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Exploring the determinants and performance effects of digital dashboard use by management accountants

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Abstract

Digital dashboards are becoming increasingly central to management accounting; however, the theory explaining their adoption and effects on performance in this professional context remains underdeveloped. This paper proposes a framework centered on management accounting by extending the technology acceptance model, UTAUT, with two domain-specific aspects: information quality (IQ) and decision quality (DQ). The framework specifies mediated and moderated mechanisms based on expectation confirmation, accountability/protection motivation, and task-technology fit arguments. We hypothesize that IQ reduces perceived effort by lowering reconciliation and search costs. In contrast, DQ increases perceived usefulness by linking dashboards to defensible analyses. We also hypothesize that IQ and DQ complement each other to improve ease of use, and that actual use relates to performance through enabling-control logics. We evaluated the framework with data from German management accountants to demonstrate its explanatory value. Conceptually, the model re-centers management accounting in technology adoption theory by treating DQ as an antecedent. This clarifies when organizational support matters most and explains why ease-of-use beliefs form immediately, while usefulness beliefs consolidate through decision experience. The framework motivates longitudinal and boundary-condition research and offers practical guidance: invest in data quality, design decision-support features, and integrate dashboards into core control routines to enable genuine managerial control through digital tools.

Keywords Dashboards · Germany · Management accounting · Survey · Technology acceptance mode

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1 Introduction

The increasing use of business intelligence (BI) with greater volumes and variety of data presents challenges in delivering information that is insightful and actionable (Rikhardsson & Yigitbasioglu, 2018; Nielsen, 2018; Park et al., 2017; Vasarhelyi et al., 2015). Dashboards are the main instruments for delivering information from BI systems by visualizing and aggregating information (Appelbaum et al., 2017; Sarikaya et al., 2019). Dashboards allow managers to access and analyze information on their own through self-service BI applications (Reinking et al., 2020a). At first glance, this may seem to make the work of management accountants obsolete, but there are several arguments why they still play a key role, especially in the implementation and use of dashboards. In particular, the ability to interpret and analyze data is essential for extracting meaningful insights from dashboards, as well as to communicate these insights and collaborate with managers (Appelbaum et al., 2017).

Empirical evidence reports a positive impact of Business Intelligence and Business Analytics on organizational value (O'Neill & Brabazon, 2019) and corporate planning and control (Richards et al., 2019). The same holds for the managerial use of dashboards in particular (Reinking et al., 2020b). While the role of management accountants is to support managers with planning and control systems (Ittner & Larcker, 2001), the use of such systems requires domain experts, management accountants (Dai & Vasarhelyi, 2023), who are capable of modeling and maintaining the decision-related information provision of dashboards. A recent study indicates that such systems can contribute to the effectiveness of management accountants who provide support to managers (Boerner et al., 2024). This underscores the significance of understanding the use or non-use of dashboards by management accountants.

However, the state of knowledge about dashboard usage by management accountants is still limited despite an increase in scholarly work (Rikhardsson & Yigitbasioglu, 2018, p. 41, 48; Yigitbasioglu & Velcu, 2012). This is unfortunate for management accounting research, given that BI and dashboards are proclaimed as tools for increasing productivity (Arnaboldi et al., 2017; Warren et al., 2015), but the adoption of BI and dashboards seems to be rather low (Andrews et al., 2018; Gierten et al., 2021; Raguseo, 2018; Zolas et al., 2020), creating a tension between aspiration and reality. The same tension is evident when examining the challenges from the perspective of non-technical users, such as management accountants. Such users interact with data intermittently; they must rely on dashboards designed for passive data consumption rather than active analysis. Furthermore, existing dashboards do not fit into the workflows of such users, so they have to make workarounds and combine different tools to get what they need (Tory et al., 2023). Hence, it may not come as a surprise that they still rely more on spreadsheets (Schmidt et al., 2020). However, practitioners see dashboards as a very important tool (BARC-Institut, 2024), which underscores this tension.

To understand such tensions in adopting technologies such as dashboards, researchers apply the established Unified Theory of Acceptance and Use of Technology (UTAUT) (Blut et al., 2021), but this theory so far does not cover dashboards. Marangunic & Granić, 2015 similarly highlight the importance of extending established models such as UTAUT to new information systems and environments, further

supporting the relevance of this study in the context of dashboards for management accountants.

Understanding the adoption and impact of dashboards in management accounting is crucial for scholars and practitioners alike. Dashboards, as tools for delivering insights from big data and business intelligence (Appelbaum et al., 2017), have the potential to significantly enhance decision-making and organizational behavior coordination, which are core functions of management accounting (Horngren et al., 2015; Merchant & van der Stede, 2017).

Based on this lack of evidence and insight into the driving forces of dashboard usage, this study derives two research questions: (1) What factors drive the intention and use of digital dashboards by management accountants and (2) what impact does the use of digital dashboards have on their job performance?

Although multiple research questions could be derived from the increasing role of dashboards in management accounting, this study prioritizes two key aspects: the determinants of dashboard adoption and the performance implications of their use. The purpose of the study is to contribute to the literature by developing and testing an extended UTAUT model tailored to management accounting. This model will improve our understanding of how digital dashboards are adopted and used in practice. It also allows for exploration of both direct and indirect pathways to adoption, reflecting the complexity of decision-making in professional technology use.

The importance of this research is underscored by several factors: (a) by applying an adapted UTAUT, this study aims to identify key factors driving or hindering dashboard adoption among accountants because technology acceptance is a well-established concept, also empirically supported in various areas (Yadegari et al., 2023); (b) understanding both the adoption factors and performance impacts can reveal untapped opportunities for enhancing management control practices; (c) insights into dashboard adoption and its effects can inform how these systems adapt in the digital age; (d) this research can provide both theoretical advancements and practical guidance for dashboard implementation and optimization.

The study employs an extended UTAUT model and tests it empirically with a German sample. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the study examines the impact of the core constructs—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI) and Facilitating Conditions (FC)—on Behavioral Intention (BI) and Usage Behavior (UB), with an additional focus on Decision Quality (DQ) and Information Quality (IQ) as antecedents of PE and EE. The results reveal that EE significantly influences BI, while FC plays a key role in shaping both BI and UB. In addition, DQ and IQ have been found to significantly impact PE, with indirect effects on BI.

The primary contribution of this study is to management accounting research. We demonstrate that management accountants evaluate dashboards through two distinct lenses of quality: information quality (IQ), which reduces perceived effort by cutting down on search and reconciliation work, and decision quality (DQ), which increases perceived usefulness by providing richer analytical insight. By showing that DQ—an evaluative belief rooted in decision outcomes—directly feeds into performance expectancy (PE), we offer a behavioral explanation for why management accountants adopt dashboards that promise sharper variance analyses and scenario simula-

tions, even when those tools do not further automate routine reporting. Extending the technology-acceptance model with DQ positions the dashboards squarely within the accountant's decision-support arsenal. More generally, the study extends UTAUT with task-specific constructs, offering a more nuanced understanding of technology adoption in professional contexts; second, it combines the literature on technology acceptance with performance effects of accounting technologies to provide a more holistic understanding of the determinants of digital dashboards used by management accountants and their performance effects. The study also highlights the importance of organizational support in driving dashboard usage, with practical implications for designing user-friendly dashboards and fostering a supportive infrastructure.

The paper is organized as follows. The next section discusses the literature, identifies the research gap, and derives hypotheses. Section 3 describes the measurement, sampling, and statistical inference, while Sect. 4 presents the results. Section 5 discusses the results and concludes the paper.

2 Dashboards and management accounting

2.1 Management accountants and dashboards

Management accounting and control systems exist to provide managers with information relevant to decisions and to coordinate and guide behavior (Merchant & van der Stede, 2017; Horngren et al., 2015). Drawing on information-processing theory, effective control requires a match between information supply, information needs, and user's processing capacity (Tushman & Nadler, 1978). Historically, management accountants have brokered this match for both financial and non-financial data, frequently by leveraging information technology (Stambaugh & Carpenter, 1992). This establishes the professional context in which any new analytical tool—such as dashboards—must prove its worth.

The proliferation of “big data” and business intelligence (BI) technologies (Chen & Zhang, 2014; Duan & Xiong, 2015) has made dashboards a central interface to visualize and aggregate insights (Appelbaum et al., 2017) and enabling self-service analytics (Reinking et al., 2020a). However, research shows that such tools succeed only when human expertise interprets and communicates the signals (Ain et al., 2019; Appelbaum et al., 2017). Thus, rather than being displaced, management accountants remain pivotal in translating raw analytics into actionable management information.

Despite their prominence in practitioner discourse, empirical evidence on dashboard prevalence is mixed: some sectors report high usage of interactive tools (Zolas et al., 2020), while surveys document uneven adoption of Big Data/analytics software that often underpins dashboards (Andrews et al., 2018; Raguseo, 2018). With few studies zooming in on dashboard use by management accountants specifically, the extent and nature of their adoption in this profession remain unclear, highlighting the need for focused investigation.

Dashboards can improve decision making, organizational learning, and performance (Lee & Widener, 2016; Richards et al., 2019; Sarikaya et al., 2019; Velcu-Leitinen & Yigitbasioglu, 2012). However, these benefits materialize only when

design choices fit user tasks (Nadj et al., 2020; Perkhofer et al., 2020) and when users adopt the tool (Kumar et al., 2022). Poor tailoring to workflows or limited support for interactive analysis can suppress adoption despite technical potential (Tory et al., 2023; Ain et al., 2019). This underscores why understanding the antecedents of acceptance is essential.

Spreadsheets remain the default technology for many management accountants (Church et al., 2022; Schmidt et al., 2020). As an established “all-purpose” solution, they can foster status quo bias and hybrid practices where dashboards and spreadsheets coexist (Rieg et al., 2023). Consequently, studying how management accountants perceive and accept dashboards connects directly to technology-acceptance research and motivates the model we test in this study.

