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The Impact of Business Intelligence and Analytics Usage on Decision-Making Quality: The Moderating Role of User Training

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BUSINESS
SCHOOL

Department of Accounting

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Dedication and Acknowledgement

Completing this thesis has been a long and challenging journey, and I am grateful to those who stood by me throughout the process.

I would like to thank **Professor Ana Isabel Dias Lopes** for her guidance during the final stage of this work. Her support and constructive feedback were essential in bringing the thesis to completion. I also acknowledge **Professor Mathilde Verschaeve**, who accompanied me for most of the writing process.

My deepest gratitude goes to my **parents**, who have supported me throughout my entire education. Their encouragement made this journey possible. I owe special thanks to my **mother**, whose sacrifices and dedication laid the foundation for all of my academic opportunities.

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This work is dedicated to all of you.

Resumo

Este estudo analisa a relação entre a utilização de sistemas de Business Intelligence and Analytics (BI&A) e a qualidade da tomada de decisão (DMQ) na contabilidade de gestão, bem como o potencial papel moderador da formação dos utilizadores finais. Com base em dados de inquérito a especialistas em contabilidade de gestão e profissionais relacionados, a utilização de BI&A é avaliada em quatro dimensões (finalidade, âmbito, tempo e natureza da utilização), enquanto a DMQ é medida em termos de eficácia e eficiência. A formação é analisada através da qualidade, normalização, intensidade e assiduidade. As análises de regressão demonstram que a utilização de BI&A tem um impacto positivo significativo na qualidade da tomada de decisão. Em particular, a qualidade da decisão revela-se superior quando os sistemas de BI&A são aplicados de forma ampla a múltiplas finalidades, em vez de estarem limitados a uma única aplicação. Em contrapartida, o estudo não encontra evidência robusta de que a formação modere a relação entre BI&A e DMQ. Isto sugere que a eficácia da formação poderá depender de fatores contextuais ou organizacionais adicionais não contemplados no presente estudo. Consequentemente, investigações futuras deverão explorar que tipos de desenho de formação, competências dos utilizadores ou ambientes organizacionais permitem que a formação complemente de forma mais eficaz a utilização de BI&A na melhoria da qualidade da decisão.

Palavras-chave

Business Intelligence and Analytics (BI&A); Qualidade da Tomada de Decisão; Formação de Utilizadores Finais; Contabilidade de Gestão; Análise de Moderação

Classificação JEL

M41 – Accounting

M15 – IT Management

Abstract

This study examines the relationship between the use of Business Intelligence and Analytics (BI&A) systems and decision-making quality (DMQ) in management accounting, as well as the potential moderating role of end-user training. Drawing on survey data from management accountants and related professionals, BI&A usage is assessed across four dimensions (purpose, scope, time, and nature of use), while DMQ is evaluated in terms of effectiveness and efficiency. Training is measured through quality, standardization, intensity, and attendance. Regression analyses demonstrate that BI&A usage has a significant positive impact on decision-making quality. In particular, decision quality is higher when BI&A systems are applied broadly across multiple purposes, rather than being restricted to a single application. By contrast, the study does not find strong evidence that training moderates the BI&A–DMQ relationship. This suggests that the effectiveness of training may depend on additional contextual or organizational factors not captured in the present study. Consequently, future research should explore which training designs, user competencies, or organizational environments enable training to more effectively complement BI&A usage in enhancing decision quality.

Keywords

Business Intelligence and Analytics (BI&A); Decision-Making Quality; End-User Training; Management Accounting; Moderation Analysis

JEL Classification

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1 Introduction

1.1 Background and Relevance

Industry reports consistently highlight BI&A as a top corporate investment priority. Surveys show that a majority of organizations adopt analytics tools with the explicit goal of improving managerial decision making (Strategy One, 2025). At the same time, many firms acknowledge difficulties in realizing the expected benefits. (Foster, 2024) notes that while most companies recognize the potential of BI&A, they struggle to embed insights into decision processes. Singla et al. (2025) similarly reports that massive investments in analytics and AI have not always translated into improved outcomes. These observations illustrate the practical importance of understanding under which conditions BI&A delivers value for decision making.

The rapid digitalization of business has simultaneously transformed the role of data in managerial decision making. Organizations increasingly rely on BI&A systems to process large volumes of structured and unstructured information to improve the timeliness and quality of decisions. In management accounting, BI&A is particularly relevant because accountants are no longer limited to reporting historical performance but are expected to support managers with forward-looking insights, scenario analyses, and strategic guidance (Franke & Hiebl, 2023).

At the same time, the growing complexity of business environments creates pressure for more reliable and transparent decision processes. BI&A systems promise to address this challenge by providing descriptive, predictive, and prescriptive capabilities that enhance managerial foresight and reduce uncertainty (Appelbaum, Kogan, Vasarhelyi, & Yan, 2017). From a practical perspective, organizations want to ensure that these costly investments deliver tangible improvements in decision making, while from an academic standpoint, researchers seek to understand under what conditions such benefits actually materialize.

For management accounting research, this context raises important questions. Decision-making quality is a core concern of the field, yet prior studies suggest that BI&A adoption does not automatically translate into better outcomes. Mixed empirical evidence indicates that the value of BI&A depends not only on the technology itself but also on how it is used and embedded into organizational processes (Rikhardsson & Yigitbasioglu, 2018). In this sense, management accountants are at the forefront of a broader shift: leveraging BI&A to move from a technical reporting role to that of a strategic partner in data-driven decision making.

1.2 Research Gap

Although Business Intelligence and Analytics (BI&A) have become central to management accounting practice, existing research provides mixed evidence on whether these systems consistently improve decision-making outcomes. Much of the prior literature has focused on adoption, system success, or firm-level performance effects, while the impact on decision-making quality in management accounting remains less developed (Rikhardsson & Yigitbasioglu, 2018; Appelbaum et al., 2017). In particular, studies often treat "use" as a broad construct and do not distinguish between decision-making effectiveness (validity, justification, accuracy) and efficiency (speed, resource use). This distinction is important, as BI&A may strengthen the informational substance of decisions without necessarily accelerating processes.

Another shortcoming in existing research is the limited attention to training as a contextual factor. Training has usually been modeled as an antecedent of system success or user satisfaction (Popovič et al., 2012; Medina et al., 2014), rather than as a moderator of the relationship between BI&A usage and decision outcomes. Recent reviews highlight that more work is needed to examine human and organizational conditions that shape BI&A effectiveness in management accounting (Franke & Hiebl, 2023). Yet little empirical research has tested whether training quality, intensity, or perceived relevance actually condition the benefits of BI&A usage for decision quality.

This study addresses these gaps by examining (1) how BI&A usage influences decision-making quality in management accounting, with a specific focus on effectiveness versus efficiency, and (2) whether different forms of end-user training moderate this relationship. In doing so, it responds to recent calls for research that integrates human and organizational dimensions into BI&A success models and that clarifies the conditions under which BI&A contributes to improved decision making.

1.3 Research Objective and Questions

The aim of this thesis is to investigate how the use of Business Intelligence and Analytics (BI&A) systems shapes the quality of managerial decision making in management accounting. While BI&A systems promise to improve decisions, prior research offers mixed evidence, and it remains unclear what aspects of system use actually translate into better decision outcomes.

A second objective is to examine the role of end-user training. Organizations often invest heavily in BI&A tools but underestimate the human side of adoption. Training is frequently assumed to be critical, yet little is known about whether and how it strengthens the link between BI&A usage and decision-making quality.

Against this background, the study is guided by the following research question:

How does the use of BI&A systems influence decision-making quality in management accounting, and what role does end-user training play in this relationship?

To address this question, two sub-questions are considered:

Which aspects of BI&A usage are most important for improving decision-making quality?

Does training enhance the benefits of BI&A usage for decision-making quality?

1.4 Approach and Contribution

To address the research question, this study applies a quantitative survey design. Data were collected from 73 professionals working in management accounting and related roles across different industries. BI&A usage was measured along multiple dimensions to capture how systems are applied in practice, while decision-making quality was assessed through perceptions of both effectiveness and efficiency. Training was considered in terms of quality, intensity, relevance, and standardization. The data were analyzed using regression-based moderation models (Hayes PROCESS), complemented by robustness checks with control variables and alternative specifications.

This approach contributes to academic research in several ways. First, it clarifies the relationship between BI&A usage and decision-making quality by distinguishing between decision effectiveness and efficiency. Second, it advances the understanding of BI&A "use" by focusing on qualitative aspects of how systems are applied to decision tasks, rather than relying on simple measures of frequency or time of use. Third, it extends existing research by examining the role of training not merely as an antecedent to adoption but as a potential condition shaping decision outcomes.

From a practical perspective, the study provides guidance for organizations seeking to maximize returns on BI&A investments. The findings highlight that system value stems less from how often BI&A is used and more from how it is embedded in decision-critical processes. While training did not emerge as a robust moderator, descriptive evidence suggests it can still facilitate more effective use. These insights can help managers design BI&A initiatives that combine technical capabilities with human competencies, ensuring that accountants are equipped to translate data into actionable business insights.

2 Literature Review

2.1 BI&A in Management Accounting

The term Business Intelligence & Analytics (BI&A) encompasses techniques, technologies, and methods that support the collection, processing, analysis, and visualization of internal and external business data. Its purpose is to extract valuable, timely, accurate, and relevant information from large volumes of data, enabling data-driven decision making and providing a competitive advantage for the company (Popovič et al., 2012).

Over the past three decades, Business Intelligence and Analytics (BI&A) has undergone several waves of development. Early systems in the 1990s and early 2000s focused mainly on structured internal data through data warehouses, ETL routines, OLAP, and standardized reporting, a stage often labeled BI&A 1.0. From the mid-2000s onward, BI&A 2.0 expanded the scope to unstructured content such as social media and web logs, supported by techniques like text mining and web analytics. The most recent phase, BI&A 3.0, emphasizes real-time processing, mobile access, and integration with big data platforms, allowing for predictive modeling and artificial intelligence applications that enhance both operational and strategic decision making (Chen et al., 2012).

Recent research highlights that this evolution continues as BI&A converges with cloud computing, big data, and AI, enabling management accountants to work with increasingly complex data streams in real time. These capabilities strengthen forecasting, budgeting, and scenario planning (Chatterjee et al., 2023; Appelbaum et al., 2017). Reviews further show that BI&A is now central to the digital transformation of management accounting, with growing emphasis on automation, sustainability reporting, and advanced analytical methods (Barreto et al., 2025). Yet evidence also suggests that technological progress alone does not guarantee improved outcomes; organizational factors such as a data-driven culture and strong user competencies are critical for translating BI&A adoption into managerial value (Hurbean, 2024).

In the field of management accounting, BI&A is transforming the profession by broadening the scope of traditional accounting tasks. BI&A systems support management accountants in analyzing data outputs, contextualizing insights within strategic frameworks, and informing decision-making processes. The integration of BI&A into their work allows management accountants to move beyond traditional roles in record-keeping and compliance, positioning them as key contributors to organizational strategy. (Rikhardsson & Yigitbasioglu, 2018)

Business Analytics (BA) supports management accounting by providing differentiated insights depending on the analytical orientation applied: descriptive, predictive and prescriptive. Descriptive analytics is focusing on summarizing past events through dashboards, KPIs, and ratio analyses. It allows accountants to benchmark historical performance and monitor anomalies, but its retrospective nature limits its value for proactive decision making (Appelbaum et al., 2017).

Predictive analytics advances this perspective by applying statistical models and machine learning to anticipate future outcomes. In management accounting, predictive approaches enhance planning accuracy, such as improving demand forecasts or identifying liquidity risks. Appelbaum et al. (2017) highlight applications in cash flow forecasting, while Duan, Cao, and Edwards (2020) show how predictive models strengthen environmental scanning and innovation capabilities. Cases such as Capital One's use of predictive testing to anticipate customer behavior illustrate how forward-looking analytics generate competitive advantage (Nielsen, 2018).

Prescriptive analytics extends beyond forecasting by recommending optimal actions, often through optimization or simulation models. Appelbaum et al. (2017) provide the example of manufacturing firms applying prescriptive optimization to vendor selection, reducing costs while increasing revenues. Prescriptive methods can also refine strategies dynamically, for instance by re-running optimization models as new data becomes available. While identified as the most ambitious stage, prescriptive analytics is still rarely applied in management accounting practice (Nielsen, 2018).

These distinctions illustrate an evolution from retrospective reporting to proactive and strategic decision support. Davenport (2013) describes this broader transition as "Analytics 3.0," where descriptive, predictive, and prescriptive methods converge into embedded, organization-wide capabilities. For management accountants, engaging with this full spectrum of analytics is central to shifting from traditional reporting roles toward becoming strategic partners in decision making.

