derivations for future research. Additionally, the study assessed trust in AI as key factor influencing the perceived quality of the decision-making process.

6 Part II: Possible Changes in the Quality of Decision-Making Processes Through the Use of AI

In corporate decision-making processes, AI-based systems can reduce decision complexity, structure and analyze existing data, identify relevant information or develop suitable alternatives (cf. Kalimeris et al. 2022; Phillips-Wren 2012). In doing so, they can enhance both the speed and quality of decision-making (cf. e.g., Baabdullah 2024), partly by reducing errors and cognitive biases (Dear 2019; El Khatib and Al Falasi 2021). With regard to Spetzler et al. (2016), AI could therefore not only support the selection and analysis of data (*relevant and reliable information*), but also assist in defining and limiting the decision framework (*appropriate frame*) as well as values and objectives of the decision (*clear values and tradeoffs*) through targeted questions and suggestions. AI can also be used to search for alternative courses of action (*creative alternatives*) and to justify the selection of a final one (*sound reasoning*). The sixth criterion *commitment to action* may be indirectly strengthened by the use of an AI, as a transparent and stringent justification of the decision can increase the willingness to implement decisions. Thus, the use of AI systems can enhance the quality of decision-making processes, but this potential can only be realized if there is willingness to adopt these systems (e.g., Schwesig et al. 2023) and integrate them into decision-making processes.

Despite those advantages that some AI systems theoretically offer, there are often difficulties related to the practical implementation of such systems (Kitsios and Kamariotou 2021). In many cases, companies lack the necessary knowledge about how to integrate AI systems into daily operations and thus into their existing workflows (Merkel-Kiss and von Garrel 2023). In addition, the impact on employees who have to work with the AI system should be taken into account: the implementation of AI can disrupt established routines and workflows, requiring adaption to newly designed or altered processes (Stowasser et al. 2023) and thus can cause technostress among employees (Chang et al. 2024). However, it is crucial to consider that companies cannot fully predict the reactions of their employees, for example due to AI anxiety (Chang et al. 2024), before implementing AI. This means that it is not clear for companies in advance what impact the personal attitudes of their employees will have on their intention to use AI (Chang et al. 2024). The use of AI systems in decision-making processes and thus human-AI collaboration is also associated with further challenges: for example, cooperation depends on emotional responses to AI (e.g., Yao et al. 2024), i.e., as part of the social response theory (Nass and Moon 2000), or on the perception of the AI in its role (e.g., Siemon 2022; Zhang et al. 2023).

The efficiency of AI-supported decision-making therefore depends on employees' attitudes toward the system, whether they value it or remain skeptical (cf. Cao et al. 2021). In this context, trust is often considered as a prerequisite for the interaction of potential users with AI applications (Chowdhury et al. 2022; Jacovi et al. 2021; Kelly et al. 2023). Trust in AI can be defined as "the extent to which a user is confident in, and willing to act on the basis of, the recommendations, actions, and decisions of an artificially intelligent decision aid" (Madsen and Gregor 2000, p. 1). Trust is again influenced by various factors, such as the transparency of the AI application (e.g., Glikson and Woolley 2020; Wang and Ding 2024), its perceived ability and integrity (e.g., Lalot and Bertram 2024) as well as its tangibility and reliability (e.g., Glikson and Woolley 2020). When both the process and the results of AI are transparent, trust in AI is generally higher (e.g., Kostopoulos et al. 2024). Moreover, the perceived extent to which it is possible to control and intervene in AI-supported processes affects users' trust in such systems (cf. Batut et al. 2024; Becker and Fischer 2024). When users have a sense of control, it is easier for them to trust AI, accept its results, and rely on them (Küper et al. 2025; Solberg et al. 2022).