2.2 Technology acceptance models for dashboard use

The seminal studies of Davis (Davis, 1989; Davis et al., 1989) introduced the Technology Acceptance Model (TAM), which is foundational in understanding how and why users accept technology. TAM posits that technology can improve productivity if it is accepted by users, with perceived usefulness (PU) and perceived ease of use (PEOU) being the key determinants that predict actual technology usage. Over time, TAM has been extensively tested and expanded to improve its predictive power and adapt it to specific contexts, resulting in various extensions (Venkatesh et al., 2003; Yadegari et al., 2023; Lee et al., 2003; Rondan-Cataluña et al., 2015). Several meta-analyses confirmed that TAM remains an important model to explain technology acceptance (Marikyan et al., 2023; King & He, 2006; Marangunić & Granić, 2015).

However, to provide a more comprehensive framework for understanding technology adoption, especially in organizational contexts, Venkatesh et al., (2003) developed the UTAUT model. It integrates elements from eight prominent models of technology acceptance, including TAM, and introduces four core constructs—performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)—as direct determinants of behavioral intention to use (BI) and direct or indirectly affecting usage behavior (UB). Performance expectancy and effort expectancy align closely with the concepts of PU (Venkatesh et al., 2003, p. 447) and PEOU in TAM, while social influence and facilitating conditions introduce new dimensions that account for the impact of the social and organizational environment on technology adoption.

The UTAUT model is particularly relevant for studying the adoption of digital dashboards by management accountants because it considers the broader organizational context in which technology adoption occurs. For example, social influence and facilitating conditions are critical in understanding how management accountants, who often work within structured and hierarchical environments, adopt new technologies such as dashboards. The comprehensive approach of UTAUT has been shown to explain a greater variance in technology adoption behaviors (Venkatesh et al., 2003; Venkatesh et al., 2012; Blut et al., 2021; Dwivedi et al., 2020), making it an ideal framework for exploring the drivers behind dashboard adoption in management accounting.

However, several critical aspects of management-accounting work fall outside the original UTAUT, justifying its extension with domain-specific aspects. The first aspect is Information Quality (IQ). Management accounting is a nexus of increasingly digital and diverse information flows (Bredmar, 2017), including sustainability data, which increases the skills needed to extract insight and avoid overload (Burnay et al., 2023). Dashboards with visual analytics can help accountants turn heterogeneous data into faster and higher-quality analyses. IQ captures whether outputs are precise, timely, and complete (DeLone & McLean, 2003; Wixom & Todd, 2005; Petter & McLean, 2009). For management accountants, these qualities are prerequisites for credible decisions (Knauer et al., 2020). Embedding IQ in UTAUT clarifies how reliable information raises Performance Expectancy (PE)—because better data underpin better decisions—and lowers Effort Expectancy (EE)—because clean data reduces reconciliation work (cf. Davis, 1989). Previous acceptance studies have already integrated IQ (Uzoka et al., 2008; Zwain, 2019), and two meta-analyses confirm its relevance (Petter & McLean, 2009; Blut et al., 2021). Thus, extending UTAUT with IQ aligns the model with the realities of management-accounting practice and prepares the ground for our hypotheses.

The second aspect and a central purpose of dashboard solutions in management accounting is decision support. In a broader context, digitalization of management accounting can improve decision quality (in short DQ) (Möller et al., 2020; Papiorek & Hiebl, 2023). In this study, Decision Quality (DQ) is positioned as an expected outcome and analyzed as an antecedent to both Performance Expectancy (PE) and Behavioral Intention to Use (BI) within the UTAUT framework. Unlike traditional studies that treat DQ as an outcome of technology use (Clark et al., 2007; Kamis & Davern, 2005; Visinescu et al., 2017), this study considers how the anticipated improvement in DQ—specifically, the expectation that dashboards will lead to quicker, more informed, and accurate decisions—shapes users' expectations about the technology's usefulness (PE) and their intention to adopt it (BI), which is explained by expectation confirmation theory (Bhattacharjee, 2001; Hossain & Quaddus, 2012). In the context of management accountants, where decision-making is a critical task, expected DQ directly influences PE by providing a tangible reason to believe that dashboards will enhance job performance. Additionally, when users anticipate that dashboards will significantly improve decision quality, this positive expectation can also drive their Behavioral Intention to Use the technology, as they are motivated by the prospect of making better decisions. This dual influence of DQ on both PE and BI enriches the UTAUT model, allowing it to better capture the specific motivations and expectations that drive technology adoption among management accountants. Considering DQ as a key determinant, this study highlights the importance of task-specific expectations in shaping technology acceptance, as supported by the broader literature on perceived usefulness and intention to use.

Lastly, performance (PER), defined as the perceived impact of dashboards on a user's effectiveness, efficiency, and productivity, is a valuable addition to the UTAUT framework, particularly in the context of management accountants. The inclusion of PER as an outcome in this model is supported by theories like the Task-Technology-Fit (TTF) model (Goodhue & Thompson, 1995), which posits that a good fit between technology and task directly enhances individual performance. According to the TTF

model, when management accountants perceive those dashboards to align well with their tasks—such as analyzing financial data and making informed decisions—this alignment leads to improved job performance. Additionally, the DeLone and McLean Information Systems Success Model (DeLone & McLean, 2003) provides a theoretical basis for linking Usage Behavior (UB) to Performance (PER). Their model suggests that the quality of system use or the extent to which a system is effectively used directly influences individual and organizational performance outcomes.

Incorporating PER into the UTAUT model recognizes that the ultimate goal of technology adoption is not merely usage, but also the realization of tangible performance benefits. As users engage with dashboards more frequently and effectively (UB), they are likely to experience enhancements in their work performance, which in turn reinforces the technology's perceived value and encourages continued use. This link is crucial in understanding how technology adoption translates into real-world benefits for management accountants. By linking UB directly to PER, this study underscores the importance of examining not just the intention to use technology, but also the actual performance outcomes that result from its sustained use.

2.3 Research model and hypotheses

The previous discussion in Sect. 2.2 illustrated the potential benefits of using and extending UTAUT. Figure 1 shows the resulting research model, followed by a discussion of the hypotheses. The first six hypotheses relate to UTAUT (Venkatesh et al., 2003) and apply them to dashboard usage, while the next five hypotheses relate to the extensions argued in Sect. 2.2.

Performance Expectancy (PE) is a well-established predictor of Behavioral Intention (BI) in technology adoption, particularly through its emphasis on perceived utility and job performance enhancement (Venkatesh et al., 2003). For management accountants, dashboards improve decision-making accuracy, efficiency, and speed, making them valuable tools for managing complex data tasks (Sarikaya et al., 2019; Appelbaum et al., 2017). Empirical studies confirm that tools that offer enhanced

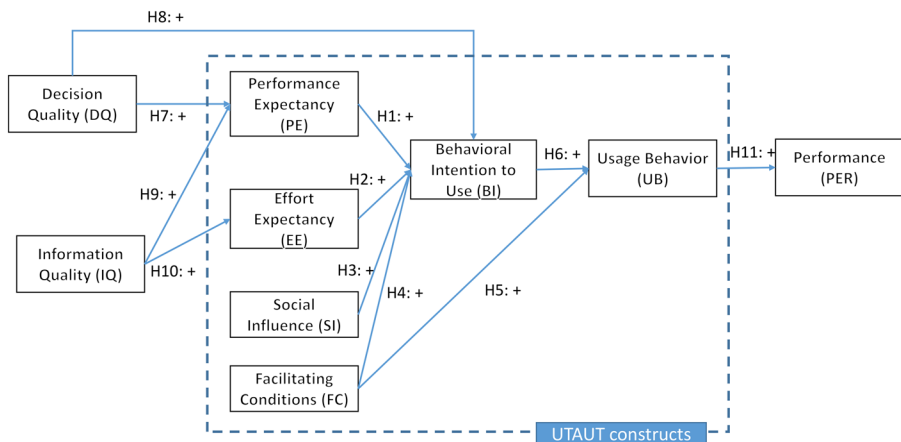


Fig. 1 Conceptual research model based on UTAUT with extensions

performance capabilities foster stronger adoption intentions (Reinking et al., 2020b; Duan & Xiong, 2015; Ain et al., 2019). Meta-analyses of UTAUT applications further validate PE as a critical driver of BI across contexts, especially in roles requiring high decision quality (Dwivedi et al., 2020; Blut et al., 2021). Thus, consistent with UTAUT and supported by these additional studies, we hypothesize:

Hypothesis H1 Performance Expectancy (PE) positively influences Behavioral Intention (BI) to use digital dashboards among management accountants.

Effort Expectancy (EE), reflecting the perceived ease of use, is a key determinant of Behavioral Intention (BI), particularly during early technology adoption (Venkatesh et al., 2003). Digital dashboards that are intuitive and user-friendly reduce cognitive load, making them more appealing to management accountants who operate in data-intensive roles. Research confirms that ease of use significantly improves adoption intentions for advanced tools by minimizing the effort required to achieve effective utilization (Ifinedo, 2012; Al-Emran et al., 2018). Studies in related contexts emphasize that user-friendly interfaces are critical for driving BI, especially for technologies requiring frequent interaction with complex data (Davis, 1989; Sarikaya et al., 2019). Therefore:

Hypothesis H2 Effort Expectancy (EE) positively influences Behavioral Intention (BI) to use digital dashboards among management accountants.

Social Influence (SI), representing the perceived expectations of peers and superiors, plays a crucial role in shaping Behavioral Intention (BI) to adopt technology, particularly in professional settings where norms and peer behavior heavily influence decision-making (Venkatesh & Davis, 2000). In accounting departments, peer recommendations and managerial encouragement significantly impact the adoption of new tools, as evidenced by studies on accounting technology use (Leonard-Barton & Deschamps, 1988; Goretzki & Messner, 2019). SI is particularly influential in hierarchical environments, where conformity to professional expectations often drives technology adoption decisions. Based on UTAUT and these findings, the next hypothesis reads:

Hypothesis H3 Social Influence (SI) positively influences Behavioral Intention (BI) to use digital dashboards among management accountants.