Research on BI&A in management accounting has gradually shifted from adoption questions toward its practical implications for planning and control. Early studies emphasized the organizational and technological conditions needed for successful implementation by stressing the alignment of BI&A initiatives with corporate strategy and the availability of suitable infrastructure and expertise (Rikhardsson & Yigitbasioglu, 2018). More recent work points to the growing role of big data as well as real-time analytics, cloud platforms, and machine learning. It sheds light on their potential to enhance forecasting, budgeting, and performance measurement in accounting contexts (Bhimani & Willcocks, 2014; Warren et al., 2015)

As BI&A applications have matured, research attention has moved from questions of adoption to their influence on management control and performance evaluation. Empirical studies show that advanced analytics can strengthen cost management, strategic planning, and the ongoing monitoring of operational and financial outcomes (Elbashir et al., 2008; Vukšić et al., 2013). At the same time, scholars emphasize that technical functionality alone is insufficient: the extent to which managers adopt and benefit from BI&A systems depends heavily on ease of use, adaptability, and perceived support for decision processes. Consequently, system design and user experience have emerged as decisive factors in determining BI&A success (Hou, 2012; Popovič et al., 2012).

2.2 BI&A-enabled Decision Making

Decision making is a core function of management accounting, linking analytical evidence to organizational strategy. Accountants provide information that supports planning, cost control, and resource allocation, all of which directly shape performance (Ghasemaghaei & Turel, 2021). Because decision environments are often complex and uncertain, reliable information has long been seen as essential for reducing ambiguity and aligning actions with strategic goals (Simon, 1977). With the rise of big data, this informational role has expanded: firms can act on more timely and fact-based analyses, though the benefits depend strongly on accountants' analytical skills, as data quality alone does not guarantee better outcomes (Franke & Hiebl, 2023).

Traditional reliance on standardized reports and manual analysis is increasingly insufficient in volatile, data-rich contexts. Organizations exposed to rapid market change or regulatory pressures require more agile decision support. BI&A tools address this need by improving forecasting accuracy, strengthening risk assessment, and enhancing resource allocation. Their value lies in processing large volumes of diverse financial and operational data quickly and effectively (Elbashir et al., 2008; Appelbaum et al., 2017; Wieder & Ossimitz, 2015).

Recent applications demonstrate that BI&A can transform accountants' role from retrospective reporting to forward-looking analysis. Real-time monitoring of key indicators allows early detection of trends or irregularities, supporting proactive rather than reactive responses (Rikhardsson & Yigitbasioglu, 2018). Predictive methods extend this capability by enabling scenario exploration and forecasting of market or revenue shifts, while prescriptive approaches suggest optimized strategies in areas such as pricing or resource allocation (Thanasas & Kampiotis, 2024; Appelbaum et al., 2017). These features enhance decision-making quality by improving the informational foundation of choices and accelerating responses to dynamic conditions.

Decision-making quality (DMQ) is typically described through two dimensions: effectiveness and efficiency. Effectiveness reflects the accuracy and relevance of decisions in achieving strategic and operational objectives, while efficiency refers to the speed and resource use of the process (Fourné, Guessow, Margolin, & Schäffer, 2023; Shamim, Zeng, Shariq, & Khan, 2019). In practice, the two are intertwined—timely insights improve efficiency, while reliable data strengthen effectiveness (Ghasemaghaei, 2019).

BI&A systems contribute to both aspects. They improve data accuracy and completeness, ensuring a stronger informational basis for decisions, and they streamline the decision process by reducing delays in data access and analysis (Wieder & Ossimitz, 2015). For example, visualization functions in BI tools have been shown to increase accuracy by presenting information in clearer, more actionable ways (Abu-AlSondos, 2023).

However, BI&A's impact on decision quality is not determined by technology alone. System and data quality, integration across processes, and usability strongly affect whether outputs are trusted and applied (Popovič et al., 2012). Equally, user expertise and satisfaction are decisive: accountants with strong analytical skills are better equipped to interpret system outputs and apply them effectively (Franke & Hiebl, 2023), while satisfaction fosters greater integration into routine decision processes (Hou, 2012; Medina et al., 2014). Organizational factors also matter. A supportive culture, adequate resources, and IT infrastructure encourage the effective use of BI&A, whereas usability issues or excessive complexity may limit adoption (Işık et al., 2013; Deng & Chi, 2012).

Despite this evidence, little research has addressed whether structured training helps accountants translate BI&A outputs into higher-quality decisions. Studies in related fields show that training enhances self-efficacy, knowledge acquisition, and system use (Bedard et al., 2003; Medina et al., 2014), but BI&A research has largely concentrated on system characteristics and user competence. More attention is needed to assess whether training can strengthen both the technical confidence and decision-making capabilities of accountants, helping them fully exploit the potential of BI&A in practice.

2.3 User Training in the Context of MA and BI&A Utilization

Training refers to activities that build the knowledge and skills needed to perform tasks effectively (Goldstein & Ford, 2002). In technology-driven environments, user training is particularly important because it prepares individuals to interact with complex systems in ways that go beyond basic instruction. Effective training not only develops technical proficiency but also strengthens users' confidence in applying new tools, which in turn supports engagement and long-term adoption (Compeau & Higgins, 1995; Bedard et al., 2003). In the BI&A context, this means that users must combine technical know-how with interpretive skills to translate analytical outputs into meaningful insights (Appelbaum et al., 2017; Deng & Chi, 2012; Popovič et al., 2012). Without this blend, even advanced systems may fail to improve decision quality (Wieder & Ossimitz, 2015).

For management accountants, the importance of training has increased with the shift from traditional reporting tasks toward data-driven analysis. Earlier training emphasized compliance, financial reporting, and cost control (Johnson & Kaplan, 1987). Today, the profession also demands competence in data analytics, scenario modeling, and performance measurement (Bhimani & Willcocks, 2014; Cokins, 2013). This expansion reflects the broader strategic role of management accounting, where expertise in areas such as risk management and sustainability reporting is now expected (Bhimani, 2021; Pedroso & Gomes, 2023).

Several theoretical perspectives explain why training matters in BI&A adoption. From a control systems perspective, training can reinforce organizational objectives by shaping how employees use information (Simons, 1995). The Technology Acceptance Model (Davis, 1989) suggests that well-designed training increases perceptions of ease of use and usefulness, thereby encouraging integration of BI&A into daily work (Bedard et al., 2003). The Resource-Based View further positions training as a strategic asset that enhances analytical capabilities and strengthens competitive advantage (Barney, 1991).

Despite its potential, training has received limited attention in BI&A research. Evidence shows that it can raise users' self-efficacy and improve acceptance of accounting information systems (Medina et al., 2014; Bedard et al., 2003). Yet most BI&A studies still emphasize technical factors such as system quality and usability (Popovič et al., 2012; Işık et al., 2013), leaving gaps in understanding how training shapes the effective use of BI&A for decision quality. Addressing this gap is crucial if management accountants are to realize the full benefits of analytics in practice.

3 Conceptual Model and Hypothesis Development

3.1 Objective and Research Question

Building on the theoretical considerations discussed in Chapter 2, this thesis seeks to empirically examine how the use of Business Intelligence & Analytics (BI&A) systems influences decision-making quality (DMQ) in management accounting, and what role end-user training plays in this relationship.

The objective of this study is therefore twofold. First, it investigates the relationship between BI&A usage and decision-making quality, distinguishing between decision-making effectiveness and efficiency. Second, it assesses whether training functions as a factor that strengthens this relationship.

Accordingly, the central research questions are:

RQ1: How does the use of BI&A systems affect decision-making quality in management accounting?

RQ2: What role does end-user training play in shaping the relationship between BI&A usage and decision-making quality?

3.2 BI&A Usage and Decision-Making Quality

Simon's (1977) decision-making framework emphasizes that decision-makers operate under bounded rationality and depend on available information to reduce uncertainty and make effective choices. In this context, BI&A systems enhance decision making by extending users' cognitive capacity through structured, data-driven insights. Prior research shows that system and information quality improve analytical decision making and thereby increase decision quality (Popovič et al., 2012). Accordingly, BI&A usage is expected to positively influence the decision-making quality of management accountants, whose individual judgments collectively shape organizational outcomes.

BI&A enhances decision-making quality by equipping employees with tools to process large volumes of complex data. By providing structured analyses that reveal trends, anticipate risks, and recommend courses of action, BI&A reduces uncertainty and improves both the content (e.g., accuracy, completeness) and process (e.g., timeliness, confidence) of decisions (Appelbaum et al., 2017). Accordingly, greater BI&A usage is expected to lead to higher-quality decisions among management accountants.

The Technology Acceptance Model (TAM) emphasizes that user adoption depends on perceptions of usefulness and ease of use rather than technical features alone (Davis, 1989). Applied to BI&A, if management accountants perceive the tools as intuitive and valuable, they are more likely to integrate them into their analytical tasks. Empirical evidence shows that positive perceptions of big data analytics increase confidence in decision making and improve decision quality (Ghasemaghaei & Turel, 2021).

Similarly, the Resource-Based View (RBV) suggests that competitive advantage arises from valuable organizational resources, including technological assets as well as human capital (Barney, 1991). Applied to BI&A, the systems themselves are important resources, but their contribution to decision quality depends on the analytical skills and competencies of users. Evidence shows that limitations in user expertise, such as insufficient data literacy, can reduce BI&A effectiveness and lead to variability in decision outcomes (Deng & Chi, 2012). This perspective highlights the need for training and skill development to ensure that management accountants can fully exploit BI&A as a strategic resource for decision making.

However, the extent to which BI&A improves decision making varies depending on multiple factors. Some users encounter challenges in interpreting complex system outputs or experience knowledge gaps that undermine decision effectiveness (Deng & Chi, 2012). In addition, weaknesses in system design and usability have been identified as barriers to adoption, particularly for users with limited technical expertise (Popovič et al., 2012; Işık et al., 2013). These challenges suggest that while BI&A has the potential to improve DMQ, its actual impact depends on how effectively users can navigate, interpret, and apply system-generated insights.

Based on these theoretical foundations, the following hypothesis is proposed:

Hypothesis 1 (H1): There is a positive association between Business Intelligence and Analytics (BI&A) usage and decision-making quality (DMQ).

3.3 The Moderating Role of User Training

The relationship between BI&A usage and decision-making quality (DMQ) is not determined by technology alone but also by the user's ability to interpret and apply system outputs. Training is therefore expected to moderate this relationship by equipping users with the knowledge and confidence needed to leverage BI&A effectively. Evidence shows that training interventions increase user competence and self-efficacy in technology adoption (Bedard et al., 2003) and that BI&A benefits depend on users' analytical skills and contextual understanding (Appelbaum et al., 2017). At the same time, research highlights that technical system quality alone does not guarantee decision improvements (Popovič et al., 2012; Hou, 2012) and that knowledge gaps often persist after adoption (Deng & Chi, 2012). Together, these findings suggest that training can strengthen the link between BI&A usage and DMQ by enabling management accountants to translate system outputs into higher-quality decisions.

The importance of training in maximizing BI&A effectiveness has been reinforced in enterprise-level studies, which highlight that simply having access to BI&A tools is insufficient unless users possess the skills to interpret and apply analytical insights effectively (Al-Okaily et al., 2023). Their findings suggest that training quality, alongside data and service quality, is a key determinant of BI&A system success, further underscoring that BI&A's impact on decision making is not solely technology-driven but also dependent on human competencies.

The Technology Acceptance Model (TAM) emphasizes that user perceptions of usefulness and ease of use are central determinants of system adoption (Davis, 1989). In management accounting, where tasks such as forecasting and scenario analysis involve complexity and uncertainty, these perceptions are critical for encouraging effective BI&A use. Training strengthens such perceptions by reducing cognitive barriers and enhancing self-efficacy—the belief in one's ability to use BI&A successfully (Compeau & Higgins, 1995). Recent studies also show that user-related perceptions and behaviors significantly influence whether analytics use translates into improved decision quality, underscoring the importance of training in shaping these perceptions (Ghasemaghaei & Turel, 2021).

RBV views human capital as a strategic resource; in BI&A contexts, training develops the analytical and technological competencies that make that resource valuable (Barney, 1991). In management accounting, such competencies enable accountants to interpret BI&A outputs and convert them into actionable insights, which has been linked empirically to higher decision quality when accountants possess stronger analytics skills (Franke & Hiebl, 2023). At the same time, BI&A outcomes depend on more than the technology itself: information content quality and an analytical decision-making culture shape how much information is actually used in decisions (Popovič et al., 2012). Persistent user knowledge gaps and data/workflow issues can constrain benefits after adoption, underscoring the role for systematic, formal training to close competency gaps (Deng & Chi, 2012).