Individuals who already have experience using AI in decision-making tend to show more (initial) trust in these systems (cf. Choung et al. 2023; Glikson and Woolley 2020). Their familiarity with such systems enables them to better assess the capabilities and potential applications of AI and therefore recognize more advantages in its use (cf. Glikson and Woolley 2020). In contrast, individuals with no prior experience with AI systems tend to perceive them or their role as difficult to understand; they are more skeptical and uncertain concerning the necessity of implementation and its significance for their own careers (Daly et al. 2025) as well as the capabilities and reliability of AI which leads to less trust (e.g., Hoff and Bashir 2015; Jeffrey 2020). As Wang and Ding (2024) highlight, there is a distinction between actual trust in an AI and user's self-reported trust: while a transparent AI can enhance actual trust, it does not necessarily increase self-reported trust. In addition, trust in AI as dynamic construct (Dorton and Harper 2022) tends to grow with prolonged interactions (cf. Dorton and Harper 2022; Glikson and Woolley 2020), potentially leading to better decision outcomes. Trust also increases decision-making certainty (cf. Lyons et al. 2011) and can therefore also impact the quality of the decision-making process.

Since no empirical studies have yet been conducted on the six quality criteria according to Spetzler et al. (2016) with regard to the use of AI, but such systems can specifically support various aspects of a decision-making process, as already described at the beginning of this chapter, this construct will also be the focus of the following study. As there is a lack of quantitative studies in which the use of AI is not only anticipated, but in which experiences and perceptions from human-AI collaborations that have already taken place are collected, this quantitative study will focus on a group comparison by examining whether differences in the assessments of AI-supported decision-making processes are recognizable between employees who have already worked with AI and employees who have not yet had any experience with AI and should therefore anticipate its use. Given the proven benefits of AI in decision-making, but also due to potential reservations on the part of employees before the introduction of such systems, the following hypotheses are derived as part of *RQ3*:

H4 *The quality of the AI-supported decision-making process is rated higher with actual AI deployment than with anticipated AI deployment.*

H5 *Trust in AI is rated higher with actual AI deployment than with anticipated AI deployment.*

H6 *Greater trust in AI leads to a higher assessment of the quality of the AI-supported decision-making process.*

According to Yao et al. (2024), not only pure trust in an AI system itself plays a central role, but also how this trust interacts with emotional responses and the intention to use the system. This leads to the assumption that the actual use can possibly be evaluated more strongly than the anticipated one. In addition, the evaluations by the anticipated group could be lower than the evaluations by the group with actual experience due to the status quo bias (Samuelson and Zeckhauser 1988), as individuals tend to prefer their current state and are therefore more negative about change. Based on this, the assumptions about trust in an AI and the lack of empirical research comparing actual and anticipated AI deployment in connection with the quality of decision-making processes, the following hypothesis is formulated as part of *RQ3*:

H7 *The results on the relation between trust in AI and the quality of the decision-making process are significantly different when comparing actual and anticipated deployment.*

7 Part II: Method

7.1 Sample

From the sample described in Part I, 40 participants stated that they had already worked with an AI as part of their selected team decision. These attendees had different professional backgrounds, but the majority assigned themselves to the sector *technology and IT* ($n = 13$). Of these participants, 14 identified as *female* and 26 as *male*. The average age was 41.92 years ($SD = 10.53$; min = 28.00; max = 65.00). To avoid biases in the generation of the results and to focus on the representativeness, simple random sampling was conducted using the bootstrapping method to select 40 participants (*female* gender: 21, *male* gender: 19) from the group with anticipated AI deployment. In this group, the average age was 48.58 years ($SD = 10.18$; min = 28.00; max = 65.00).

7.2 Procedure

The AI-related constructs were assessed as separate section within the online questionnaire, described in Part I. To ensure a common understanding, participants were first provided with an AI definition. If the participants had already worked with an AI when making the team decision described, they had to evaluate its real-life deployment. Conversely, if they stated that they had worked without AI in their team decision, they were asked to anticipate that an AI had been used. Participants evaluated their trust in AI and the quality of the decision-making process in the context of AI usage.

Statistical analyses were carried out using the *RStudio software*. The analysis of histograms and the Shapiro-Wilk test indicated a non-normal distribution of the data and due to variance heterogeneity as indicated by significant results of the Levene test (cf. Backhaus et al. 2016), a non-parametric method was chosen (Schäfer 2011) to test the Hypotheses *H4* and *H5*. Specifically, a Wilcoxon test was conducted for both the trust construct and the quality of the decision-making process construct to examine the group differences between actual and anticipated deployment of AI.