Facilitating Conditions (FC), defined as the availability of resources, training, and organizational support, are critical for fostering Behavioral Intention (BI) to adopt new technologies (Venkatesh et al., 2003). For management accountants, compatible systems, technical assistance, and adequate training reduce barriers to dashboard adoption. Studies in related contexts affirm that organizational support significantly enhances BI by ensuring users feel equipped to utilize technology effectively (Schmidt et al., 2020; Ifinedo, 2012). In addition, comprehensive infrastructure and user guidance have been shown to alleviate implementation challenges and reinforce adoption intentions for analytics tools (Lennerholt et al., 2021; Daradkeh, 2019). Hence:

Hypothesis H4 Facilitating Conditions (FC) positively influence Behavioral Intention (BI) to use digital dashboards among management accountants.

Facilitating Conditions (FC), which encompass resources, training, and technical support, directly influence Usage Behavior (UB) by enabling users to transition from intention to actual adoption. The UTAUT framework posits that sufficient organizational and technical support mitigates barriers to technology use, encouraging sustained engagement (Venkatesh et al., 2003). Empirical studies affirm that well-structured training programs, accessible user support, and system compatibility significantly enhance actual usage by addressing practical adoption challenges (Ifinedo, 2012; Lennerholt et al., 2021). In data-driven environments, such as management accounting, the presence of robust FC ensures that professionals can effectively leverage dashboards for decision-making, reinforcing the direct link between FC and UB. Therefore:

Hypothesis H5 Facilitating Conditions (FC) positively influence Usage Behavior (UB) of digital dashboards among management accountants.

Behavioral Intention (BI) is a key predictor of Usage Behavior (UB) within the UTAUT framework, consistently validated across technology adoption studies (Venkatesh et al., 2003). The intention to use a system, influenced by perceived performance benefits, ease of use, and social norms, often translates into actual use. For management accountants, the decision to adopt dashboards for improved decision-making aligns with established findings that BI is the strongest determinant of UB in professional and data-intensive contexts (Ain et al., 2019; Davis, 1989). The robust link between BI and UB underscores its reliability as a key mechanism to predict the usage of the dashboard. Thus:

Hypothesis H6 Behavioral Intention (BI) positively influences Usage Behavior (UB) of digital dashboards among management accountants.

Decision quality (DQ) refers to the expected ability of a dashboard to support faster, more informed decisions through timely, accurate, and relevant information (Bhattacharjee, 2001; Hossain & Quaddus, 2012). Building on expectancy-confirmation theory, we argue that if management accountants believe that a dashboard will improve decision making, they will infer broader gains in job performance (Knauer et al., 2020; Duan & Xiong, 2015). Put differently, when the technology provides effective decision support, users expect that this tool will improve their overall work productivity, effectiveness, or even professional recognition, i.e., performance expectancy (PE) (Venkatesh et al., 2003). Thus, the expectation of improved decision quality creates a general belief that the dashboard will lead to better job outcomes.

Hypothesis H7 Decision Quality (DQ) positively influences Performance Expectancy (PE) in the use of digital dashboards among management accountants.

In addition to shaping perceptions of overall performance, we find that decision quality can also create a direct impetus to adopt dashboards. In professional contexts where accountability is high, people can adopt tools as a protective measure against the threat of making poor decisions. Drawing on accountability theory (Lerner & Tetlock, 1999; Frink et al., 2014), management accountants who expect to justify their decisions to superiors or clients may be particularly motivated to avoid errors. Similarly, protection motivation theory (Rogers & Prentice-Dunn, 1997; Larrick, 1993) suggests that when individuals perceive a clear threat - in this case, the negative consequences of making inaccurate decisions - they often adopt recommended protective behaviors (e.g., using a reliable dashboard) to mitigate that risk.

In short, professionals may intend to use dashboards directly to protect against suboptimal decisions, regardless of whether they link this improvement to broader job performance gains (Bhattacharjee, 2001; Kamis & Davern, 2005). In particular in managerial accounting, where decision errors can have financial and reputational consequences, the desire to prevent errors or demonstrate due diligence can drive technology adoption. Thus, we hypothesize the following.

Hypothesis H8 Decision Quality (DQ) positively influences Behavioral Intention (BI) to use digital dashboards among management accountants.

Overall, H7 posits that perceived improvements in decision quality shape broader performance beliefs (i.e., Performance Expectancy), aligning with theories of expectation-confirmation (Bhattacharjee, 2001; Hossain & Quaddus, 2012). In contrast, H8 captures a more immediate, direct motivation to adopt dashboards, drawing from accountability theory (Lerner & Tetlock, 1999; Frink et al., 2014), and protection motivation theory (Rogers & Prentice-Dunn, 1997; Larrick, 1993). Specifically, when management accountants anticipate that dashboards can help them avoid costly errors—thus mitigating accountability pressures and negative consequences—this narrower, risk-focused rationale can spur Behavioral Intention independently of broad performance expectations. By differentiating these two paths, we recognize that some users adopt dashboards to enhance general job performance, while others may be motivated primarily by the desire to reduce the risk of inaccurate decisions.

Concerning the next hypothesis, Information Quality (IQ), characterized by attributes such as accuracy, timeliness, and relevance, affects users' perceptions of how useful a system will be rather than their immediate motivation to adopt it. For management accountants, dashboards offering high-quality information increase confidence in their ability to make well-informed and efficient decisions, shaping expectations of improved performance. Empirical studies consistently link IQ to higher perceptions of technology utility because high-quality data is a prerequisite for deriving value from information systems (Petter & McLean, 2009; Wixom & Todd, 2005). Unlike decision quality, which is outcome-oriented (i.e., how well the system enables better decision-making), information quality influences system expectations by reducing uncertainty and increasing trust in data reliability (Duan & Xiong, 2015; Bhattacharjee, 2001). In dashboard-specific contexts, research shows that when users perceive information as precise and relevant, they develop stronger beliefs that the technology will enhance their performance, regardless of their immediate intention to adopt it

(Sarikaya et al., 2019). Thus, IQ primarily reinforces Performance Expectancy (PE), rather than Behavioral Intention (BI).

Hypothesis H9 Information Quality (IQ) positively influences Performance Expectancy (PE) in the use of digital dashboards among management accountants.

Effort Expectancy (EE), reflecting the perceived ease of use, is strongly influenced by the quality of information provided by a system. For management accountants, high Information Quality (IQ)—characterized by precision, timeliness, and clear organization—reduces the cognitive effort required to interpret and apply dashboard data. This alignment between IQ and user-friendliness simplifies technology interaction and fosters perceptions of ease of use. Foundational research on technology acceptance consistently links high-quality information to reduced effort perception (Davis, 1989; Wixom & Todd, 2005). Additionally, tools that streamline information processing and minimize complexity have been shown to improve user experience, reinforcing EE in professional contexts (Petter & McLean, 2009; Sarikaya et al., 2019).

Hypothesis H10 Information Quality (IQ) positively influences Effort Expectancy (EE) in the use of digital dashboards among management accountants.

Usage Behavior (UB), reflecting the actual use of technology, is a critical predictor of Performance (PER) outcomes. For management accountants, the frequent and effective use of dashboards enables better data analysis, reporting, and decision-making, directly enhancing job performance. The Task-Technology-Fit (TTF) model asserts that when technology aligns closely with task requirements, greater usage leads to improved efficiency and productivity (Goodhue & Thompson, 1995). Similarly, the DeLone and McLean Information Systems Success Model highlights that the extent and quality of system use significantly influence performance improvements, reinforcing the importance of UB (DeLone & McLean, 2003). Empirical evidence shows that dashboard usage fosters decision quality and productivity gains, particularly in data-intensive environments (Petter & McLean, 2009; Sarikaya et al., 2019).

Hypothesis H11 Usage Behavior (UB) positively influences Performance (PER) in the use of digital dashboards among management accountants.

In line with the UTAUT framework (Venkatesh et al., 2003), which includes age, gender, experience, and voluntariness as control variables, this study focuses on age and experience. Empirical evidence in the management accounting context suggests that these factors are more directly related to technology adoption behavior (Morris & Venkatesh, 2000). In contrast, gender and voluntariness have been found to have a negligible influence in task-specific settings, such as dashboard adoption (Gefen & Straub, 1997; Daradkeh, 2019). Therefore, only age and experience were included as controls to account for variations in both behavioral intention and usage behavior.

Although UTAUT specifies direct paths from PE, EE, SI, and FC to BI and UB, prior IS research shows that system and information qualities often exert their influence indirectly through these proximal beliefs (Petter et al., 2008; Wixom & Todd,

2005). In our context, Information Quality (IQ) reduces perceived effort because high relevance, accuracy and timeliness reduce search and reconciliation work ($IQ \rightarrow EE$), while Decision Quality (DQ) increases perceived usefulness because accountants anticipate more accurate and defensible decisions ($DQ \rightarrow PE$). PE and EE then transmit these effects to BI and, ultimately, to UB—implying the specific mediations we test (e.g., $IQ \rightarrow EE \rightarrow BI$; $DQ \rightarrow PE \rightarrow BI$). This logic is consistent with belief-updating views in Expectation–Confirmation Theory (Bhattacharjee, 2001), and continuance research (Bhattacharjee & Premkumar, 2004), where distal qualities shape usage through cognitive evaluations.

We also theorize a complementarity-based interaction between DQ and IQ on EE. As argued also in the supplementary file, high-quality information alone is insufficient if users doubt it, they can leverage it for better decisions, and high decision-quality expectations crumble without trustworthy data (Petter & McLean, 2009; DeLone & McLean, 2003). Drawing on Task–Technology–Fit and resource complementarity ideas (Goodhue & Thompson, 1995), we propose that management accountants experience dashboards as easier to use when both data and decision-support cues are strong because the joint presence minimizes cognitive effort. Consequently, we test the interaction between $DQ \times IQ \rightarrow EE$ interaction a priori.