Despite strong arguments for training as a moderator, some studies emphasize that its effectiveness is constrained by contextual factors. For instance, research shows that BI&A outcomes depend heavily on system and information quality as well as usability, meaning that even well-trained users may struggle if system design is overly complex or data quality is inadequate (Popovič et al., 2012). Similarly, the broader decision environment and organizational culture shape whether BI&A can be effectively applied in practice (Işık et al., 2013). These findings suggest that training alone may be insufficient; the benefits of BI&A also hinge on the technological and organizational context in which users operate.

Another important consideration is the variability in training effectiveness, which depends on program design (technical and task components), delivery, and user characteristics. Evidence shows that training which strengthens both technical (computer) and task-specific self-efficacy improves system perceptions and acceptance, whereas programs focused only on tools risk leaving users unable to embed outputs in the decision context (Bedard et al., 2003). Moreover, effects are heterogeneous: Bedard et al. find stronger gains for less-experienced users (preparers) but little change among senior reviewers—consistent with diminishing returns when baseline competence is high. At the same time, post-adoptive use issues differ by user type and phase and often arise from data, reporting, workflow, and access (role authorization) problems in addition to knowledge gaps, underscoring that training interacts with broader sociotechnical conditions (Deng & Chi, 2012/13).

Based on this discussion, the following hypothesis is proposed:

Hypothesis 2 (H2): User training moderates the relationship between BI&A usage and decision-making quality (DMQ) in management accounting, such that the relationship is more positive for BI&A users with higher levels of training.

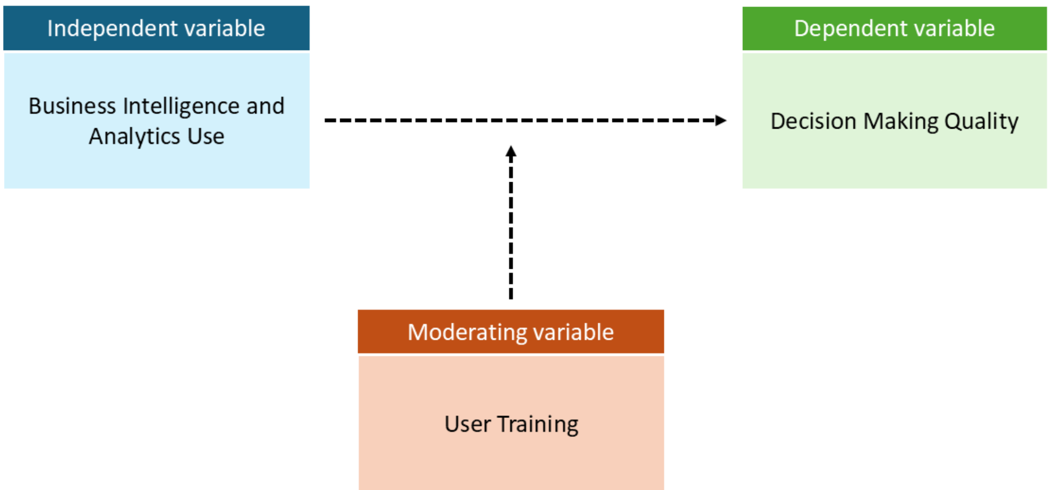
4 Methodology

4.1 Research Design

This study investigates the relationship between Business Intelligence & Analytics (BI&A) usage and decision-making quality (DMQ), as well as the moderating role of user training. The research model guiding this study is illustrated in Figure 1.

Figure 1

Conceptual model of the relationship between BI&A usage, decision-making quality, and the moderating role of end-user training.



To examine these relationships, a survey-based, cross-sectional research design is employed.[1] This design allows for statistical analysis of BI&A usage and decision-making quality across multiple industries. (Kazdin, 2003).

The target respondents of this study are professionals engaged in BI&A-supported decision making within organizations. These include management accountants, controllers, financial and business analysts, auditors, CFOs, CEOs, and other financial decision-makers. Their roles are directly connected to

[1] The full survey instrument used in this study can be provided upon request. Access will be granted under the condition of maintaining participant confidentiality.

the use of BI&A systems for managerial and strategic decisions, which ensures that the collected data reflects the perspectives of individuals actively involved in relevant processes.

This study employs a cross-sectional survey design, collecting data at a single point in time. Such designs are frequently used in BI&A adoption research and have proven effective in capturing user perceptions and current organizational practices (Ain et al., 2019; Duan et al., 2020; Popovič et al., 2012; Hou, 2012; Wieder & Ossimitz, 2015; Ghasemaghaei & Turel, 2021). While this approach does not account for potential long-term dynamics of training effects, it provides a robust snapshot of how BI&A usage and end-user training relate to decision-making quality in the present context.

This study includes a range of industries. By not restricting the study to a single sector, the research increases the generalizability of its findings, allowing for potential industry comparisons (see Section 4.2 for details on the sample composition).

Second, while several constructs of the survey rely on self-reported perceptions (e.g., decision quality, satisfaction with BI&A systems), others capture more objective behaviors, such as the frequency of BI&A tool use, the types of analytics applied (e.g., descriptive, predictive, prescriptive), and hours of formal training. Including both perceptual and behavioral measures strengthens the study's validity by reducing the risk of common method bias (Podsakoff, MacKenzie, & Podsakoff, 2003), and providing a more comprehensive view of BI&A usage and its effects.

To minimize response bias, the survey is administered anonymously. This approach allows participants to provide honest insights without the pressure of social desirability influencing their responses. These precautions enhance the credibility and robustness of the study's findings, ensuring that the results accurately reflect the relationship between BI&A usage and decision-making quality (Podsakoff, MacKenzie, & Podsakoff, 2003).

4.2 Sample Selection and Data Collection

The participants in the study were mainly reached through calls for participation on LinkedIn, professional forums, and industry-specific online networks. Due to the limitations of access, time, and feasibility typical of master's-level research, the final sampling relied on non-probabilistic convenience sampling. This approach allowed rapid and targeted distribution to professionals with relevant BI&A experience across a range of roles and geographies. Data collection took place between May 28, 2025, and July 27, 2025.

A total of 100 responses were initially collected. Following a rigorous data quality screening process, 73 valid responses were retained for analysis. The screening process involved several criteria to ensure data integrity and participant attentiveness. First, a completion time filter was applied to exclude responses completed in under 4 minutes filtering rushed responses. Second, only entries with 100% completion progress and marked as "Finished = True" within the Qualtrics platform were retained. Third, responses displaying patterns of inattention (e.g., straight lining) were excluded from the final dataset.

The final sample consisted of 75.3% male and 24.7% female participants. Most respondents (52.1%) held a master's degree, followed by bachelor's degree holders (30.1%) (see Table 1). The largest job role group was controllers (52.1%), with smaller proportions of managers (12.3%), directors (11.0%), and analytics-related positions such as data analysts (6.8%).

The geographic distribution of respondents was concentrated in Europe. A large majority originated from Germany (n = 64; 87.7%), while smaller groups were based in the Netherlands (n = 2; 2.7%), Portugal (n = 2; 2.7%), and Belgium (n = 1; 1.4%). In addition, four responses were recorded from outside Europe or with invalid location data, including cases located in Bangladesh, Turkey, and Saudi Arabia, as well as one missing value. Given this distribution, the results are primarily reflective of the German context, with limited representation from other European countries.

Regarding experience, over half (46.6%) had 1–5 years of BI&A usage, while 23.3% reported 6–10 years. Age distribution was relatively balanced, with 28.8% under 30, 27.4% aged 30–39, 17.8% aged 40–49, and 26.0% aged 50 or older.

Participants were drawn from a range of industries, most prominently logistics (27.4%) and finance (24.7%), followed by technology (11.0%), manufacturing (9.6%), healthcare (6.8%), and several smaller sectors. This diversity strengthens the generalizability of the findings and enables potential industry-level comparisons.

Although the final sample size was below the theoretical ideal, it is consistent with recommendations for exploratory quantitative studies and exceeds minimum thresholds for regression-based modeling (Green, 1991; Hair et al., 2019). The findings should nevertheless be interpreted with caution and seen as indicative rather than conclusive.

Table 1
Demographic Characteristics of Respondents (N = 73)

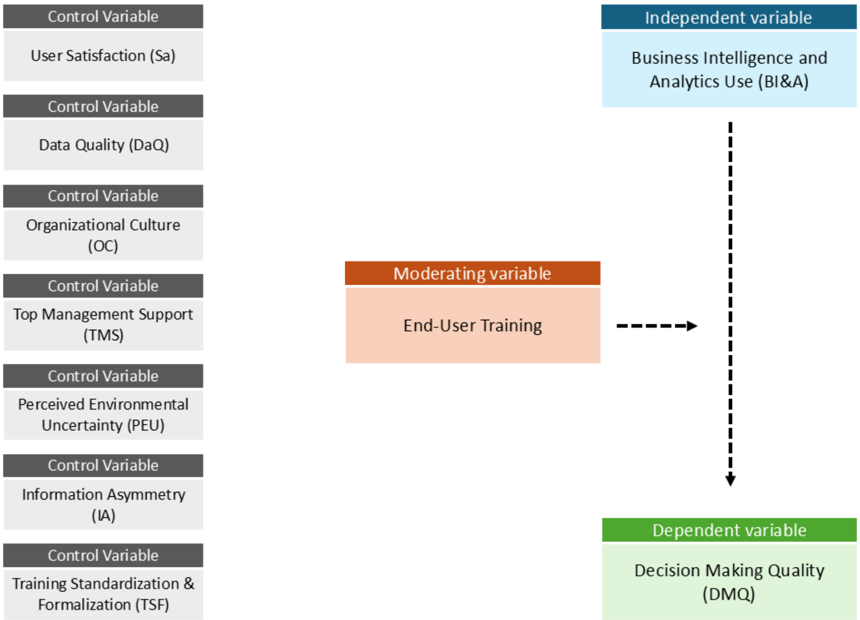
Variable	Category	n	%
Gender	Male	55	75.3
	Female	18	24.7
Age Group	Under 30	21	28.8
	30–39	20	27.4
	40–49	13	17.8
	50+	19	26.0
Level of Education	Master’s degree	38	52.1
	Bachelor’s degree	22	30.1
	PhD/Doctorate	7	9.6
	High School degree	6	8.2
Job Role Title	Controller	38	52.1
	Manager	9	12.3
	Director	8	11.0
	Data Analyst	5	6.8
	Other	13	17.8
BI&A Experience	< 1 year	12	16.4
	1–5 years	34	46.6
	6–10 years	17	23.3
	11–15 years	2	2.7
	> 15 years	8	11.0
Industry	Logistics	20	27.4
	Finance	18	24.7
	Technology	8	11.0
	Manufacturing	7	9.6
	Healthcare	5	6.8
	Retail	2	2.7
	Public sector	2	2.7
	Other	11	15.1

4.3 Measurement of Variables

This section outlines how the independent variable (BI&A usage), dependent variable (DMQ), moderating variable (user training), as well as the control variables are operationalized (**Figure 2Figure 2**).

Figure 2

Conceptual model of the relationship between BI&A usage and decision-making quality, moderated by end-user training, with control variables



The measurement choices draw on prior research in BI&A and decision-making studies to ensure validity and comparability. To assess the constructs' validity and reliability, exploratory factor analysis and reliability tests were conducted in SPSS. Factor loadings, indicator reliability, composite reliability (CR), Cronbach's α, and average variance extracted (AVE) were calculated and evaluated against recommended thresholds (e.g., factor loadings > .70, CR > .70, α > .70, AVE > .50; Hair et al., 2019).

4.3.1 Business Intelligence and Analytics (BI&A) Usage

To capture BI&A usage in decision making, this variable is operationalized as a second-order construct composed of four distinct first-order dimensions: Purpose of Use, Scope of Use, Time of Use, and Nature of Use. Each dimension reflects a different aspect of how users engage with BI&A systems in practice. All items were measured using a 5-point Likert scale ranging from 1 = "Strongly Disagree" to 5 = "Strongly Agree."

The dimension Purpose of Use (PU) captures the cognitive and problem-solving motives behind using BI&A, specifically how individuals employ the system to acquire insights, identify causes, or explore alternatives in their decision-making processes. The construct was measured with four items adapted from Candra and Nainggolan (2022). Reliability and validity tests indicated strong internal consistency (α = 0.818; CR = 0.884; AVE = 0.656), confirming that the items consistently measure the construct and that a substantial share of variance is explained (s. Table 2)

Scope of Use (SOU) refers to the range and sophistication of analytics methods applied, including descriptive, predictive, and prescriptive techniques. The construct was measured with three items adapted from Duan et al. (2020). Reliability analysis showed an acceptable Cronbach's alpha (α = 0.690), satisfactory composite reliability (CR = 0.821), and an AVE above the recommended threshold (0.618). The relatively lower alpha is attributable to the weaker correlation of the "descriptive analytics" item (SOU1) with the other two items, which is theoretically plausible given differing adoption levels across analytics types.