Two linear regression analyses were conducted to test the Hypotheses *H6* and *H7*. One analysis examined the influence of trust in AI on the evaluation of the quality of the decision-making process in the context of actual AI use, while the second analyzed this relationship for the anticipated use. Both analyses used the trust construct as a predictor for the quality of the decision-making process.

Prior to calculating the regression models, the prerequisites for carrying out the analyses were checked for each model. Both models largely met the required assumptions, including linearity (see Backhaus et al. 2016), normal distribution (graphical analysis of histograms and Q-Q plots; see Osborne and Waters 2002), homoscedasticity of residuals (graphical analysis of residual plots and Breusch-Pagan test; see McGibney 2023; Osborne and Waters 2002) and independence of residuals (see Backhaus 2016). When identifying potential outliers, one data set was excluded from the analysis in the model assessing actual AI deployment, as its studentized residual exceeded ± 3 (see Merza and Al-Anber 2021). No outliers were detected in the model examining anticipated AI deployment.

7.3 Measures

In order to assess the effects of the actual and anticipated AI deployment on the quality of the decision-making process, the items based on the decision quality criteria according to Spetzler et al. (2016) were applied and supplemented with a reference to the AI use. The following half-sentence was placed in front of the items for actual use: "The deployment of the AI system as part of the decision-making process has …" (see Online Appendix 7), and for the evaluation of anticipated use: "The deployment of the AI system as part of the decision-making process would have …" (see Online Appendix 8).

To assess trust in AI in the context of the group decision both in actual and anticipated terms, two five-item scales were developed based on a meta-analysis by Chowdhurry et al. (2022) (see Online Appendix 9 and Online Appendix 10).

All items were measured using a six-point Likert scale (*1 = strongly disagree* to *6 = strongly agree*).

8 Part II: Results

The descriptive statistics of the study variables can be found in Table 1. The values for Cronbach's alpha all demonstrate good reliability (cf. Schmitt 1996).

On a descriptive level, it can be seen that the quality of the decision-making process as well as trust in AI are rated better under actual AI deployment than under anticipated use. In addition, the *SD* values show that there is less variance under actual AI deployment than in the other group.

Table 1 Mean, standard deviation (*SD*) and Cronbach's α

Variable	Mean	*SD*	Cronbach's α
1. Decision-making process quality under actual AI deployment (QP_act)	4.7	0.71	0.82
2. Trust in AI under actual deployment (AI_trust_act)	4.7	0.77	0.80
3. Decision-making process quality under anticipated AI deployment (QP_antic)	2.7	1.4	0.95
4. Trust in AI under anticipated deployment (AI_trust_antic)	2.5	1.2	0.88

Table 2 Results of the linear regression on the influence of trust in AI on the quality of the decision-making process under actual deployment of an AI

	Decision-making process quality under actual AI deployment (QP_act)[a]				
	B	*ß*	SE	*t*	*p*
Intercept	4.66	–	0.08	55.51	<.001***
Trust in AI under actual deployment (AI_trust_act)	0.59	0.66	0.11	5.38	<.001***
R^2 (adjusted R^2)	0.44 (0.42)				
F statistic	$F(1, 37)=28.93$, $p<.001$***				

[a]Significance codes: ****p*<.001 | ***p*<.01 | **p*<.05

The results of the group comparison for the different constructs can be seen in Online Appendix 11. The Wilcoxon test shows significant differences between the groups for both *quality of decision-making process* and *trust in AI*. Both for the *quality of decision-making process* (W = 1442.0, $p<.001$) and for *trust in AI* (W = 1476.5, $p<.001$), group 1, i.e., the group with actual AI deployment, has significantly higher values. The calculation of Cliff's delta also shows that the differences between the two groups for the quality construct (δ = 0.8025, 95% CI[0.64, 0.90]) and also the trust construct (δ = 0.8456, 95% CI[0.67, 0.93]) have a high effect size. Therefore, both Hypotheses *H4* and *H5* are supported by the data.

The results of the regression model under actual AI deployment in the context of a team decision can be seen in Table 2.

The results of the regression model examining the effects of actual AI use show that trust in AI has a strong and significantly positive influence on the quality of the decision-making process under deployment of an AI ($ß = 0.66$, $p<.001$, 95% CI[0.37, 0.82]). With regard to the model parameters, 44% of the variance in the quality of the decision-making process is explained by trust in AI.