3 Research methods

3.1 Sampling and data

Research on technology acceptance relies predominantly on survey data (Lee et al., 2003); hence, for this study, a questionnaire was developed including items for the constructs above and added with several questions for characterizing the sample. These were: the hierarchical position and function of respondents, industry, legal form of organization, affiliation to a group, number of employees of the organization, and total net revenue of the firm. The questionnaire was pretested with several management accountants who provided additional feedback and confirmed the comprehensibility and feasibility of the survey. The online questionnaire included a short description and visualization of dashboards using the example of Microsoft Power BI (Appendix 2).

The survey was conducted in Germany, a developed economy with a mature management accounting profession and high digital readiness. The sample of 3,000 companies was randomly selected from the NEXIS database to ensure a broad representation of industries and firm sizes. Data collection occurred between 20 June 2020 and 24 July 2020, during the early stages of the COVID-19 pandemic, a period marked by significant shifts in organizational practices.

The pandemic catalyzed widespread remote work and accelerated the adoption of digital tools, including dashboards, to support decision-making under uncertainty. Several studies (Ulrich & Kratt, 2021; Ho et al., 2023) highlight that management accountants increasingly relied on dashboards for timely and accurate insights as their roles evolved to meet crisis-driven demands. Gathmann et al., (2024) and Ge et

al., (2023) further emphasize that digital tools improved operational resilience and supported critical functions during this period.

Although this study does not provide pre-pandemic or longitudinal data, the timing of the survey captures a unique snapshot of dashboard adoption under heightened reliance on digital tools. The findings align with evidence that the pandemic created a push toward leveraging digital solutions for efficiency and decision support (Reuschl et al., 2022; Bedford et al., 2022). However, the cross-sectional nature of the study limits inferences about changes before or after the pandemic.

The study's focus on one country, Germany, provides an advantageous setting for testing the UTAUT model. As a highly developed economy, German organizations generally have robust access to digital infrastructure, technical resources, and skilled professionals. This setting allows us to examine the core UTAUT constructs (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions) without the confounding effects of technical infrastructure limitations or digital literacy barriers that might be present in developing economies. Thus, the findings represent how UTAUT factors influence dashboard adoption when basic technical prerequisites are met, providing insights into adoption behavior under well-funded conditions.

Despite extensive mailing of the questionnaire, the final sample size of $n=61$ is comparatively small and seems not to be an exception in technology acceptance research (Turner et al., 2010). On the one hand, this could be because the topic is very specific, both in terms of the target group and the subject of the research. On the other hand, some organizations reported that they had no capacity during the survey period due to various circumstances. This may also be related to the COVID-19 pandemic during this period.

Table 1 presents descriptive statistics on the respondents and their organizations. A large portion comes from small to mid-sized firms, often belonging to a group (61%) and in the legal form of corporations (54%) or private companies (26%). The majority of respondents work in management accounting and have management positions. This is advantageous because the construct of decision quality is more relevant for this group than for non-managerial employees.

Table 1 Characteristics of the sample

No. of employees	n	%	net revenue	n	%	Industry	n	%
1-50	5	8.2%	≤ 250 T€	2	3.3%	manufacturing	23	37.7%
51-250	14	23.0%	> 250 T€ - 1 m€	0	0.0%	construction	4	6.6%
251-1,000	21	34.4%	> 1 m€ - 10 m€	4	6.6%	automobile	4	6.6%
1,001-5,001	11	18.0%	> 10 m€ - 50 m€	19	31.1%	information, communication	6	9.8%
5,001 - 10,000	3	4.9%	> 50 m€ - 100 m€	7	11.5%	financial industry	4	6.6%
10,001 - 20,000	2	3.3%	> 100 m€ - 500 m€	15	24.6%	public services	4	6.6%
>20,000	5	8.2%	> 500 m€ - 5 b€	9	14.8%	others	16	26.2%
	61	100%	> 5 b€ - 10 b€	3	4.9%		61	100%
			> 10 b€	2	3.3%			
				61	100%			
Age of respondents	n	%	Position of respondents	n	%	Function of respondents*		%
18 - 24 years	3	4.9%	staff members	16	26.2%	management accounting		57.4%
25 - 34 years	11	18.0%	team lead	9	14.8%	financial accounting		22.1%
35 - 44 years	27	44.3%	department head	18	29.5%	tax and audit		6.9%
45 - 54 years	16	26.2%	division manager	9	14.8%	Other areas		13.7%
55 - 64 years	4	6.6%	managing director	4	6.6%			
> 64 years	0	0.0%	others	5	8.2%			
	61	100%		61	100%			

*) multiple answers possible

*) multiple answers possible

The experience of the respondents with dashboards varies: 39% (24) reported no experience, 20% (12) experience up to 12 months, and 41% (25) experience from one to several years. Regarding the first research question, the results show a significant portion of dashboard users, higher than Raguseo, 2018 in his sample. This result helps to answer the first research question, the majority of respondents has experience with dashboards in this sample.

Two common issues in cross-sectional studies are common-method bias and non-response bias. The former arises when measurement artifacts inflate relationships due to respondents answering in a biased manner, while the latter occurs when differences exist between early and late respondents, potentially threatening generalizability. To assess common-method bias, Harman's Single-Factor Test was conducted using exploratory factor analysis on all indicators in the PLS-SEM model. The first factor explained 35% of the total variance, which is well below the critical 50% threshold (Podsakoff et al., 2003), suggesting that common-method bias is unlikely to be a major concern in this study. To examine non-response bias, a Wilcoxon rank-sum test was used to compare early and late respondents across all variables. The results indicated no significant differences (all p -values > 0.05), suggesting that non-response bias does not pose a threat to the validity of our findings (Armstrong & Overton, 1977). Finally, the problem of the social desirability of respondents' answers (King & Bruner, 2000) seems less relevant given the professional and task-oriented nature of the questions in this study. Further details on these tests are provided in the supplementary file.

3.2 Measurement of constructs

The constructs in the technology acceptance models are typically latent and need to be operationalized through scales and items. The research model in Fig. 1 is based on constructs from previous research that have been combined for the specific purpose of this study. Therefore, the selected items have been developed and tested in previous research and can be considered reliable and valid indicators. Table 2 presents the constructs with references in alphabetical order. Appendix 1 lists the items per construct.

The scales for the construction elements were 7-point scales with 1 = "Do not agree at all" and 4 = "neutral", up to 7 = "completely agree". Such a 7-point scale is common in technology acceptance research (e.g. Venkatesh et al., 2003).

A major concern with measuring technology acceptance research is that many of these constructs measure self-reported perceptions rather than actual usage (Lee et al., 2003), yet a review by Turner et al., 2010 concludes that BI shows a clear positive correlation with actual usage. This does not eliminate this concern, but reduces its magnitude.

3.3 Control variables

Following the theoretical rationale discussed in Sect. 2.3, only age and experience were incorporated as control variables. These variables were measured through survey questions that captured the chronological age of the respondents and the years of

Table 2 List of constructs and references

Construct		In UTAUT	References
Behavioral intention to use	BI	BIU	Venkatesh et al., 2003, p. 460
Facilitating conditions	FC	FC	Venkatesh et al., 2003, p. 453
Usage behavior	UB	UB	Venkatesh et al., 2003, p. 468
Social influence	SI	SI	Venkatesh et al., 2003, p. 451
Performance Expectancy	PE	Performance expectancy	Venkatesh et al., 2003, p. 447
Effort expectancy	EE	Effort expectancy	Venkatesh et al., 2003, p. 450; Blut et al., 2021
Decision Quality	DQ	-	Wieder et al., 2012; Holsapple & Sena, 2005
Information Quality	IQ	-	DeLone & McLean, 2016, 2003; Petter & McLean, 2009
Performance	PER	-	Kuo & Lee, 2009; Goodhue & Thompson, 1995
Age	AGE	AGE	Venkatesh et al., 2003, p. 467
Experience	EXPERIENCE	EXP	Venkatesh et al., 2003, p. 467

dashboard experience, respectively. The categories used are mentioned in Appendix 1.

In line with the UTAUT framework, we focus on Behavioral Intention (BI) and Usage Behavior (UB) as key outcomes of technology adoption. Age and experience are known to affect both BI (intention to adopt) and UB (actual use), with older individuals often being more resistant to new technologies, while younger users and less experienced individuals tend to be more open to adopting them (Venkatesh et al., 2003; Morris & Venkatesh, 2000). By including these control variables, the model accounts for variations in BI and UB across different age groups and experience levels, providing a more accurate understanding of dashboard adoption. In contrast, constructs like Performance Expectancy (PE) and Effort Expectancy (EE) are primarily shaped by perceptions of the technology itself, rather than demographic factors.

3.4 Statistical inference

To estimate parameters for the conceptual models as in Fig. 1 in the technology acceptance field, many researchers use Partial Least Square Structural Equation Modeling, or PLS-SEM for short (Venkatesh et al., 2003; Venkatesh et al., 2012). However, PLS-SEM is the subject of heated debate between two groups. One group rejects it altogether, while the other group supports exaggerated claims (Rigdon, 2016). As Rigdon, 2016 argues, both camps have their misconceptions and misaligned expectations. In summary, PLS-SEM is just another statistical method that needs to be based on a sound theoretical model and used appropriately (Hair et al., 2019). PLS-SEM, like factor-based SEM, uses the measured items to construct proxy variables that are related to the unobservable variable. Specifically, while the construct performance expectancy PE is measured with three items, PE1, PE2, and PE3, the theoretical notion of performance expectancy may include other aspects that are not covered by this PE construct. Thus, the use of PE is a proxy for the theoretically argued perceived usefulness and is not identical to it. However, this holds for all such methods.

The second main concern is applicability to small samples, which is touted by PLS-PM proponents and heavily criticized by PLS-PM opponents. Small samples pose a risk for all statistical methods because they increase the risk of false positives and increase the margin of error. The issue is not the small sample per se, but the relationship of the sample with the relevant population (Hair et al., 2019). Here, we expect the population of management accountants using dashboards to be rather small (Sect. 2.1), and so the sample will be small.