Time of Use (TOU) reflects the temporal intensity of BI&A engagement and captures how frequently and extensively us-ers interact with the system in their daily work. Three items adapted from Venkatesh et al. (2008) showed excellent reliability (α = 0.892; CR = 0.934; AVE = 0.824).

Nature of Use (NOU) addresses the technical and integrative complexity of BI&A usage, such as advanced analysis, visualization, and information synthesis across systems and devices. The items were adapted from Srinivasan and Swink (2017), who conceptualized analytics usage in terms of its integrative deployment across organizational processes. Although one item (NOU5) exhibited a weaker loading, it was retained to preserve the conceptual breadth of the construct, as it captures the practical deployment of BI&A insights across devices. The construct overall demonstrated acceptable reliability and validity (α = .744; CR = .829; AVE = .503).

Table 2
Factor Loadings, Indicator Reliability, Composite Reliability, Cronbach's Alpha, and AVE for BI&A Usage Constructs

Construct	Item	Loading	Indicator Reliability	Composite Reliability	Cronbach's Alpha	AVE
PU	PU1	0.85	0.723	0.884	0.818	0.656
	PU2	0.846	0.716			
	PU3	0.815	0.664			
	PU4	0.723	0.523			
SOU	SOU1	0.912	0.832	0.821	0.690	0.618
	SOU2	0.879	0.773			
	SOU3	0.501	0.251			
ToU	ToU1	0.951	0.904	0.934	0.892	0.824
	ToU2	0.899	0.808			

	ToU3	0.872	0.760			
NOU	NOU1	0.805	0.648	0.829	0.744	0.503
	NOU2	0.798	0.637			
	NOU3	0.748	0.560			
	NOU4	0.704	0.496			
	NOU5	0.419	0.176			

4.3.2 Decision-Making Quality

Managerial decision-making quality was operationalized as a second-order construct, comprising two dimensions: decision-making *effectiveness* and decision-making *efficiency*. These dimensions reflect both the outcome orientation, and the process efficiency of the decisions made. All items were measured on a 5-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree.

The first dimension, Decision-Making Effectiveness (DEFS), reflects the extent to which decisions are based on sound logic, aligned with organizational strategy, financially grounded, and effective in supporting business objectives. Six items were adapted from Fourné et al. (2023), who assessed decision quality in the context of controller–manager collaboration and cognitive flexibility. The items were originally part of a broader assessment of strategic decision making and were slightly reworded for clarity and standardization. The scale demonstrated good internal consistency (Cronbach's α = 0.804), with factor loadings ranging from 0.531 to 0.903 and an Average Variance Extracted (AVE) of 0.524, indicating adequate convergent validity (s. Table 3). Composite reliability was 0.863.

The second dimension, Decision-Making Efficiency (DEFY), reflects the extent to which decisions are made while minimizing time and resources. Four items were adapted from Shamim et al. (2019), originally developed in the context of big data decision-making capability. One item (DEFY2) was reverse coded prior to analysis (DEFY2_R). The initial four-item scale showed low internal consistency (Cronbach's α = 0.463) and an AVE of 0.415, indicating weak alignment between items. This was especially evident in the case of DEFY2_R (s. Table 3), which showed a very low factor loading (0.197) and minimal indicator reliability (0.039), justifying its removal. Notably, this item had also been excluded in the original study by Shamim et al. (2019).

After dropping DEFY2_R, the adjusted three-item scale (DEFY_adj) demonstrated improved reliability (Cronbach's α = 0.580), with factor loadings between 0.688 and 0.767, composite reliability of 0.784, and AVE of 0.548. The remaining items correlated positively and significantly with each other, supporting their internal coherence and suitability for measuring decision-making efficiency.

Table 3
Factor Loadings, Indicator Reliability, Composite Reliability, Cronbach's Alpha, and AVE for Decision-Making Quality Constructs

Construct	Item	Loading	Indicator Reliability	Composite Reliability	Cronbach's Alpha	AVE
DEFS	DEFS1	0.574	0.329	0.863	0.804	0.524
	DEFS2	0.556	0.309			
	DEFS3	0.903	0.815			
	DEFS4	0.848	0.719			
	DEFS5	0.531	0.282			
	DEFS6	0.830	0.689			
DEFY	DEFY1	0.729	0.531	0.711	0.463	0.415
	DEFY2_R	0.197	0.039			
	DEFY3	0.707	0.500			
	DEFY4	0.767	0.588			
DEFY_adj	DEFY1	0.688	0.473	0.784	0.580	0.548
	DEFY3	0.764	0.584			
	DEFY4	0.767	0.588			

4.3.3 User Training

The moderating variable User Training captures the extent to which respondents have personally received, participated in, and benefited from BI&A-related training within their organizations. This construct is multidimensional but focuses on the individual user's training experience rather than purely structural or organizational aspects. This decision reflects the study's interest in the mechanisms by which training directly affects an individual's ability to use BI&A effectively for decision making. While organizational formalization of training is controlled for separately (see Section 4.3.5), the moderating construct captures personal exposure to, and perceived benefits of, training—factors shown to be decisive in shaping user competence and system success (Bedard et al., 2003; Medina et al., 2014). It therefore reflects the perceived quality, relevance, and intensity of training, as well as whether respondents have attended training sessions. Measurement draws on established training and personnel control literature, as well as adaptations from prior BI&A evaluation studies, to ensure theoretical alignment and comparability. Except for Training Attendance (binary: yes/no) and Training Intensity (ordinal scale), all items were measured using a 5-point Likert scale ranging from 1 = "Strongly Disagree" to 5 = "Strongly Agree."

The first dimension, Training Attendance (TA), is a binary indicator capturing whether respondents have personally participated in BI&A training sessions. This self-developed measure enables differentiation between trained and untrained respondents, supporting subgroup analyses. A conditional branching mechanism ensured that respondents who answered “No” to Training Attendance skipped all subsequent questions relating to Training Intensity, Training Quality, and Perceived Practical Relevance. Frequency statistics for Training Attendance are reported in the Results section.

The second dimension, Training Intensity (TI), measures the extent of training participation in terms of total hours completed within the past 12 months (TI1) and frequency of attendance (TI2). Both items are self-developed with categorical response formats, reducing recall burden while capturing meaningful variation in training exposure. Frequency distributions are presented in the Results section.

The third dimension, Training Quality (TQ), reflects participants’ evaluations of the adequacy, skill impact, and real-world applicability of BI&A training. Four items (TQ1–TQ4) were adapted from Al-Okaily et al. (2023), with wording refined to emphasize decision making in management accounting and confidence in BI&A tool usage. The scale showed good internal consistency (Cronbach’s $\alpha = 0.808$), acceptable composite reliability (CR = 0.880), and convergent validity (AVE = 0.647) (s. Table 4).

Finally, Perceived Practical Relevance (PPR) assesses the extent to which training content aligns with participants’ daily BI&A-related work tasks. Two items (PPR1, PPR2) were adapted from Liebermann and Hoffmann (2008), reframed to emphasize practical BI&A tool application. The two-item scale achieved acceptable internal consistency (Cronbach’s $\alpha = 0.763$), composite reliability (CR = 0.894), and convergent validity (AVE = 0.808), with a strong and significant inter-item correlation ($r = 0.655$, $p < .001$).

Table 4
Factor Loadings, Indicator Reliability, Composite Reliability, Cronbach’s Alpha, and AVE for Training Constructs

Construct	**Item**	**Loading**	**Indicator Reliability**	**Composite Reliability**	**Cronbach's Alpha**	**AVE**
TQ	TQ1	0.895	0.801	0.880	0.808	0.647
	TQ2	0.784	0.615			
	TQ3	0.773	0.598			
	TQ4	0.759	0.576			
PPR	PPR1	0.899	0.808	0.894	0.763	0.808
	PPR2	0.899	0.808			

Note. Two-item scale; inter-item correlation = 0.655 ($p < .001$)

4.3.4 Demographic and Organizational Characteristics

To account for potential differences in respondents’ backgrounds and organizational contexts, several demographic and organizational variables were collected as single-item indicators. Gender was recorded categorically (male, female, other/prefer not to say), and age was entered in years. Education level captured the highest completed degree (high school, bachelor's, master's, PhD). Job role was measured through a predefined list of common positions (e.g., CEO, CFO, director, manager, analyst, auditor, accountant, management accountant, controller, data analyst, business analyst, data scientist), with an "other" option available. Respondents also reported their years of experience in the current role and their BI&A experience using a categorical scale (< 1 year, 1–5 years, 6–10 years, 11–15 years, > 15 years). Company size was measured by number of employees (< 100, 100–499, 500–999, 1,000–4,999, 5,000–9,999, > 10,000). Finally, industry type was identified from a predefined list (finance, retail, manufacturing, logistics, healthcare, technology, public sector, other).

4.3.5 Contextual and System-Related Control Constructs

In addition to the demographic and organizational characteristics described, several multi-item constructs were measured as control variables. These constructs capture contextual and system-related factors that prior research has identified as potential confounders in the relationship between BI&A usage, decision-making quality, and user training. For instance, prior studies emphasize the role of user satisfaction (Hou, 2012), data quality (Al-Okaily et al., 2023), and top management support (Boerner, Wiener, & Guenther, 2024) in shaping BI&A-related outcomes. All items were measured using a five-point Likert scale (1 = Strongly disagree, 5 = Strongly agree), unless stated otherwise.

User Satisfaction (Sa) measures the extent to which BI&A systems meet users' informational needs in terms of content, accuracy, format, ease of use, and timeliness. The construct consists of 12 items adapted from Hou (2012), grouped into five dimensions: content (SaCo1–4), accuracy (SaAc1–2), format (SaFo1–2), ease of use (SaEoU1–2), and timeliness (SaTi1–2). Minor wording adjustments were made to ensure consistent references to BI&A systems. Reliability checks indicated acceptable internal consistency across most dimensions (see Annex Table A1 and Table A2).

Data Quality (DaQ) captures the perceived accuracy, correctness, consistency, and comprehensiveness of the data underlying BI&A solutions. Four items were adapted from Al-Okaily et al. (2023), with minimal changes to wording. Reliability and validity measures indicate a solid internal consistency and good convergent validity for this construct.

Organizational Culture (OC) reflects the extent to which an organization emphasizes data-driven values and practices in decision making and innovation. The construct was measured with five items adapted from Duan et al. (2020), which reflect the perceived importance of data for decision making (OC1, OC3, OC5) as well as openness to new ideas and innovation through data-based insights (OC2, OC4). Minor wording adjustments were made for clarity in the online survey format. Reliability analysis indicated high internal consistency across the items.

Top Management Support (TMS) assesses the degree to which top management promotes, supports, and prioritizes the use of analytics tools in the management control function. The construct contains three items adapted from Boerner et al. (2024), with minor rewording to fit the BI&A context and the respondent's perspective. The results suggest a high reliability level and strong item loadings.

Perceived Environmental Uncertainty (PEU) measures the extent to which the external environment of the organization is unpredictable and subject to change. It consists of five items adapted from Lewis and Harvey (2001), with minimal adjustments for consistency. Reliability analysis shows that the construct meets acceptable thresholds, although a few items contribute less strongly to the overall variance explained.

Information Asymmetry (IA) measures the extent to which respondents possess more or possess less information about their area of responsibility compared to their superior. Six items, adapted from Dunk (1993), were rated on a five-point comparative scale (1 = My superior has much more, 5 = I have much more), where the midpoint value of 3 represented perfect symmetry and deviations from 3 indicated greater asymmetry. For this study, responses were recoded into a three-point directional scale to facilitate interpretation and maintain consistency across items. Reliability statistics indicate a solid internal consistency and item performance for this construct.

Training Standardization & Formalization (TSF) measures the extent to which BI&A training is formally embedded in organizational processes (e.g., onboarding requirements, regular refreshers). Although initially considered part of the training moderator, it reflects an organizational-level factor and was therefore treated as a control variable, alongside factors such as organizational culture and top management support. The three-item scale (TSF1–TSF3), adapted from Donnelly et al. (2018), demonstrated excellent reliability and validity (Cronbach's $\alpha = 0.890$, CR = 0.933, AVE = 0.822).

4.4 Reliability & Validity

Reliability and validity of the measurement instruments were assessed using several established criteria. For all multi-item constructs, standardized loadings, indicator reliabilities, composite reliabilities, Cronbach's α, and average variance extracted (AVE) were reported in Section 4.3. Two-item constructs were additionally evaluated using Cronbach's α and inter-item correlations, which indicated satisfactory consistency. For the binary scale Training attendance and the ordinal scale Training intensity, descriptive frequency distributions were presented in Section 4.3.