The results of the regression model under anticipated deployment of an AI are shown in Table 3.

The results of the regression model under anticipated deployment of an AI also show a strong and significantly positive influence of trust in AI on the quality of the decision-making process ($ß = 0.70$, $p<.001$, 95% CI[0.54, 1.09]). 49% of the variance in the quality of the decision-making process is explained by trust in the anticipated AI.

Based on the results of both regression models, Hypothesis *H6* can be confirmed.

Table 3 Results of the linear regression on the influence of trust in AI on the quality of the decision-making process under anticipated deployment of an AI

	Decision-making process quality under anticipated AI deployment (QP_antic)[a]				
	B	*ß*	SE	*t*	*p*
Intercept	2.73	–	0.16	17.39	<.001***
Trust in AI under anticipated deployment (AI_trust_antic)	0.81	0.70	0.14	6.00	<.001***
R^2 (adjusted R^2)	0.49 (0.47)				
F statistic	$F(1, 38)=36.00$, $p<.001$***				

[a]Significance codes: ***$p<.001$ | **$p<.01$ | *$p<.05$

The test statistic for a comparison of the beta coefficients of both groups shows no statistically significant differences (z = −1.25, p=.211, 95% CI[- 0.56, 0.12]). Accordingly, the strength of the correlation between trust in AI and the quality of the decision-making process is comparable for both groups. Hypothesis *H7* cannot be confirmed.

9 Part II: Discussion

9.1 Theoretical and Practical Implications

The results of the Wilcoxon test indicate that actual AI use leads to a higher assessment of the quality of the decision-making process compared to the assessment based on an anticipated use. The application of AI thus supports high-quality decision-making processes in the sense of Spetzler et al. (2016). Although existing literature emphasizes the potential of AI as decision support (Baabdullah 2024; Kalimeris et al. 2022; Merkel-Kiss and von Garrel 2023), there still seem to be clear reservations among individuals without actual experience with its deployment. In addition, the higher standard deviation in this group signals greater dispersion and little consensus in their evaluation. The conducted group comparison suggests that the suspected reservations may be due to a lack of trust in the system used. Both trust in AI and the quality of the decision-making process are rated more positively when AI is actually used compared to when its use is anticipated. Since trust in AI, according to Lalot and Bertram (2024), is influenced by its perceived ability and integrity, it is plausible that trust tends to be higher among those who actively use it, as they can directly assess these qualities. However, individuals' attitudes toward AI can change with increasing experience and knowledge (Daly et al. 2025), supporting the view that trust is dynamic (Dorton and Harper 2022): people who initially have a negative attitude can develop a more positive attitude toward such systems through interaction as they can learn more about the technology and become familiar with its advantages (Daly et al. 2025). The results of the group comparison may reflect these processes, as participants with actual experience show a more positive attitude and greater trust in AI. For companies, this means that testing AI, e.g., in the shape of training sessions or experimental phases prior to implementation, could help to reduce mistrust and reservations about intelligent systems. This may also indicate the need to define, design and explain the intelligent system to employees at an early stage so that they have the opportunity to familiarize themselves with the specific AI.

The context of the decision may also have an influence on trust in the AI system (cf. Schwesig et al. 2023). Participants who only imagined AI use evaluated a past team decision that may not has aligned well with later AI deployment, potentially leading to lower trust and lower perceived decision quality.

However, the lower evaluation of the quality could also be due to the fact that the participants were not able to anticipate AI as part of a GDM and thus to imagine a socio-technical interaction. According to Seeber et al. (2020), AI deployment involves three design areas (*machine artifact design*, *collaboration design* and *institution design*), which might be difficult to anticipate without experience or a concrete system description. For this reason, when testing AI systems, companies should provide collaborative settings that are as realistic as possible, taking into account the three design areas.