A third main concern is the use or misuse as an exploratory method. As Rigdon, 2016 argues, this does not and should not mean inductively analyzing a sample. Both SEM and PLS-PM must be grounded on a solid theoretical foundation to have valid arguments for using and measuring certain constructs the way they do. Exploratory means here that the PLS-SEM, based on UTAUT, is applied to a new area of technology acceptance and the underlying theory is extended by new constructs.

However, researchers are advised to follow recommended practices, which is also the case for PLS-SEM. The study follows the guidelines of Benitez et al., 2020 and Hair et al., 2019 and uses SmartPLS 4.0 and SPSS for statistical analyses.

4 Results

4.1 Measurement model

Table 3 shows statistics for items and constructs. Looking at the means in column (a), it seems that the constructs SI ($M=4.7486$) and FC ($M=4.5738$) were received relatively neutrally. The determinant FC4 (“A specific person (or group) is available to help with system problems.”) shows the lowest mean, indicating a perceived lack of support for the respondents.

The outer loadings of the measurement model indicate that most indicators demonstrate strong relationships with their respective latent variables, with loadings above the generally accepted threshold of 0.7. Some indicators, such as DQ3 (0.663), EE3 (0.691), FC3 (0.691), and SI3 (0.633), fall below this threshold but are retained due to their importance in the underlying theoretical model UTAUT (Venkatesh et al., 2003). Additionally, the relatively small sample size ($n=61$) may have contributed to the slightly lower loadings. The values of the variation inflation factor (VIF) are mainly within acceptable limits, except BI1 and BI2, which show moderate multicollinearity ($VIF=5.753$). Additional analyses with one or two indicators for BI did not lead to significant differences. Hence, all indicators are retained to preserve the integrity of the original model and its theoretical framework.

Table 4 shows statistics on factor analysis for constructs. Reliability and validity analyses of the measurement model show strong internal consistency across most constructs. Cronbach’s alpha values for the constructs range from 0.765 to 0.952, with all values above the commonly accepted threshold of 0.7 (Streiner, 2003), demonstrating good reliability. Composite Reliability (CR) values are similarly robust, with all constructs exceeding 0.7, further confirming the reliability of the construct. In terms of convergent validity, the Average Variance Extracted (AVE) for all constructs is well above the 0.5 threshold, indicating that the constructs explain a sig-

Table 3 Statistics on items and constructs (theoretical range for all indicators is 1 ... 7)

Indicators	(a)	(b)	(c)	(d)	(f)		(g)	(h)
	Mean	Standard deviation	Outer loadings	VIF	observed		Kurtosis	Skewness
BI1	6.164	0.961	0.976	5.753	4	7	-0.226	-0.908
BI2	6.197	0.826	0.978	5.753	4	7	-0.175	-0.746
DQ1	5.361	1.355	0.836	2.062	1	7	0.977	-0.932
DQ2	5.016	1.531	0.843	2.208	1	7	0.616	-0.871
DQ3	5.230	1.298	0.663	1.419	1	7	0.746	-0.673
DQ4	5.082	1.322	0.877	2.388	1	7	1.531	-0.897
EE1	6.016	0.983	0.858	2.707	3	7	0.316	-0.882
EE2	6.033	1.008	0.837	2.634	3	7	1.180	-1.152
EE3	4.820	1.409	0.691	1.403	1	7	-0.381	-0.320
EE4	5.426	1.063	0.704	1.211	3	7	-0.347	-0.348
FC1	4.557	1.797	0.860	3.037	1	7	-1.240	-0.243
FC2	5.082	1.582	0.872	2.981	2	7	-0.852	-0.495
FC3	4.426	1.788	0.691	1.375	1	7	-0.969	-0.106
FC4	4.230	2.099	0.739	1.570	1	7	-1.305	-0.083
IQ1	5.393	1.075	0.872	2.050	3	7	-0.499	-0.365
IQ2	5.082	1.191	0.928	3.570	1	7	0.864	-0.699
IQ3	5.115	1.202	0.910	3.115	2	7	0.026	-0.575
PE1	5.885	1.175	0.944	4.217	2	7	0.662	-0.953
PE2	6.066	0.973	0.928	3.893	3	7	0.104	-0.792
PE3	5.459	1.222	0.891	2.382	3	7	-0.715	-0.400
PER1	5.000	1.187	0.969	4.846	2	7	-0.126	-0.181
PER2	5.344	1.240	0.975	4.846	2	7	0.014	-0.479
SI1	4.459	1.532	0.890	2.634	1	7	0.334	-0.341
SI2	4.623	1.462	0.934	2.909	1	7	0.633	-0.443
SI3	5.164	1.495	0.633	1.242	1	7	-0.015	-0.711
UB1	3.869	2.131	1.000	1.000	1	7	-1.309	0.051

Table 4 Construct statistics

Construct	alpha	CR (rho_a)	AVE	R ² adj.	Q ² predict	SQRT(AVE)	max corr
BI	0.952	0.955	0.954	0.319	0.072	0.977	0.480
DQ	0.819	0.829	0.654			0.809	0.750
EE	0.778	0.788	0.602	0.062	0.017	0.776	0.579
FC	0.803	0.823	0.631			0.794	0.495
IQ	0.887	0.887	0.816			0.903	0.611
PE	0.910	0.914	0.848	0.583	0.565	0.921	0.679
PER	0.942	0.949	0.945	0.373	0.175	0.972	0.619
SI	0.765	0.833	0.689			0.830	0.403
UB				0.223	0.222		

alpha = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted;

R² adj. = adjusted R² for endogeneous constructs, Q² predict = predictive relevance

SQRT(AVE) = square root of AVE, max corr = max correlations between constructs

Table 5 Path coefficients (based on one-tailed tests)

Hypotheses	relation	Path		confidence interval		f-square
		coefficients	p values	5%	95%	
H1	PE -> BI	0.128	0.228	-0.171	0.398	0.009
H2	EE -> BI	0.401	0.007	0.119	0.659	0.165
H3	SI -> BI	0.274	0.028	0.058	0.533	0.070
H4	FC -> BI	-0.152	0.130	-0.369	0.08	0.022
H5	FC -> UB	0.477	0.000	0.284	0.646	0.281
H6	BI -> UB	0.068	0.252	-0.085	0.248	0.006
H7	DQ -> PE	0.604	0.000	0.482	0.722	0.557
H8	DQ -> BI	0.088	0.321	-0.219	0.409	0.005
H9	IQ -> EE	0.279	0.025	0.055	0.524	0.084
H10	IQ -> PE	0.235	0.007	0.082	0.393	0.084
H11	UB -> PER	0.619	0.000	0.476	0.752	0.623

Table 6 Key indirect effects

Path	Indirect Effect Size	Confidence Interval		Key Mediator	Interpretation Summary
		5%	95%		
FC -> UB -> PER	0.295	0.147	0.449	UB	Strong indirect effect of Facilitating Conditions on Performance via Usage Behavior.
IQ -> EE -> BI	0.112	0.023	0.259	EE	Information Quality impacts Behavioral Intention through Effort Expectancy.
DQ -> PE -> BI	0.078	-0.077	0.268	PE	Data Quality influences Behavioral Intention through Performance Expectancy.
EE -> BI -> UB	0.027	-0.022	0.138	BI	Effort Expectancy indirectly affects Usage Behavior via Behavioral Intention.
BI -> UB -> PER	0.042	-0.051	0.157	UB	Behavioral Intention influences Performance of accountants via Usage Behavior.

nificant portion of variance in their indicators. In particular, BI and PER exhibit very high AVE values (0.954 and 0.945, respectively), signifying exceptional convergent validity. The adjusted R^2 values indicate moderate explanatory power for BI (0.319) and FC (0.373), while PE (0.583) has the highest explained variance among endogenous constructs. These results confirm the reliability and validity of the measurement model, although the low explained variance for DQ (R^2 adj. = 0.062) suggests that the model could benefit from further refinement to predict this construct.

Both the Heterotrait-Monotrait Ratio (HTMT) and the Fornell-Larcker criterion confirm the discriminant validity of the model. All HTMT values are below the recommended threshold of 0.9, indicating adequate discriminant validity between constructs. Additionally, the Fornell-Larcker criterion shows that the square root of the AVE for each construct is greater than the correlations with other constructs, further supporting that the constructs are distinct from each other (see Table 4 and Tables S-5 and S-6 in the supplementary file).

The general assessment of the measurement model shows that it meets the necessary criteria for reliability, convergence validity, and discriminant validity. The strong internal consistency of the constructs, as reflected by high Cronbach's alpha and Composite Reliability values, alongside sufficient AVE for each construct, ensures that the model is both reliable and valid. Although some indicators have loadings

below 0.7, they are justified on the basis of theoretical importance, and the model's discriminant validity is supported by both the HTMT ratio and the Fornell-Larcker criterion. Despite some potential areas for refinement, particularly for the EE construct, the measurement model as a whole is robust and suitable for further structural analysis.

4.2 Structural model results

The results of the structural model, presented in Table 5; Fig. 2, highlight several key insights into the drivers of user intentions and behavior. Effort Expectancy (EE) and Social Influence (SI) significantly predict Behavioral Intention (BI), while Facilitating Conditions (FC) are a strong determinant of Use Behavior (UB). Additionally, Decision Quality (DQ) has a substantial impact on Performance Expectancy (PE), further emphasizing the importance of high-quality data in shaping users' perceptions of system performance. Interestingly, Performance Expectancy (PE) does not significantly influence Behavioral Intention (BI), and Behavioral Intention (BI) itself does not predict Use Behavior (UB), suggesting that other factors, such as facilitating conditions, play a more prominent role in determining system use.