To further assess construct validity, **discriminant validity** was examined using the Fornell–Larcker criterion, confirming that the square root of each construct's AVE exceeded its inter-construct correlations. In this study, all constructs met this condition, indicating that each construct is empirically distinct from the others (s. Table 5)

Table 5

Fornell–Larcker Criterion: Correlation Matrix with √AVE on the Diagonal

	PU	SOU	ToU	NOU	DEFS	DEFY	TSF	TQ	SaCo	SaAc	SaFo	SaEoU	SaTi	DaQ	OC	TMS	PEU	IA
PU	**.810**	.332	.501	.440	.436	.244	.166	.243	.256	.177	.269	.156	.282	.237	.152	.166	.149	−.048
SOU	.332	**.786**	.295	.437	.494	.154	.209	.417	.152	−.040	.306	.103	−.055	.051	−.057	−.153	.107	.007
ToU	.501	.295	**.909**	.677	.211	.269	.109	.248	.377	.223	.396	.259	.288	.313	.051	.065	.111	.012
NOU	.440	.437	.677	**.709**	.456	.229	.301	.448	.417	.171	.464	.332	.216	.334	.057	.078	.045	−.055
DEFS	.436	.494	.211	.456	**.724**	.301	.296	.399	.175	.214	.356	.229	.079	.166	.108	−.183	.064	.020
DEFY	.244	.154	.269	.229	.301	**.740**	.106	.387	.314	.231	.204	.151	.297	.236	−.022	−.088	−.055	.102
TSF	.166	.209	.109	.301	.296	.106	**.907**	.356	.297	.230	.225	.175	.100	.296	.311	.362	.337	.162
TQ	.243	.417	.248	.448	.399	.387	.356	**.804**	.322	.431	.557	.271	.176	.144	−.012	−.030	.076	−.217
SaCo	.256	.152	.377	.417	.175	.314	.297	.322	**.868**	.648	.664	.478	.565	.560	.248	.180	.164	−.094
SaAc	.177	−.040	.223	.171	.214	.231	.230	.431	.648	**.966**	.611	.460	.524	.698	.340	.204	.174	−.090
SaFo	.269	.306	.396	.464	.356	.204	.225	.557	.664	.611	**.836**	.556	.545	.494	.222	.129	.192	−.081
SaEoU	.156	.103	.259	.332	.229	.151	.175	.271	.478	.460	.556	**.949**	.416	.405	.358	.210	.130	−.054
SaTi	.282	−.055	.288	.216	.079	.297	.100	.176	.565	.524	.545	.416	**.864**	.548	.242	.282	.104	−.088
DaQ	.237	.051	.313	.334	.166	.236	.296	.144	.560	.698	.494	.405	.548	**.858**	.357	.307	.128	−.091
OC	.152	−.057	.051	.057	.108	−.022	.311	−.012	.248	.340	.222	.358	.242	.357	**.787**	.631	.465	−.096
TMS	.166	−.153	.065	.078	−.183	−.088	.362	−.030	.180	.204	.129	.210	.282	.307	.631	**.898**	.420	−.042
PEU	.149	.107	.111	.045	.064	−.055	.337	.076	.164	.174	.192	.130	.104	.128	.465	.420	**.733**	−.041
IA	−.048	.007	.012	−.055	.020	.102	.162	−.217	−.094	−.090	−.081	−.054	−.088	−.091	−.096	−.042	−.041	**.758**

Legend: PU = Purpose of Use; SOU = Scope of Use; ToU = Time of Use; NOU = Nature of Use; DEFS = Decision-Making Effectiveness; DEFY = Decision-Making Efficiency; TSF = Training Standardization & Formalization; TQ = Training Quality; SaCo = User Satisfaction – Content; SaAc = User Satisfaction – Accuracy; SaFo = User Satisfaction – Format; SaEoU = User Satisfaction – Ease of Use; SaTi = User Satisfaction – Timeliness; DaQ = Data Quality; OC = Organizational Culture; TMS = Top Management Support; PEU = Perceived Environmental Uncertainty; IA = Information Asymmetry.

Note. Diagonal elements are the square root of the Average Variance Extracted (√AVE). Off-diagonal entries are Pearson correlations between constructs (two-tailed). Discriminant validity is supported when each construct's √AVE (diagonal) exceeds its correlations with other constructs.

Common method bias was tested using Harman's single-factor test; the first factor explained 19.6% of the variance, well below the 50% threshold, suggesting that common method variance is unlikely to bias the results.

Construct adequacy was further evaluated with the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity (s. Table 6), both of which indicated that the data were suitable for factor analysis.

Table 6

Kaiser–Meyer–Olkin (KMO) and Bartlett's Test of Sphericity for All Constructs

Construct	**KMO**	**χ^2**	**df**	**p**
PU	.791	102.64	6	< .001
SOU	.534	58.07	3	< .001
ToU	.680	138.76	3	< .001
NOU	.750	86.44	10	< .001
DEFS	.715	196.42	15	< .001
DEFY_adj	.626	20.39	3	< .001
TSF	.671	137.85	3	< .001
TQ	.738	64.26	6	< .001
PPR†	-	20.85	1	< .001
SaCo	.813	177.32	6	< .001
SaAc†	-	97.87	1	< .001
SaFo†	-	12.11	1	< .001
SaEoU†	-	72.79	1	< .001
SaTi†	-	19.78	1	< .001
DaQ	.832	149.54	6	< .001
OC	.803	143.60	10	< .001
TMS	.734	114.02	3	< .001
EU	.778	97.78	10	< .001
IA	.817	188.27	15	< .001

Legend: PU = Purpose of Use; SOU = Scope of Use; ToU = Time of Use; NOU = Nature of Use; DEFS = Decision-Making Effectiveness; DEFY = Decision-Making Efficiency; TSF = Training Standardization & Formalization; TQ = Training Quality; SaCo = User Satisfaction – Content; SaAc = User Satisfaction – Accuracy; SaFo = User Satisfaction – Format; SaEoU = User Satisfaction – Ease of Use; SaTi = User Satisfaction – Timeliness; DaQ = Data Quality; OC = Organizational Culture; TMS = Top Management Support; PEU = Perceived Environmental Uncertainty; IA = Information Asymmetry.

Note. χ^2 = Chi-Square statistic for Bartlett's Test of Sphericity.
† For two-item constructs (PPR, SaAc, SaFo, SaEoU, SaTi)

Taken together, these results support the reliability and validity of the measures used in this study.

4.5 Ethical Considerations

This research was conducted in strict accordance with ethical guidelines established by Iscte – Instituto Universitário de Lisboa for studies involving human participants. Ethical integrity was maintained throughout the study in relation to informed consent, data protection, anonymity, and voluntary participation.

All participants were presented with an informed consent statement on the first page of the online survey. The statement clearly explained the study's purpose, the expected duration of participation, the types of questions asked, and the voluntary nature of participation. It was explicitly stated that participants could withdraw from the study at any time without providing a reason and without any penalty. Only participants who agreed to the terms by proceeding beyond the consent screen were included in the dataset.

To ensure anonymity, no personal identifiers—such as names, email addresses, IP addresses, or organizational affiliations—were collected. All responses were stored and analyzed in an aggregated format. The survey was administered via Qualtrics, a GDPR-compliant platform, and no personally identifiable data was exported or retained. Results are reported at the group level only, with no individual-level data traceable.

Data collected through the Qualtrics platform was stored on secure, encrypted servers. After data collection, the dataset was exported into SPSS (Version 29.0.2.0) for analysis. The working dataset was stored locally on a password-protected device accessible only to the researcher. No data was shared externally, and raw data will be permanently deleted after the thesis is submitted and defended, in line with Iscte's data retention policies.

This research posed minimal or no risk to participants. The questions focused solely on participants' professional use of BI&A tools and perceptions of organizational processes, with no sensitive or intrusive topics included. The study was designed to avoid psychological, legal, or social risks. All question wording was neutral and aligned with professional workplace contexts.

Prior to survey deployment, the study was formally reviewed and approved by the Ethics Council of Iscte – Instituto Universitário de Lisboa. The ethical clearance confirmed that the study met the institutional requirements for research involving human participants, including anonymity, informed consent, and minimal risk. Although the exact approval date was handled through the supervisor's correspondence with the board, formal authorization was received before data collection began.

The research adhered to high standards of ethical conduct, protecting participants' autonomy, privacy, and data. These safeguards ensure the validity, integrity, and social responsibility of the study's findings.

5 Results, findings

This chapter presents the empirical findings in a structured manner. First, descriptive statistics are reported, including central tendency, dispersion, distribution checks, correlations, and the distribution of training variables. Next, the hypotheses are tested using regression models. The analysis proceeds stepwise: (1) testing the direct relationship between BI&A usage and decision-making quality (H1) and (2) examining the moderating role of training (H2).

5.1 Descriptive statistics and correlations

Table 7 presents the descriptive statistics of the study variables, including central tendency, dispersion, and distribution checks.

For BI&A Usage, Purpose of Use (PU) showed the highest mean (M = 4.01) and a negative skew with high kurtosis (–1.28; 2.87), indicating responses clustered at the upper end of the scale. Scope of Use (SOU) (M = 3.51, SD = 0.94) and Nature of Use (NOU) (M = 3.48, SD = 0.86) were at moderate levels with moderate dispersion, suggesting uneven adoption of advanced techniques. Time of Use (TOU) had the lowest mean (M = 3.24, SD = 1.16), reflecting less frequent and more heterogeneous engagement across respondents.

For Decision-Making Quality, Effectiveness (DEFS) was consistently rated high (M = 4.11, SD = 0.59) with a relatively normal distribution, while Efficiency (DEFY_adj) was lower (M = 3.48, SD = 0.73), suggesting that BI&A is more strongly associated with decision quality than with timeliness or resource efficiency.

For Training, evaluations were generally positive where training was offered. Training Quality (TQ) (M = 3.72) showed a left-skewed, peaked distribution (–1.18; 1.82), reflecting favorable but clustered responses. Perceived Practical Relevance (PPR) (M = 3.47, SD = 0.98) was slightly lower.

Among Control Variables, Training Standardization & Formalization (TSF) (M = 2.62, SD = 1.25) showed both the lowest mean and high dispersion, highlighting strong variation across organizations in how systematically training is implemented. In addition, User Satisfaction (Sa) (M = 3.61) and Data Quality (DaQ) (M = 3.66) were moderately high, while Organizational Culture (OC) (M = 3.96) and Top Management Support (TMS) (M = 3.82) were evaluated positively but with some variation across contexts. Perceived Environmental Uncertainty (PEU) (M = 3.26) was moderate. Information Asymmetry (IA) (M = 2.08, SD = 0.56, on a 1–3 scale) indicated perceptions of relatively symmetric information access between managers and superiors, though variation across organizations was present.

Table 7
Central tendency and distribution checks of study variables

Variable	Construct	N	M	SD	Skewness	Kurtosis
BI&A Usage	POU	73	4.01	0.75	–1.28	2.87
	SOU	73	3.51	0.94	–0.35	–0.64
	TOU	73	3.24	1.16	0.01	–1.23
	NOU	73	3.48	0.86	–0.45	–0.33
Decision-Making Quality	DEFS	73	4.11	0.59	–0.96	1.14
	DEFY_adj	73	3.48	0.73	0.04	–0.16
Training	TQ	46	3.72	0.77	–1.18	1.82
	PPR	46	3.47	0.98	–0.48	–0.45
Control Variables	Sa	73	3.61	0.68	–0.63	0.94
	DQ	73	3.66	0.84	–0.52	0.31
	OC	73	3.96	0.70	–0.62	0.21
	TMS	73	3.82	0.87	–0.51	–0.27
	EU	73	3.26	0.77	–0.32	0.34
	IA	73	2.08	0.56	–0.15	–0.82
	TSF	73	2.62	1.25	0.24	–1.17

Note. M = mean; SD = standard deviation. IA was recoded so that 1 = high asymmetry,
2 = moderate, 3 = high symmetry.

Table 8 presents the correlation matrix of the study variables. As expected, the four BI&A usage dimensions were positively and significantly interrelated, with the strongest association between Nature of Use and Time of Use ($r = .68$, $p < .01$). Purpose of Use also correlated moderately with Scope of Use ($r = .33$, $p < .01$) and Nature of Use ($r = .44$, $p < .01$), suggesting that organizations employing BI&A for decision support also tend to broaden their analytical scope and integration.