The results of both regression models confirm that trust in an AI system has a notable correlation with the assessment of the quality of the decision-making process. This correlation is equally strong in both groups, indicating that higher trust consistently enhances the perceived quality of the decision-making process, possibly in part because trust increases decision confidence (cf. Lyons et al. 2011), which in turn influences the perception of the quality of the associated decision-making process. Since trust was evaluated lower in the group with anticipated AI deployment and given that trust emerged as a significant predictor of quality in both groups according to the results of the regression analysis, it is understandable that perceived decision quality was rated lower for the anticipated deployment and higher for the actual deployment. Although previous research might suggest a significant difference regarding the strength of the relationship for actual use due to emotional reactions and therefore stronger evaluations (cf. Yao et al. 2024), the present study does not confirm that actual deployment leads to a significantly stronger relationship than anticipated use.

9.2 Limitations and Future Directions

In addition to the limitations already mentioned in the first study, it can be noted for this study that other samples could certainly have been tested comparatively. The present results on the anticipated use of AI in GDM are based on a randomly generated sample selected from the data set in order to obtain a comparison with as low systematic biases as possible. A stratified sample selection, i.e., an adjustment of both samples with regard to age, gender or other relevant variables, could be an alternative to increase the comparability of the groups in further studies.

Furthermore, the number of participants who have already applied AI in the context of a team decision-making process was limited and the two samples therefore relatively small. Larger samples could be used for future studies and the specific AI applications used could be determined more precisely. Since providing concrete information on the applied AI systems was optional in the study, it was not possible to obtain a complete picture of the applications. Generated responses referred, among others, to AI support in the following activities: image and text generation, reviewing CVs, risk management and root cause analysis, and the use of a surgery robot. This shows that both the operation of the systems and the level of automation, as well as the scope of training for use within a team, can vary. Nevertheless, this may indicate that the results can be generalized due to the diversity of the AI applications represented. But in contrast, AI systems and their impact on work activities are highly heterogeneous and the progress of the functionalities of such systems is rapid, which makes it difficult to generalize the results for all decision support AI systems. Therefore, subsequent studies should focus on the investigation of specific AI systems in their respective application context.

In addition, although trust was measured using various items in the present study, future studies could focus more specifically on potential influencing factors concerning trust in intelligent systems. Based on actual usage, different factors were implied for individuals with real experience, such as greater knowledge of how to use the system, but these were not directly measured for reasons of survey economy, nor were they measured for the group of individuals with no previous experience.

In the sense of a human-centered design of work with AI, other aspects of sociotechnical systems should also be taken into account. These include, for example, how people interact with digital or intelligent systems: according to Nass and Moon's (2000) social response theory, individuals tend to transfer the rules and expectations they have towards the cooperation with other humans to interaction with such systems. Therefore, the assumption and allocation of responsibilities as well as tasks should therefore be clearly defined and communicated in advance to support human-AI collaboration (e.g., Kluge et al. 2021). In addition, the conscious application of AI and a human-centered approach to collaborative work design can increase social acceptance of the system (Kluge et al. 2021) and therefore its potentials to enhance decision process quality.

10 Conclusion

This article shows that the quality criteria proposed by Spetzler et al. (2016) can serve as a comprehensive approach to capture decision-making process quality in the context of corporate GDM and that process quality is of central importance for the perceived decision success. Companies should therefore promote decision process quality through providing organizational resources (tangible and intangible) for teams and by managing the perceived relevance of the decisions (e.g., through the associated communication and framing of the decision) in order to ultimately achieve successful team decisions. Since the application of AI as decision support can also (in the future) be part of the resources that companies make available to their teams in order to simplify and support different steps of decision-making processes and to improve quality, e.g., by reducing errors and biases, data on the quality of decision-making processes using AI systems was also collected. The exploratory study on AI use in the context of team decision-making provides initial indications that this kind of decision support significantly impacts the quality of a decision-making process and that this influence correlates strongly with trust in the AI. This finding is unaffected by whether or not experience has already been gained with an AI as part of a decision-making process. However, when assessing the constructs themselves, it becomes evident that actual AI deployment is rated more positively than merely imagining it. This leads to the conclusion that firsthand experience with AI or trials and tests with such systems, thus user-centered introduction processes, could encourage future adoption and foster trust among employees rather than relying solely on theoretical knowledge about AI characteristics and advantages and thus make the potential of AI to improve the quality of decision-making processes more accessible.

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Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request via OSF.

Declarations

Competing Interests The authors declare no competing interests.

Ethical Approval The study was conducted in full compliance with the European Code of Ethics in Social Science and Humanities.

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