A notable finding is the strong impact of Decision Quality (DQ) on Performance Expectancy (PE), despite moderate indicator loadings in the measurement model. This highlights the critical importance of high-quality data in shaping user' perceptions of system performance, even if some indicators of the construct are not as robust. This result underscores the importance of expected decision outcomes in shaping users' perceptions of the usefulness of the technology. This finding contributes to the literature by showing that DQ is not merely an outcome, but a predictor of technology acceptance, particularly in data-driven professional environments like management accounting. The positive and significant path from DQ to Performance Expectancy ($\beta=0.32$, $p<0.01$) supports H7 and aligns with expectation-confirmation theory: when a dashboard demonstrably improves decision quality, accountants per-

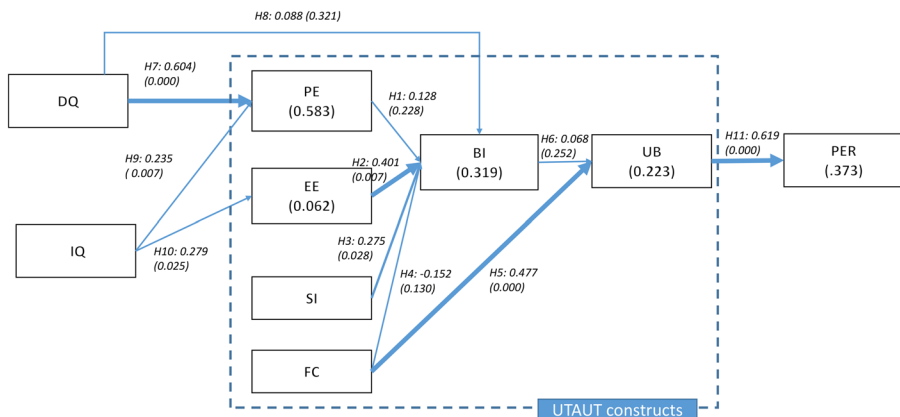


Fig. 2 PLS model estimated. Significant path coefficients in bold, p values in brackets. Constructs with R^2 adjusted

ceive their prior performance expectations as confirmed, increasing the perceived usefulness of the system (Bhattacharjee, 2001).

Additionally, Information Quality (IQ) positively influences both Performance Expectancy (PE) and Effort Expectancy (EE), underscoring the value of accurate and relevant information in enhancing both perceived usefulness and ease of use. As EE is formed during the first interaction, users notice improvements in usability the moment reliable data and decision cues coincide. In contrast, PE — and, by extension, BI — materialize only after a portfolio of successful task completions has been accumulated. This mirrors the distinction between pre- and post-adoption beliefs (Karahanna et al., 1999), and the staged belief updating observed in IT continuance research (Bhattacharjee & Premkumar, 2004). Therefore, the insignificant $DQ \times IQ \rightarrow PE$ path at time t_0 is theoretically expected, underlining the need for longitudinal evidence.

Of the hypotheses tested, H2 ($EE \Rightarrow BI$), H3 ($SI \Rightarrow BI$), H5 ($FC \Rightarrow UB$), H7 ($DQ \Rightarrow PE$), H9 ($IQ \Rightarrow EE$), H10 ($IQ \Rightarrow PE$), and H11 ($UB \Rightarrow PER$) were supported, while H1 ($PE \Rightarrow BI$), H4 ($FC \Rightarrow BI$), H6 ($BI \Rightarrow UB$), and H8 ($DQ \Rightarrow BI$) were rejected, indicating that not all expected relationships in the UTAUT model are relevant in this context.

The rejection of hypothesis H1 contradicts previous research, in which PE is consistently found to positively influence BI (Venkatesh et al., 2003; Ain et al., 2019). A possible explanation for this divergence is the complexity of dashboards in management accounting, where other constructs, such as facilitating conditions (FC), play a more significant role in determining behavioral intention. Additionally, the relatively small sample size may have contributed to statistical insignificance. Future research should explore whether this result persists in larger samples or in different accounting environments.

The relationship between BI and UB was insignificant and did not support hypothesis H6. Although the UTAUT model posits a strong relationship between BI and UB (Venkatesh et al., 2003), our findings suggest this may not hold in the specific context of dashboard usage by management accountants. This discrepancy could be due to external organizational factors, such as mandated system usage or organizational culture, which could override individual behavioral intentions. Alternatively, the complexity of dashboards can cause a gap between intention and actual use. Previous studies have highlighted similar inconsistencies (Turner et al., 2010), suggesting that more research is needed to examine the organizational barriers preventing BI from translating into actual usage.

The non-significant effects of Facilitating Conditions (FC) on Behavioral Intention (BI) (H4) and Decision Quality (DQ) on BI (H8) provide important insights into the dynamics of dashboard adoption among management accountants. Although FC significantly influences actual Usage Behavior (UB), its lack of effect on BI suggests that the mere availability of support, training, and infrastructure does not necessarily shape users' motivational intentions to adopt dashboards. This is consistent with the UTAUT literature, which positions FC as more directly related to usage than intention, especially in structured environments where technology adoption may be externally driven (Venkatesh et al., 2003; Ifinedo, 2012).

Similarly, although DQ was found to strongly influence performance expectancy (PE), its nonsignificant direct effect on BI (H8) does not support our accountability/PMT-based expectation from Sect. 2.3, suggesting that accountability-driven motives may require additional efficacy cues (e.g. via PE) or organizational reinforcement to translate into intention; we return to this in Sect. 5. These results suggest that anticipated decision benefits may be cognitively recognized, but not sufficient to drive intention without supporting perceptions of ease or social support. This is further supported by the more general results of the model in which PE itself does not significantly affect BI, suggesting that, in this context, perceived performance improvements are less critical to intention formation than Effort Expectancy (EE) and Social Influence (SI). These findings underscore the importance of usability and peer expectations over system attributes such as DQ and FC in motivating initial adoption decisions.

The analysis of indirect effects reveals key insights into how various factors in the model influence outcomes through mediating pathways (Table 6 and supplementary file Table S-7). Facilitating Conditions (FC) have strong indirect effects on both Use Behavior (UB) and the performance of management accountants (PER), indicating that the availability of support resources not only influences users' system usage, but also enhances the performance of management accountants through greater system use. The strong indirect effects of FC on both UB and PER support previous studies on the importance of organizational support in technology adoption (Ifinedo, 2012). However, the relatively weaker indirect effects of IQ and DQ, particularly on UB through BI, suggest that while information quality and decision-making improvements are perceived as important, other factors such as ease of use and organizational integration may play a more dominant role in actual system use.

Information Quality (IQ) and Decision Quality (DQ) also play significant roles, particularly in how they influence Behavioral Intention (BI) via mediators such as Effort Expectancy (EE) and Performance Expectancy (PE). These indirect pathways suggest that high-quality data and information positively impact users' perceptions of system ease of use and usefulness, thereby indirectly driving their intentions to use the system. However, DQ and IQ have a limited impact on actual use behavior when mediated through intention, highlighting the importance of other factors, such as Facilitating Conditions.

As described in Sect. 2.3, we theorized and therefore tested a set of indirect (mediated) paths and the DQ $\times$ IQ interaction on EE in addition to the direct UTAUT relationships. The interaction between Decision Quality (DQ) and Information Quality (IQ) significantly influences Effort Expectancy (EE) ($\beta=0.307$, $p=0.006$), indicating that dashboards are perceived as easier to use when they improve both decision support and information reliability. This effect further translates into an indirect positive influence on Behavioral Intention (BI) via EE ($\beta=0.126$, $p=0.048$). However, no significant direct interaction effects were observed for Performance Expectancy (PE) or BI, suggesting that adoption is driven more strongly by perceptions of ease of use than expected performance improvements. These findings, fully documented in the supplementary file (Sect. 6), underscore the importance of usability in fostering dashboard acceptance.

Overall, the model shows that indirect effects, particularly those involving Facilitating Conditions, Information Quality, and Decision Quality, play an essential role in shaping user behavior and management accountants' performance.

These significant indirect effects also have theoretical implications, particularly in light of some non-significant direct paths. Although some direct effects in the model were not statistically significant, several significant indirect effects provide additional theoretical insights into the pathways of influence in dashboard adoption. For example, although Performance Expectancy (PE) did not directly predict Behavioral Intention (BI) (H1), the significant indirect effect of Decision Quality (DQ) on BI through PE indicates that PE plays an important mediating role. This suggests that PE may not directly motivate intention but acts as a cognitive filter through which task-specific beliefs, such as DQ, are translated into adoption motivation. Similarly, while DQ does not have a significant direct effect on BI (H8), it significantly affects BI through its influence on PE, supporting the inclusion of PE as a theoretical bridge in the extended UTAUT model. These results suggest that, in the context of management accountants, expectations of improved decision quality enhance perceptions of dashboard usefulness (PE), which then shape intentions—highlighting the importance of mediating mechanisms over direct effects. Thus, although some hypotheses were formally rejected, indirect effects support the theoretical rationale of the extended UTAUT model and refine our understanding of how task-specific beliefs influence intention through perceived usefulness.

4.3 Impact of control variables

The inclusion of the control variables, Age and Experience, had varying impacts on the model (Table 7). For Behavioral Intention (BI), the explained variance (R^2) decreased slightly from 0.319 in the core model to 0.310 with control variables, indicating that the addition of Age and Experience had a minimal effect on the variance explained in BI. However, the path coefficients revealed that Age had a small negative effect on BI (path coefficient = -0.111), while Experience had a weaker negative impact (path coefficient = -0.047).

In contrast, the addition of control variables had a substantial impact on the ability of the model to predict Usage Behavior (UB). The R^2 for UB increased significantly from 0.223 in the core model to 0.477 with controls, indicating that Age and Experience considerably enhanced the explained variance in UB. Experience had a strong positive effect on UB (path coefficient = 0.539, $f^2 = 0.489$), while Age also positively influenced UB (path coefficient = 0.095), although to a lesser extent. A substantial indirect effect of experience through UB to PER (path coefficient 0.334) implies that users with dashboard experience and use report higher performance, which supports the task-technology fit perspective extending UTAUT.