Decision-Making Quality dimensions were positively associated with BI&A usage. Effectiveness correlated significantly with Purpose ($r = .44$, $p < .01$), Scope ($r = .49$, $p < .01$), and Nature of Use ($r = .46$, $p < .01$). Efficiency showed weaker but still positive correlations with Purpose ($r = .24$, $p < .05$) and

Time of Use ($r = .27$, $p < .05$). These patterns suggest that broader and deeper BI&A engagement is particularly linked to enhanced effectiveness, while efficiency gains are less consistent.

Training-related variables (available for the subsample of respondents with training experience, $n = 46$) were strongly correlated, especially Training Quality with Practical Relevance ($r = .71$, $p < .01$). Training Quality also correlated positively with Scope ($r = .42$, $p < .01$) and Nature of Use ($r = .45$, $p < .01$), indicating that better training is associated with more advanced and integrative BI&A usage.

Among the controls, satisfaction and data quality showed strong mutual correlation ($r = .68$, $p < .01$) and were both positively related to usage intensity (e.g., Time of Use with satisfaction: $r = .38$, $p < .01$; with data quality: $r = .31$, $p < .01$). Organizational culture and top management support were highly correlated ($r = .63$, $p < .01$) and also linked to higher training formalization ($r = .36$, $p < .01$). Perceived environmental uncertainty correlated moderately with organizational culture ($r = .47$, $p < .01$) and top management support ($r = .42$, $p < .01$), reflecting contextual variation. Information asymmetry showed no notable correlations with the main constructs.

Table 8

Correlation matrix of study variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. PU	—														
2. SOU	.33**	—													
3. ToU	.50**	.30*	—												
4. NOU	.44**	.44**	.68**	—											
5. DEFS	.44**	.49**	.21	.46**	—										
6. DEFY	.24*	.15	.27*	.23	.30**	—									
7. TQ	.24	.42**	.25	.45**	.40**	.39**	—								
8. PPR	.16	.66**	.19	.39**	.49**	.18	.71**	—							
9. TSF	.17	.21	.11	.30**	.30*	.11	.36*	.46**	—						
10. Sa	.28*	.12	.38**	.40**	.27*	.30*	.48**	.45**	.26*	—					
11. DaQ	.24*	.05	.31**	.33**	.17	.24*	.14	.01	.30*	.68**	—				
12. OC	.15	-.06	.05	.06	.11	-.02	-.01	.07	.31**	.36**	.36**	—			
13. TMS	.17	-.15	.07	.08	-.18	-.09	-.03	-.05	.36**	.25*	.31**	.63**	—		

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
14. PEU	.15	.11	.11	.05	.06	-.06	.08	.17	.34**	.19	.13	.47**	.42**	—	
15. IA	-.05	.01	.01	-.06	.02	.10	-.22	-.25	.16	-.10	-.09	-.10	-.04	-.04	—

Legend: PU = Purpose of Use; SOU = Scope of Use; ToU = Time of Use; NOU = Nature of Use; DEFS = Decision-Making Effectiveness; DEFY = Decision-Making Efficiency; TSF = Training Standardization & Formalization; TQ = Training Quality; Sa = User Satisfaction; DaQ = Data Quality; OC = Organizational Culture; TMS = Top Management Support; PEU = Perceived Environmental Uncertainty; IA = Information Asymmetry.

Note. N = 73 (unless otherwise noted; training-related variables TQ and PPR: n = 46).

p < .05, p < .01 (two-tailed).

Table 9 presents the distribution of BI&A training variables. Most respondents (63%) reported having attended training. Training intensity was skewed toward the lower categories, with more than half of participants who received training reporting 0–5 hours (54.4%). Medium-to-high intensity training (≥6 h) was less common, though still present across the sample (45.6%). Training frequency was most often occasional (50%), while only a quarter reported regular participation (≥3× per year).

For the subsequent analyses, training intensity was grouped into three categories: (1) no training (n = 27), (2) low-to-medium training (0–5 h; n = 25), and (3) medium-to-high training (≥6 h; n = 21). This grouping provides a structured basis for testing the moderating role of training in the relationship between BI&A usage and decision-making quality.

Table 9
Training Attendance and Intensity

Variable	Category	n	% (valid)
Training Attendance	No	27	37.0
	Yes	46	63.0
Training Hours	0–2 h	12	26.1
	3–5 h	13	28.3
	6–10 h	9	19.6
	11–20 h	5	10.9
	>20 h	7	15.2
Training Frequency	One time only	11	23.9
	Occasionally (≤2× year)	23	50.0
	Regularly (≥3× year)	12	26.1

5.2 Structural Model Analysis

Before testing the hypotheses, regression assumptions were checked. Multicollinearity was examined using variance inflation factors (VIF). In the extended H1 models (overall BI&A usage and subdimensions, see Table A3), all VIFs ranged between 1.00 and 2.10, far below the conventional threshold of 5, which rules out collinearity problems. In the moderation models estimated with PROCESS (H2), predictors were mean centered to minimize collinearity. As expected, the moderator and its interaction term showed inflated VIF values (>30), a common feature in moderation analyses that does not bias results when robust estimators such as PROCESS are used (Hayes, 2022). Residual diagnostics confirmed normally distributed errors and the absence of influential outliers.

Explanatory power is reported using the coefficient of determination (R^2), together with changes in explained variance (ΔR^2) when additional predictors, controls, or interaction terms were added. Path coefficients were estimated by regression analysis (H1) and Hayes' PROCESS macro with heteroskedasticity-consistent (HC3) standard errors (H2). Robustness checks included re-estimation of models with controls and alternative specifications, described in the following sections.

5.2.1 H1: Effect of BI&A Usage on Decision-Making Quality

H1 predicted a positive association between BI&A usage and decision-making quality (DMQ). The base regression model supported this assumption. As shown in Table 10, Panel A, BI&A usage was a significant predictor of DMQ ($\beta = .477$, $p < .001$), explaining 22.8% of the variance ($R^2 = .228$). This confirms that higher levels of BI&A usage are associated with higher perceived decision-making quality.

To further examine whether the overall effect was driven by specific dimensions, BI&A usage was disaggregated into its four sub-constructs: purpose of use (PU), scope of use (SOU), time of use (ToU), and nature of use (NOU). The regression results in Panel B indicate that PU was significant ($\beta = .26$, $p = .038$), SOU showed a positive but marginal effect ($\beta = .20$, $p = .090$), NOU was positive but non-significant ($\beta = .24$, $p = .114$), and ToU was non-significant ($\beta = -.05$, $p = .721$). These findings suggest that the positive relationship between BI&A usage and DMQ is not dependent on a single usage dimension but appears consistently across most sub-constructs.

Panel C of Table 10 reports the regression results for descriptive, predictive, and prescriptive analytics as predictors of decision-making quality. The use of descriptive analytics did not show a significant effect ($\beta = .095$, $p = .425$). By contrast, both predictive ($\beta = .423$, $p < .001$) and prescriptive analytics (β

= .318, p = .006) displayed significant positive effects what highlights that more advanced analytics contribute more strongly to decision-making quality.

As an additional robustness check, the two dimensions of decision-making quality were analyzed separately. As shown in Panel D of Table 10, BI&A usage remained a strong and significant predictor of decision-making effectiveness (DEFS; β = .501, p < .001), whereas the effect on decision-making efficiency (DEFY) was weaker and only marginally significant (β = .293, p = .012). This suggests that BI&A contributes primarily to improving the accuracy, validity, and strategic alignment of decisions, while its influence on timeliness and cost efficiency appears more limited.

Finally, the robustness of H1 was tested by re-estimating the model including control variables (user satisfaction, data quality, organizational culture, top management support, perceived environmental uncertainty, information asymmetry, and training standardization). As presented in Table A4, the explanatory power of the model increased to 36.6% ($R^2 = .366$, $\Delta R^2 = .138$, p = .071). Importantly, BI&A usage remained a strong and significant predictor of DMQ (β = .365, p = .002). Among the controls, only top management support reached significance, showing a negative effect (β = –.366, p = .008).

Taken together, the results confirm H1, which predicted a positive association between BI&A usage and decision-making quality. BI&A usage explained 22.8% of the variance in DMQ in the base model, and the effect remained significant after including controls (β = .365, p = .002; $R^2 = .366$).

Table 10
Regression results for H1: Effect of BI&A usage, its subdimensions, and analytics types on decision-making quality (DEFS and DEFY)

Panel A. Main model (BI&A usage → DMQ overall)

Predictor	**B**	**SE**	**β**	**t**	**p**
BI&A Usage	0.36	0.08	.48	4.58	<.001***
$R^2 = .228$, Adjusted $R^2 = .217$, $F(1, 71) = 20.94$, $p < .001$					

Panel B. BI&A subdimensions (PU, SOU, ToU, NOU → DMQ)

Predictor	**B**	**SE**	**β**	**t**	**p**
Purpose of Use (PU)	0.19	0.09	.26	2.12	.038**
Scope of Use (SOU)	0.11	0.07	.20	1.72	.090*

Time of Use (ToU)	–0.02	0.07	–.05	–0.36	.721
Nature of Use (NOU)	0.15	0.09	.24	1.60	.114
R^2 = .266, Adj. R^2 = .222, F(4,68) = 6.15, p < .001					

Panel C. Analytics types (Descriptive, Predictive, Prescriptive → DMQ)

Predictor	**B**	**SE**	**β**	**t**	**p**
Descriptive analytics	0.058	0.072	.095	0.803	.425
R^2 = .009, Adj. R^2 = –.005, F(1,71) = 0.645, p = .425					
Predictive analytics	0.169	0.043	.423	3.931	<.001***
R^2 = .179, Adj. R^2 = .167, F(1,71) = 15.449, p < .001					
Prescriptive analytics	0.126	0.045	.318	2.824	.006**
R^2 = .101, Adj. R^2 = .088, F(1,71) = 7.972, p = .006					

Panel D. DMQ subdimensions (BI&A usage → DEFS and DEFY)

Predictor	**B**	**SE**	**β**	**t**	**p**
Dependent Variable: DEFS					
BI&A Usage	0.414	0.085	.501	4.873	<.001***
R^2 = 0.251, Adj. R^2 = 0.240, F(1,71) = 23.749, p < .001					
Dependent Variable: DEFY					
Constant	2.416	0.420	—	5.756	<.001***
BI&A Usage	0.299	0.116	.293	2.585	.012**
R^2 = 0.086, Adj. R^2 = 0.073, F(1,71) = 6.680, p = .012					

Note. Unstandardized coefficients (B), standard errors (SE), standardized coefficients (β), t-values, and p-values are reported. ***p < .01; **p < .05; *p < .10. n.s. = not significant.

5.2.2 H2: Moderating Role of Training in the BI&A–DMQ Relationship

H2 proposed that the relationship between BI&A usage and decision-making quality (DMQ) is moderated by training. The hypothesis was tested using four alternative operationalizations of training: training quality (TQ0), grouped training quality (low, medium, high), training intensity (none, low/medium ≤5h, high ≥6h), and perceived practical relevance (PPR0).

As shown in Table 11, BI&A usage consistently exhibited a positive and significant main effect across specifications (b ranging from .333 to .369, all $p < .05$). However, in all four models the interaction terms between BI&A usage and the respective training variable were small ($|b| \leq .068$) and statistically non-significant (all $p > .75$). The additional explained variance attributable to the interaction was negligible ($\Delta R^2 \leq .002$). These results indicate that none of the training measures moderated the BI&A–DMQ relationship.

As a robustness check, the models were re-estimated with organizational and system-related controls (user satisfaction, data quality, organizational culture, top management support, perceived environmental uncertainty, information asymmetry, and training standardization/formalization). The results (Annex Table A5) confirm that BI&A usage remained a positive predictor, while interaction terms again failed to reach significance ($\Delta R^2 \leq .014$).

Further analyses considered alternative moderators (training standardization and formalization, training attendance, purpose of use as predictor) and industry-specific models for finance and logistics. These tests (Annex Table A6) likewise showed no moderating effects. Finally, combined moderation tests (PROCESS Models 2 and 3) were run with training quality and BI&A experience. Neither the parallel nor the three-way interaction terms were significant, indicating that experience did not alter the non-significant role of training (Annex Table A7).

Table 11
Moderation analyses testing the effect of training (TQ0, grouped quality, intensity, and perceived practical relevance) on the relationship between BI&A usage and decision-making quality (N = 73)

Panel A: Continuous Training Quality (TQ0)

Predictor	**b**	**SE**	**t**	**p**	**ΔR^2**
BI&A usage	.348	.159	2.18	.033**	
Training Quality	–.057	.181	–.31	.756	
BI&A × Training Quality	.010	.051	0.20	.843	.001

Panel B: Grouped Training Quality

Predictor	b	SE	t	p	ΔR²
BI&A usage (Med vs Low)	.363	.103	3.53	.001***	
TQ_Med	.059	.970	0.06	.952	
BI&A × TQ_Med	–.044	.254	–.17	.862	.001
BI&A usage (High vs Low)	.355	.118	3.01	.004***	
TQ_High	.228	.759	0.30	.765	
BI&A × TQ_High	–.045	.204	–.22	.828	.001

Panel C: Training Intensity (TI_grp3)

Predictor	b	SE	t	p	ΔR²
BI&A usage (Low/Med vs None)	.333	.117	2.85	.006***	
TI_LM	–.322	.800	–.40	.689	
BI&A × TI_LM	.068	.215	0.31	.754	.002
BI&A usage (High vs None)	.352	.107	3.28	.002***	
TI_HI	–.306	.952	–.32	.749	
BI&A × TI_HI	.057	.247	0.23	.817	.001

Panel D: Perceived Practical Relevance (PPR0)

Predictor	b	SE	t	p	ΔR²
BI&A usage	.369	.155	2.38	.020**	
PPR0	–.030	.173	–.17	.863	
BI&A × PPR0	.002	.048	0.04	.965	.000

Taken together, the analyses provide no support to not reject H2. While BI&A usage robustly predicts decision-making quality, none of the training measures, not matter if alone or combined, moderated this relationship.

6 Discussion

6.1 Summary of findings

The analyses provide clear support for H1: BI&A usage is positively associated with decision-making quality. Across all models, usage emerged as a robust predictor, explaining a notable share of variance. This effect was particularly pronounced for decision-making effectiveness, while the link to efficiency was weaker. Thus, BI&A contributes more strongly to the quality and validity of managerial decisions than to their speed or resource efficiency.

A closer look at the dimensions of BI&A usage shows that the breadth of purposes for which BI&A is applied emerged as the strongest driver of decision quality. In contrast, the time dimension played only a minor role, suggesting that the way systems are used matters more than their mere frequency of use. Scope and nature of use also contributed, but with more modest effects, indicating that benefits arise especially when usage is targeted and decision focused.

With regard to H2, the analyses provide no empirical support for the moderating role of training. Across all specifications—continuous and grouped training quality, training intensity, and perceived practical relevance—the interaction terms between BI&A usage and training were consistently small and statistically non-significant. Even when alternative models (parallel moderation, moderated moderation) were tested, neither training quality nor BI&A experience altered the strength of the BI&A–DMQ relationship. This indicates that while BI&A usage itself robustly improves decision-making quality, these improvements are not significantly conditioned by training characteristics in this sample.

Finally, the inclusion of control variables confirmed the robustness of these results. User satisfaction and data quality were positively associated with both BI&A usage and decision-making quality, yet their presence did not eliminate the main effect of BI&A. Interestingly, top management support showed a negative effect in some specifications, hinting at possible tensions between top-down pressure and bottom-up system use.

6.2 Theoretical implications

This study examined the impact of BI&A usage on decision-making quality in management accounting and the role of end-user training in conditioning this relationship. The findings offer several theoretical implications for information systems and management accounting research.

First, the results confirm that BI&A usage significantly enhances decision-making quality, though the effect was concentrated on decision effectiveness rather than efficiency. This distinction is theoretically important. In line with Simon's (1977) bounded rationality perspective, BI&A extends the cognitive capacity of decision-makers by providing richer, structured information, thereby increasing the validity and justification of decisions. At the same time, the lack of efficiency gains suggests that BI&A reduces uncertainty but does not necessarily accelerate processes. This nuance refines how decision-making quality should be conceptualized in information systems research: rather than assuming a broad improvement across all dimensions, the evidence indicates that BI&A primarily improves the informational substance of decisions, not their procedural speed.

Second, the analysis provides insights into the dimensions of BI&A usage. The Purpose of Use, defined as applying BI&A for analysis, problem diagnosis, exploring alternatives, and acquiring knowledge, emerged as the strongest driver of decision quality. By contrast, the time dimension showed no significant effect, indicating that frequency or duration of use is not sufficient for value creation. This finding challenges the way "use" is often operationalized in TAM (Davis, 1989) and IS Success research (DeLone & McLean, 2003), where system use is frequently equated with intensity or frequency. The evidence here suggests that qualitative engagement—using BI&A in ways that are directly connected to decision processes—matters more than quantitative measures of use. Scope of use across descriptive, predictive, and prescriptive analytics provided only marginal benefits, which implies that while advanced analytics hold potential, they remain unevenly embedded in practice. Similarly, the nature of use, encompassing advanced dashboards or mobile deployment, showed weaker effects, suggesting that technical sophistication alone is insufficient unless these features are fully integrated into workflows.

Further analyses of different analytical levels sharpen this conclusion. The use of descriptive analytics alone did not significantly improve decision quality, which aligns with prior literature that frames descriptive tools primarily as a baseline for understanding past performance and benchmarking rather than as a source of strategic advantage (Appelbaum et al., 2017; Popovič et al., 2012). By contrast, predictive analytics showed the strongest positive effect, supporting arguments that forward-looking forecasting and scenario analysis substantially enhance managerial foresight and agility (Thanasas & Kampiotis, 2024; Rikhardsson & Yigitbasioglu, 2018). Prescriptive analytics also contributed positively, though to a smaller degree, consistent with studies emphasizing its value for recommending optimal actions and aligning decisions with long-term objectives (Appelbaum et al., 2017). This differentiation advances theoretical discussions by showing that the contribution of BI&A to decision-making quality is not uniform but depends on the analytical level applied. In particular, forward-looking and action-oriented uses of BI&A emerge as the primary drivers of value in both theory and practice.

Third, the role of training turned out differently than expected. Regression analyses and additional robustness checks consistently showed that training quality, intensity, or practical relevance did not significantly moderate the BI&A–DMQ relationship. This diverges from much of the prior literature, which tends to emphasize training as a key enabler of BI&A success. Several reasons may explain the result. Training was measured only for the last 12 months, which may not capture accumulated experience or informal learning. The relatively small sample size (N = 73) also limits statistical power to detect interaction effects, which are typically harder to identify and require larger samples (McClelland & Judd, 1993; Aguinis et al., 2017). Finally, other contextual factors may outweigh formal training in enhancing the benefits of BI&A. The implication for theory is that the role of training may be more complex and context-dependent than commonly assumed. Future studies should consider longitudinal data, informal learning processes, and interaction effects with broader organizational conditions.

The findings on control variables further nuance theoretical understanding. Data quality and user satisfaction showed positive associations with decision quality, consistent with the DeLone and McLean (2003) model, yet their inclusion did not eliminate the explanatory power of BI&A usage. This indicates that usage exerts an independent effect beyond satisfaction or perceived information quality. More unexpectedly, top management support showed a negative effect in some models. While prior studies (e.g., Candra & Nainggolan, 2022) identify managerial support as a key success factor, the results here suggest that directive or coercive forms of support may substitute for rather than encourage genuine engagement, producing compliance rather than competence. This points to the need for theory to differentiate between enabling and coercive types of support in order to capture more accurately the dynamics between organizational context and system success.

For management accounting, the findings reinforce the perspective that BI&A reshapes the accountant's role from data preparer to strategic business partner (Rikhardsson & Yigitbasioglu, 2018). BI&A enhances decision effectiveness by supporting deeper analysis and problem exploration, which highlights the accountant's evolving role as a translator of data into actionable business insight (Franke & Hiebl, 2023). At the same time, the absence of efficiency effects tempers expectations that BI&A systems will streamline processes; their value lies more in strengthening justification, alignment, and validity of decisions than in speeding them up. The unexpected absence of training effects further suggests that capability building may occur through practice, contextual enablers, and accumulated expertise rather than short-term formal training interventions.

Overall, the study advances theory in three ways. First, it refines the BI&A–decision quality relationship by distinguishing between effectiveness and efficiency effects, thereby clarifying what kind of "quality" BI&A most strongly supports. Second, it reconceptualizes system use as purposeful and decision-oriented engagement rather than frequency or time, offering a more meaningful theoretical definition of “use” in the context of decision support. Third, it challenges the assumed moderating role of training by showing that its effect may be weaker, context-dependent, or harder to measure than commonly suggested. Together, these contributions extend existing IS Success, TAM, and RBV perspectives while enriching management accounting theory by underscoring the central role of human–technology interaction in decision making.

6.3 Practical implications

The findings also yield important implications for practice. Organizations increasingly invest in BI&A systems with the expectation of more informed and timely managerial decisions. This study shows that such benefits materialize most strongly when BI&A is used across different areas of application within decision-critical processes rather than being measured by frequency or intensity of use. Managers should therefore encourage systematic application of BI&A to tasks such as problem analysis, scenario exploration, and evaluation of alternatives, rather than solely focusing on usage hours or system access metrics.

The differentiated analysis of analytical levels provides further guidance. Using BI&A primarily for descriptive reporting, dashboards, or OLAP did not significantly improve decision quality in the sample, indicating that retrospective applications represent a baseline rather than a source of added value. In contrast, predictive analytics emerged as the strongest contributor to decision-making quality, while prescriptive analytics also provided meaningful, though smaller, improvements. For organizations, this highlights the importance of expanding BI&A use beyond descriptive reporting toward forecasting, scenario analysis, and optimization, which offer greater returns for decision quality.

This study did not find evidence that training moderates the BI&A–DMQ relationship. Organizations should therefore be cautious about expecting formal training alone to guarantee improved outcomes. Training may still contribute indirectly, for example by raising awareness and confidence, but it is unlikely to be a stand-alone lever. A fuller discussion of study design aspects that may have influenced these findings is provided in the limitations section.

The findings also emphasize the role of leadership and organizational culture. Data quality and user satisfaction showed positive associations with decision quality, highlighting the need for investments in reliable data governance, user-friendly interfaces, and timely reporting. More unexpectedly, top management support showed a negative effect in some models. This suggests that directive or coercive support may reduce genuine user engagement, producing compliance rather than competence. Leaders should therefore focus on enabling support, meaning e.g., providing resources, encouraging adoption, and fostering a culture of trust, rather than enforcing BI&A usage through pressure.

For management accountants, the results reinforce the shift from data preparers to strategic business partners. BI&A supports deeper analysis and foresight, strengthening accountants' role as interpreters of data and advisors in decision-making processes. However, the absence of efficiency effects indicates that expectations should be realistic: BI&A is more valuable for improving the justification and alignment of decisions than for streamlining processes.

In sum, organizations can maximize the value of BI&A by embedding its use purposefully across decision tasks, prioritizing predictive and prescriptive applications, ensuring high data quality and user satisfaction, adopting enabling leadership practices, and complementing training with supportive organizational conditions. By doing so, firms can enhance the quality and validity of decisions while positioning management accountants as strategic partners in data-driven decision making.

6.4 Limitations and suggestions for future research

The findings of this study should be interpreted in light of several limitations. The research was based on a cross-sectional survey, which provides only a snapshot of the relationship between BI&A usage, training, and decision-making quality. This design does not allow for causal conclusions. It remains unclear whether BI&A usage leads to better decisions, or whether organizations with higher decision quality simply make broader use of BI&A. Longitudinal and experimental approaches would be needed to capture these dynamics over time, and prior studies also highlight that the effects of training and skill development often unfold gradually (Franke & Hiebl, 2023; Li et al., 2022; Chatterjee et al., 2023).

Another limitation lies in the measurement approach. Core constructs such as BI&A usage, training quality, and decision-making quality were assessed through self-reports. Although common in survey research, this method is prone to biases, including common method variance and social desirability. While behavioral indicators like training attendance and intensity were included, the study relied mainly on perceptions. Future work could complement this with objective indicators, for example usage logs, archival performance data, or forecast accuracy (Wieder & Ossimitz, 2015; Medina et al., 2014; Hou, 2012).

The scope of the conceptual model is also restricted. Factors such as user satisfaction, data quality, organizational culture, and top management support were included as controls but have not been studied on their own. The literature suggests that these elements are not just background conditions but active enablers of BI&A success (Popovič et al., 2012; Işık et al., 2013). Future studies could examine whether they operate as mediators or moderators alongside training.

The external validity of the study is limited by the sample. Although the survey included professionals from multiple industries, the number of respondents was modest (N = 73) and the sample was collected through convenience and snowball techniques. This diversity adds some breadth, but it restricts the generalizability of the results to other organizational and cultural contexts. Replication in larger and more representative samples across sectors such as healthcare, logistics, and services would help establish whether the observed dynamics hold more broadly (Duan et al., 2020; Ain et al., 2019).