The introduction of control variables led to a notable reduction in the path coefficient to Facilitating Conditions (FC) to Use Behavior, which decreased from 0.477 in the core model to 0.270. This reduction suggests that the relationship between FC and UB is partially explained by Age and Experience. Other relationships, such as Effort Expectancy (EE) → BI and Performance Expectancy (PE) → BI, showed slight

Table 7 Effect of control variables: age and experience

Panel A		R² adjusted		change
		core model	with controls	
construct				
BI		0.319	0.310	-0.009
EE		0.062	0.062	0.000
PE		0.583	0.583	0.000
PER		0.373	0.373	0.000
UB		0.223	0.477	0.254

Panel B		path coefficient		f-square	
		core model	with controls	core model	with controls
BI -> UB		0.068	0.070	0.006	0.009
DQ -> BI		0.088	0.077	0.005	0.004
DQ -> PE		0.604	0.604	0.557	0.557
EE -> BI		0.401	0.405	0.165	0.172
FC -> BI		-0.152	-0.145	0.022	0.020
FC -> UB		0.477	0.270	0.281	0.117
IQ -> EE		0.279	0.279	0.084	0.084
IQ -> PE		0.235	0.235	0.084	0.084
PE -> BI		0.128	0.152	0.009	0.013
SI -> BI		0.274	0.249	0.070	0.057
UB -> PER		0.619	0.619	0.623	0.623
AGE -> BI			-0.111		0.019
AGE -> UB			0.095		0.017
EXPERIENCE -> BI			-0.047		0.003
EXPERIENCE -> UB			0.539		0.489

increases in path coefficients after adding controls, with EE rising from 0.401 to 0.405 and PE increasing from 0.128 to 0.152.

Overall, the control variables did not substantially affect the relationships for EE, PE, or SI, but they significantly improved the model's prediction of Usage Behavior, particularly through the strong influence of Experience. The latter also shows a strong indirect effect on PER.

To further assess the robustness of the model, a multi-group analysis was conducted comparing dashboard users and non-users (Supplementary File, Sect. 5). This analysis revealed that key relationships, such as Usage Behavior (UB) → Performance (PER) and Social Influence (SI) → Behavioral Intention (BI), were significantly stronger among users than among non-users. In particular, the path from UB to PER was significant only for users, underscoring that actual use is necessary to realize performance benefits. These findings complement the analysis of control variables, which showed that increasing the dashboard experience—conceptualized as a continuum—strongly predicts UB and indirectly improves performance. Taken

together, both analyses confirm that experience and actual usage are critical boundary conditions for dashboard adoption and its impact on performance.

5 Discussion and conclusion

5.1 Summary of results

This study investigated the factors influencing the adoption and use of digital dashboards by management accountants, using the Unified Theory of Acceptance and Use of Technology (UTAUT), extended with Decision Quality (DQ), Information Quality (IQ) and Performance (PER). The aim was to identify key determinants that drive the adoption of dashboards and to assess how their use impacts job performance. Using PLS-SEM, the model was tested on a sample of management accountants based in Germany, providing insights into both the original UTAUT constructs and the relevance of task-specific extensions such as DQ and IQ.

The experience of the respondents with dashboards varies: 39% (24) reported no experience, 20% (12) reported experience up to 12 months, and 41% (25) reported experience from one to several years. Regarding the first research question, the results show a significant portion of dashboard users, higher than Raguseo, 2018 in his sample. This result helps to answer the first research question: the majority of respondents have experience with dashboards in this sample.

The degree of dashboard usage among respondents varied significantly: 61% reported being dashboard users, while 39% were non-users. This distinction aligns closely with the control variable ‘experience’, which was shown to strongly influence actual usage behavior (UB). Multi-group analysis further revealed that dashboard users experienced stronger performance gains (UB → PER) and were more influenced by social expectations (SI → BI) than non-users (see supplementary file Sect. 5). These findings underscore the importance of actual system use in realizing dashboard benefits and reinforce experience as a key contextual factor in adoption.

The results showed that Effort Expectancy (EE) significantly influenced Behavioral Intention (BI), consistent with predictions from the original UTAUT model (Venkatesh et al., 2003). In contrast, Performance Expectancy (PE) did not directly affect BI, leading to rejection of H1. However, PE played a critical mediator role in the model, transmitting the effects of Decision Quality (DQ) to BI. This indirect pathway highlights the cognitive importance of PE in forming intention, even if it does not independently motivate the use of the dashboard. Similarly, while Facilitating Conditions (FC) did not significantly impact BI (H4) (Lennerholt et al., 2021, 2023), they exerted a strong direct influence on Usage Behavior (UB) (H5), echoing findings that FCs typically support actual usage rather than intention (Ifinedo, 2012; Venkatesh et al., 2012). Thus, both PE and FC contribute meaningfully to dashboard adoption, albeit through indirect or usage-based mechanisms, refining the core assumptions of UTAUT in this context.

Beyond the core UTAUT constructs, the study’s extensions provided further insights. Both Decision Quality (DQ) and Information Quality (IQ) significantly influenced PE, suggesting that management accountants perceive dashboards as tools

that improve decision-making and improve the quality of the information they use. These constructs also had indirect effects on BI via PE, indicating that accountants are more likely to adopt dashboards when they believe that these tools will improve their job performance through better decision-making and higher-quality information.

The interaction analysis further underscores the importance of usability perceptions: the significant effect of $DQ \times IQ$ on the Effort Expectancy (EE) suggests that users find dashboards easier to use when both the quality of the information and the relevance of the decision are high. This, in turn, indirectly supports BI, reinforcing the central role of ease of use in adoption behavior (Davis, 1989; Ain et al., 2019). This pattern aligns with Expectation-Confirmation Theory, which states that beliefs about Ease of Use form immediately, while beliefs about usefulness require confirmation through repeated outcomes. Likewise, longitudinal TAM2 field studies showed that Perceived Ease of Use stabilizes earlier than Perceived Usefulness (Venkatesh & Davis, 2000). For dashboards, high DQ and IQ reduce cognitive friction initially, but sustained decision successes are necessary to cement PE and eventually strengthen BI. Additionally, while the direct path from BI to UB (H6) was not supported—contrary to much prior UTAUT research (Venkatesh et al., 2003)—indirect effects, particularly from EE to UB via BI, were significant. This suggests that intention may still function as a partial mediator, albeit less dominantly than in typical UTAUT implementations. These results contrast with previous studies emphasizing information quality as a direct determinant of usefulness and adoption (Petter & McLean, 2009; Ain et al., 2019), indicating that for dashboards, reducing cognitive effort is more influential than improving decision support.

Although we theorized through accountability theory and PMT that stronger beliefs in decision-quality would directly raise intention (H8), the BI path of $DQ \rightarrow BI$ was not significant. This pattern implies that feeling answerable (accountability) or wanting to avoid poor decisions (threat appraisal) is not sufficient unless accountants also perceive clear, immediate efficacy or receive contextual prompts to act. Our data indicate that this belief in efficacy is captured by Performance Expectancy (PE), through which DQ exerts an indirect effect on BI. Alternatively, organizational controls (e.g. mandated dashboard use, audit trails) may be necessary for accountability concerns to translate into intention. Hence, accountability- and PMT-related motives appear to operate indirectly or conditionally, refining our original H8 logic and pointing to boundary conditions for future research.

The relationship between BI and UB was found to be insignificant in this study, which deviates from much of the existing literature (Davis et al., 1989; Venkatesh et al., 2003). However, the indirect pathway from the expectation of effort (EE) to the UB via BI was significant, suggesting that intention may still serve as a partial mechanism for use. This unexpected finding suggests that there may be external factors, such as organizational constraints or technological limitations, that affect the translation of intention into actual usage. It is also possible that the relatively small sample size in this study limited the statistical power needed to detect a significant relationship between these variables.

In our setting, behavioral intention (BI) is partially limited by organizational decision rights. Often, individual management accountants cannot unilaterally adopt dashboards when none are deployed. This aspect likely compressed the BI responses

upward, creating a floor of 4 for BI1/BI2, and reduced the variance, which attenuated the relationship between BI and UB even when cognitive antecedents were present. In other words, our BI items may capture advocacy or willingness more than actionable intention. This interpretation aligns with UTAUT's emphasis on facilitating conditions and perceived control as prerequisites for intentions to translate into behavior (Venkatesh et al., 2003; Venkatesh et al., 2012).

Regarding the second research question, the analysis confirmed a strong positive link between Usage Behavior (UB) and Performance (PER), particularly in terms of efficiency and decision-making improvements. This supports prior findings on the value of actual system use in realizing performance benefits (Petter & McLean, 2009). Among the control variables, age showed only a minor influence on BI and UB, while experience demonstrated a strong direct effect on UB and an indirect effect on performance. These results underscore the importance of accumulated familiarity with dashboards as a key enabler of sustained use and benefit realization (Bhattacharjee, 2001; Venkatesh et al., 2012). The alignment between these control effects and the group analysis (supplementary file Sect. 5) confirms that both demographic and experiential factors shape adoption and outcomes.

5.2 Implications for management accounting research

This study contributes to the management accounting literature on the adoption of accounting technologies and their performance effects. (Reinking et al., 2020a; Lee & Widener, 2016; Velcu-Leitinen & Yigitbasioglu, 2012) by developing and testing a UTAUT-based model to identify the drivers of dashboard adoption by management accountants and their performance consequences. The study successfully addressed both research questions. First, it identified the key factors that influence the adoption of dashboards by management accountants, including PE, EE, SI, and FC, as well as the extended constructs DQ and IQ. These results demonstrate that management accountants view dashboards as valuable tools for improving job performance, particularly through better decision-making and information management. Second, the study confirmed that the use of dashboards positively impacts the job performance of management accountants, with UB significantly related to PER, especially for more experienced users. This supports the hypothesis that frequent and effective use of dashboards leads to improvements in efficiency, productivity, and decision-making (Bani-Hani et al., 2018).

The significant $IQ \rightarrow EE$ and $DQ \rightarrow PE$ paths show that dashboards reduce the effort to search for information from accountants and improve their perceived analytical leverage. This combination maps onto the idea of enabling control systems—tools that simultaneously simplify task execution and expand local problem-solving (Tessier & Otley, 2012). Our evidence, therefore, complements field studies reporting that management accountants embrace digital visualizations when they strengthen variance analysis and scenario planning rather than simply automate reporting (Granlund, 2011; Hall, 2010).