A further limitation concerns the operationalization of training. Training quality, intensity, and practical relevance were measured at a general level and only for the past 12 months. This likely misses long-term capability building, informal learning, and differences in delivery formats such as classroom training versus e-learning. Previous research shows that the design of training is critical for its effectiveness (Medina et al., 2014; Bedard et al., 2003). Future studies should therefore compare different training designs and follow participants over time to capture how both formal and informal learning shape BI&A outcomes.

Overall, while the study provides evidence that BI&A usage improves decision-making quality and that training did not moderate this relationship, these findings must be read with caution. Addressing the outlined limitations in future work would help clarify causal mechanisms, improve external validity, and identify the circumstances under which training and related contextual factors influence BI&A effectiveness in management accounting.

7 Conclusion

This thesis aimed to examine how Business Intelligence and Analytics (BI&A) usage influences decision-making quality (DMQ) in management accounting, and whether end-user training moderates this relationship. The research was motivated by mixed findings in prior studies, where BI&A adoption did not always translate into improved decision outcomes, raising questions about the conditions under which these technologies deliver value. This issue is also echoed in practice: despite substantial corporate investments in BI&A, many organizations report difficulties in converting these investments into tangible decision improvements, highlighting the importance of understanding the human and organizational factors behind system success.

Using a survey-based design, BI&A usage was measured across four dimensions—purpose, scope, time, and nature—and linked to decision-making effectiveness and efficiency. Training was considered as a potential moderator, assessed through training quality, intensity, perceived practical relevance, and standardization.

The results show that BI&A usage has a positive effect on decision-making quality, but the effect is concentrated on decision effectiveness. This suggests that BI&A helps improve the substance and justification of decisions rather than their speed. Among the usage dimensions, the breadth of purposes for which BI&A is applied emerged as the strongest predictor, whereas time of use had no effect. At the level of analytics, predictive and prescriptive uses contributed most strongly to decision quality, while descriptive uses alone offered limited benefits.

Contrary to expectations, training did not emerge as a statistically significant moderator of the BI&A–DMQ relationship. This finding diverges from much of the existing literature but may reflect measurement constraints, sample size, or the influence of contextual factors outside the scope of this study. Control variables provided additional insights: data quality and user satisfaction were positively associated with decision quality, while top management support showed a negative effect in some models, suggesting that directive enforcement may reduce genuine user engagement.

These findings contribute to theory in three main ways. First, they refine our understanding of BI&A's impact by distinguishing between decision-making effectiveness and efficiency. Second, they advance system use theory by showing that the value of BI&A depends more on purposeful, decision-oriented application than on frequency or duration. Third, they question the assumed moderating role of training, suggesting instead that its effect is weaker, more context-dependent, or harder to measure than commonly assumed.

The study also offers lessons for practice. Organizations should focus on embedding BI&A in decision-critical tasks, particularly predictive and prescriptive applications, while not overemphasizing usage hours or access frequency. Training remains important but should be approached as part of a broader capability-building environment rather than as a guaranteed lever for stronger outcomes. This also reflects concerns in practice: despite major investments, BI&A creates benefits only when it is applied broadly across decision tasks rather than being limited to narrow or single uses. Leadership should concentrate on enabling support—through resources, culture, and user engagement—rather than coercive enforcement. For management accountants, the results reinforce the evolving role from data preparers to strategic partners who translate BI&A insights into decisions.

Several limitations should be noted. The cross-sectional design restricts causal inference, self-reports raise the risk of bias, and the modest sample size limits generalizability. Training was measured only for the past 12 months and did not capture design features or informal learning. Future research should therefore employ longitudinal and mixed-method approaches, test mediating and moderating roles of contextual factors, and compare different training formats to better understand their impact.

In sum, this thesis shows that BI&A usage is a robust predictor of decision-making quality in management accounting, primarily by enhancing decision effectiveness. The role of training is more complex than anticipated, suggesting that organizations should adopt a broader view of capability building when implementing BI&A. These insights contribute to both theory and practice by clarifying how human and technological factors interact in shaping decision outcomes.

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Annex A: Descriptive Statistics and Reliability Analyses

Table A1

Reliability and validity multi-item contextual and system-related control constructs.

Construct	Item	Loading	Indicator Reliability	Composite Reliability	Cronbach's Alpha	AVE
SaCo	SaCo1	0.862	0.743	0.924	0.890	0.754
	SaCo2	0.931	0.867			
	SaCo3	0.898	0.806			
	SaCo4	0.775	0.601			
DaQ	DaQ1	0.894	0.799	0.918	0.875	0.737
	DaQ2	0.867	0.752			
	DaQ3	0.871	0.759			
	DaQ4	0.798	0.637			
OC	OC1	0.790	0.624	0.890	0.846	0.619
	OC2	0.782	0.612			
	OC3	0.752	0.566			
	OC4	0.855	0.731			
	OC5	0.750	0.563			
TMS	TMS1	0.873	0.762	0.926	0.879	0.806
	TMS2	0.909	0.826			
	TMS3	0.911	0.830			
EU	EU1	0.742	0.551	0.852	0.781	0.538
	EU2	0.842	0.709			
	EU3	0.766	0.587			
	EU4	0.644	0.415			
	EU5	0.656	0.430			
IA	IA_R1	0.789	0.623	0.889	0.849	0.574
	IA_R2	0.857	0.734			
	IA_R3	0.792	0.627			
	IA_R4	0.742	0.551			
	IA_R5	0.612	0.375			
	IA_R6	0.733	0.537			
TSF	TSF1	0.952	0.906	0.933	0.890	0.822
	TSF2	0.884	0.781			
	TSF3	0.883	0.780			

Table A2

Reliability two-item contextual and system-related control constructs.

Construct	Cronbach's Alpha	Pearson's inter-item correlation
SaAc	.928	.866**
SaFo	.566	.397**
SaEoU	.890	.802**
SaTi	.662	.495**

Note. * p < .05. ** p < .01.

Table A3

Collinearity Statistics for H1 and H2 Regression Models

Panel A: H1 – Overall BI&A usage

Model / Predictor	Tolerance	VIF
BI&A usage (BIAU)	1.000	1.000

Panel B: H1 – BI&A subdimensions

Model / Predictor	Tolerance	VIF
Purpose of Use (PU)	.706	1.416
Scope of Use (SOU)	.783	1.278
Time of Use (ToU)	.489	2.046
Nature of Use (NOU)	.476	2.101

Panel C: H2 – Main moderation model

Model / Predictor	Tolerance	VIF
BI&A usage	.390	2.566
Training Quality (TQ0)	.034	29.045
BI&A × Training Quality (Int_TQ0)	.030	33.833

Panel D: H2 – Robustness model with controls

Model / Predictor	Tolerance	VIF
BI&A usage	.348	2.871
Training Quality (TQ0)	.031	32.294
BI&A × Training Quality (Int_TQ0)	.026	38.573
Training Standardization & Formalization	.587	1.704
Data Quality	.488	2.051
Information Asymmetry	.919	1.088
Organizational Culture	.503	1.987
Top Management Support	.550	1.819
Perceived Environmental Uncertainty	.684	1.461
User Satisfaction	.450	2.220

Note. All predictors in H1 models exhibit VIF values well below the conventional threshold of 5, indicating no collinearity concerns. In H2 models, the moderator and interaction term show high VIF values, which is common in moderation analyses due to inherent correlations between product terms and their constituent variables. Following Hayes (2022), PROCESS uses mean-centering and robust HC3 standard errors, so these values do not bias the results.

Annex B: Robustness Checks

Table A4
Regression Results for H1 — Extended Model with Controls

Predictor Variable	Std. Beta (β)	t	Sig. (p)	VIF
BI&A Usage (BIAU_M)	.365	3.272	.002	1.25
User Satisfaction (Sa_M)	.201	1.402	.166	2.08
Data Quality (DaQ_M)	.024	0.167	.868	2.01
Organizational Culture (OC_M)	.157	1.123	.266	1.98
Top Management Support (TMS_M)	–.366	–2.727	.008	1.82
Perceived Env. Uncertainty (PEU_M)	–.069	–0.583	.562	1.42
Information Asymmetry (IA_M)	.079	0.769	.445	1.07
Training Standardization & Formalization (TSF_M)	.180	1.540	.128	1.38
R^2 = .366, Adj. R^2 = .286, ΔR^2 = .138 (ns)				

Table A5
Robustness checks: Moderation models with controls (N = 73)

Panel A: Continuous Training Quality (TQ0)

Predictor (with controls)	b	SE	t	p	ΔR²
BI&A usage	.311	.131	2.37	.021**	
Training Quality (TQ0)	–.004	.191	–.02	.985	
BI&A × TQ0	–.012	.051	–.24	.807	.001

Panel B: Grouped Training Quality

Predictor (with controls)	b	SE	t	p	ΔR²
BI&A usage (Med vs Low)	.247	.120	2.07	.043**	
TQ_Med	–.443	1.094	–.41	.687	
BI&A × TQ_Med	.100	.289	0.35	.730	.003
BI&A usage (High vs Low)	.339	.116	2.92	.005***	

TQ_High	.850	.897	0.95	.347	
BI&A × TQ_High	–.244	.232	–1.05	.298	.014

Panel C: Training Intensity (TI_grp3)

Predictor (with controls)	b	SE	t	p	ΔR²
BI&A usage (Low/Med vs None)	.263	.120	2.19	.032**	
TI_LM	–.162	.890	–.18	.856	
BI&A × TI_LM	.023	.232	0.10	.923	.000
BI&A usage (High vs None)	.257	.107	2.40	.020**	
TI_HI	–.512	.850	–.60	.549	
BI&A × TI_HI	.083	.221	0.38	.708	.002

Panel D: Perceived Practical Relevance (PPR0)

Predictor (with controls)	b	SE	t	p	ΔR²
BI&A usage	.348	.131	2.65	.010**	
PPR0	.043	.187	0.23	.820	
BI&A × PPR0	–.029	.050	–0.58	.566	.004

Table A6

Additional robustness checks: alternative moderators and industry splits

Panel E: Alternative moderators (without controls)

Predictor / Moderator	**b**	**SE**	**t**	**p**	**ΔR²**
BI&A × TSF	0.092	0.083	1.12	.269	.022
BI&A usage	0.092	0.235	0.39	.698	
TSF	–0.293	0.318	–0.92	.360	
PU × TQ0	0.009	0.048	0.18	.855	.001
Purpose of Use (PU)	0.270	0.163	1.65	.103	
Training Quality (TQ0)	–0.042	0.192	–0.22	.829	

Panel F: Industry splits (with controls*)

Predictor / Moderator	**b**	**SE**	**t**	**p**	**ΔR²**
Finance (n = 18): BI&A × TQ0	–0.022	0.455	–0.05	.963	.001
BI&A usage	0.420	0.355	1.18	.271	
Training Quality (TQ0)	–0.184	0.159	–1.15	.282	
Logistics (n = 20): BI&A × TQ0	0.097	0.181	0.54	.603	.030
BI&A usage	0.476	0.237	2.01	.073*	
Training Quality (TQ0)	–0.030	0.068	–0.44	.672	

Table A7

Robustness check: PROCESS moderation analyses (parallel and moderated moderation)

Model 2 (Parallel moderation)

Predictor / Interaction	**b**	**SE (HC3)**	**t**	**p**	**95% CI LL**	**95% CI UL**
BI&A usage (BIAU_c)	.360	.106	3.41	.001	.149	.571
Training quality (TQ0_c)	–.044	.036	–1.21	.230	–.116	.028
BI&A experience (BIEXP_c)	.114	.050	2.28	.026	.014	.213
BI&A × Training	.013	.052	0.25	.802	–.090	.117
BI&A × Experience	.082	.083	0.98	.331	–.085	.248

Model summary: $R^2 = .295$, $F(5,67) = 4.14$, $p = .003$
ΔR^2 for interactions = .015, $p = .572$

Model 3 (Moderated moderation)

Predictor / Interaction	**b**	**SE (HC3)**	**t**	**p**	**95% CI LL**	**95% CI UL**
BI&A usage (BIAU_c)	.398	.116	3.43	.001	.167	.630
Training quality (TQ0_c)	–.030	.040	–0.74	.459	–.110	.050
BI&A experience (BIEXP_c)	.085	.087	0.98	.331	–.088	.258
BI&A × Training	–.002	.058	–0.04	.972	–.118	.114
BI&A × Experience	.109	.119	0.92	.362	–.128	.347
Training × Experience	.037	.049	0.75	.453	–.060	.133
3-way Interaction	–.040	.063	–0.64	.523	–.165	.085

Model summary: $R^2 = .319$, $F(7,65) = 3.18$, $p = .006$
ΔR^2 for 3-way interaction = .007, $p = .523$

Note. Unstandardized coefficients (b), heteroscedasticity-consistent SEs (HC3), and 95% confidence intervals reported.