By treating Decision Quality (DQ) as an antecedent—not merely an outcome—we show that accountants form usefulness beliefs around the anticipated quality of subsequent decisions. This insight extends recent calls to study analytics competency

as a core element of the changing skill profile of management accountants (Moll & Yigitbasioğlu, 2019). It also nuances prior UTAUT applications in finance functions, where domain-specific outcome beliefs were often collapsed into generic performance-expectancy items.

The significant interaction of $IQ \times DQ$ in EE indicates that high-quality data amplify the perceived ease of using decision aid features. For management accounting researchers, this pinpoints a behavioral payoff to data-governance spending—an emerging cost category in digital finance transformations (Rikhardsson & Yigitbasioğlu, 2018). Future costing models may need to capitalize on dashboard-related data-quality investments rather than treat them as overhead because they lower cognitive processing costs for accountants.

More generally, the study has theoretical implications for the extension of UTAUT to professional settings such as management accounting. By incorporating DQ and IQ as antecedents to PE and BI, this research shows that domain-specific factors play a critical role in shaping technology adoption (Venkatesh et al., 2016). Traditional UTAUT models, which focus primarily on general perceptions of performance and effort, can overlook the specific needs and priorities of professionals who rely heavily on high-quality information and effective decision-making tools. These results align with prior research that emphasizes the importance of task-specific factors in technology adoption (Wixom & Todd, 2005; Petter & McLean, 2009).

The study also challenges the traditional view of DQ as purely an outcome of technology use (Clark et al., 2007; Kamis & Davern, 2005), demonstrating that it can also act as an antecedent that shapes users' expectations about the usefulness of a technology (Bhattacharjee, 2001). This re-conceptualization of DQ offers a significant contribution to both UTAUT and broader technology acceptance literature, opening up new avenues for research into how professionals evaluate the potential impact of new technologies before adopting them.

5.3 Practical implications

For management accountants, the key message is that dashboards are adopted when they help make better decisions and save cognitive effort with numbers and graphs. The results of this study show that Decision Quality (DQ) drives Performance Expectancy (PE), so the value proposition must be framed in decision terms (“better variance explanations”, “more defensible forecasts”), not merely in automation rhetoric. At the same time, Information Quality (IQ) lowers expected efforts needed: clean, timely, drillable data cuts reconciliation work, and spreadsheet hopping. These two levers can convince management accountants that dashboards are worth using.

The significance of Facilitating Conditions (FC) underlines that management accountants need more than access—they need task-shaped support. Training with specific application scenarios will help management accountants get acquainted with dashboards and employ them regularly. Such supports lower cognitive load and prevent information overload (Karr-Wisniewski & Lu, 2010; Hirsch et al., 2015), making dashboards feel like integral parts of daily control routines rather than optional add-ons.

The insignificant BI $\rightarrow$ UB path signals that positive attitudes do not automatically translate into actual use. Organizations should hard-wire dashboards into workflows and metrics: integrate key dashboard views into month-end sign-off procedures, require their use in budgeting meetings, and tie usage to performance indicators or stewardship responsibilities. Soft nudges like defaulting reports to dashboard links and hard incentives like recognizing data-driven insights in appraisal systems can both bridge the intention–behavior gap.

5.4 Future research, limitations, and contribution

The results indicate the role of domain-specific factors and boundary conditions in the acceptance of technology by management accountants. More research should continue to explore how technology acceptance is affected by factors not analyzed in this study. Such factors include task complexity (Fang et al., 2005), and information overload (Eppler & Mengis, 2008; Karr-Wisniewski & Lu, 2010). In fields where professionals manage large volumes of data, as is the case in management accounting, these factors may influence how users perceive both the usefulness and ease of use of technology (Rieg et al., 2023; Wixom & Todd, 2005). Other boundary conditions include organizational culture, technological infrastructure, and characteristics of different industries and sectors. As dashboards continue to be adopted across industries (Albuquerque & Dos Santos, 2023), understanding the interplay of these factors is crucial. For example, the alignment between an organization's digital transformation strategy and its existing IT capabilities can shape the extent to which new technologies are embraced (Venkatesh et al., 2012). Future research should further explore these contextual influences to provide a more comprehensive framework to understand dashboard adoption in diverse professional settings.

Longitudinal research could further enrich the understanding of how dashboard usage impacts job performance over time. By tracking usage patterns and performance outcomes over longer periods, future studies could identify the factors that drive continued use and user satisfaction, providing a more comprehensive picture of the long-term benefits of dashboard adoption by management accountants (Barlette & Baillette, 2022). For example, a longitudinal or experience-sampling design that reassesses DQ, IQ, EE, PE, and BI at several post-implementation milestones (e.g., onboarding, month 1, month 6) could reveal whether the DQ $\times$ IQ interaction on PE and BI emerges once users accumulate outcome evidence.

Although this study's reliance on a relatively small sample size and self-reported data presents certain limitations (Lee et al., 2003), these aspects also offer opportunities for future research. Expanding the sample size in subsequent studies could improve the generalizability of the findings and provide deeper insight into variations between industries and professional roles. Additionally, integrating objective usage data, such as system logs or observational studies, could complement self-reported measures and provide a more accurate depiction of dashboard adoption and its impact on performance (Venkatesh et al., 2012; Turner et al., 2010; Yigitbasioglu & Velcu, 2012). Future research leveraging mixed-method approaches or longitudinal designs could further strengthen the understanding of how dashboards influence decision-

making over time, addressing the inherent challenges of cross-sectional self-reported studies (Petter & McLean, 2009).

As a single-country study, this research provides a focused understanding of the acceptance of technology within a specific institutional and cultural context. Future studies should explore the adoption of technology in different countries, as management accounting roles and tasks vary between jurisdictions due to regulatory environments, organizational structures, and cultural influences (Malmi et al., 2022). Cross-cultural comparisons could uncover how contextual factors shape dashboard acceptance, offering deeper insights into the generalizability of technology acceptance models beyond a single national setting.

Although more research is needed to address these open questions, the findings of this study already offer significant contributions to research and practice. Empirically, it provides new data on how management accountants perceive and adopt dashboards, addressing a notable gap in both accounting and technology acceptance literature by focusing on task-specific factors such as DQ and IQ. Theoretically, it extends the UTAUT by integrating these domain-specific constructs, demonstrating that technology acceptance in management accounting depends not only on general perceptions of usefulness and ease of use, but also on the quality of information and decision-making support. Furthermore, it combines the literature of technology acceptance with performance effects of accounting technologies to provide a more holistic understanding of the determinants of digital dashboards' use by management accountants and their performance effects. This theoretical advancement broadens the applicability of UTAUT to professional and data-driven environments, contributing to the literature on technology acceptance in specialized settings. Practically, the study offers actionable insights for organizations looking to implement dashboards, emphasizing the importance of high-quality data and organizational support to driving successful adoption and use. These contributions respond to calls for further research on the acceptance of task-specific technology and provide a more nuanced understanding of how digital tools can enhance decision-making and performance in management accounting.

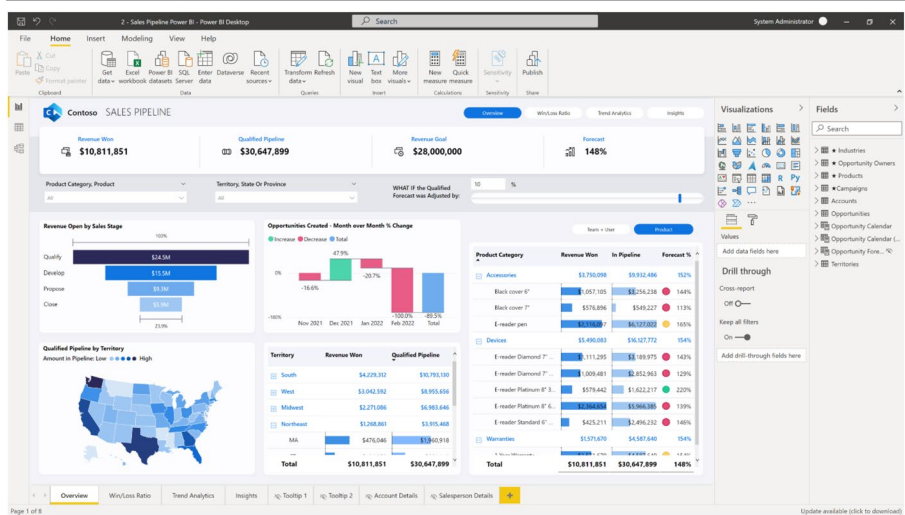
Appendix

Appendix 1 List of items per construct and measurement of control variables

Construct	Item	Description
BI	BI1	Assuming I had access to the dashboard system, I would intend to use it
	BI2	If I have access to the dashboard system, I predict I will use it.
DQ	DQ1	Using dashboards would enable me to make decisions more quickly
	DQ2	Dashboards would allow me to make more informed decisions
	DQ3	Dashboards improve my ability to process knowledge
	DQ4	In general, dashboards would allow me to improve my decisions
FC	FC1	I have the necessary prerequisites (e.g. training, manuals) for the use of dashboards
	FC2	I have the necessary knowledge to use dashboards

Appendix 1 (Continued)

Construct	Item	Description
IQ	FC3	The dashboard is compatible with other systems I use
	FC4	A specific person or group is available for help with system problems
	IQ1	Overall, I would give the information from the dashboard good ratings
	IQ2	Overall, I would attest to the high quality of the information provided by Dashboards
PER	IQ3	In general, dashboards provide me with high-quality information
	PER1	Using dashboards has had a huge, positive impact on my effectiveness, efficiency and productivity at work
	PER2	Dashboards are an important and valuable support for me in my work
EE	EE1	It would be easy for me to use dashboards
	EE2	Using dashboards is easy and understandable for me
	EE3	It's easy for me to get dashboards to do what I want them to do
	EE4	I would consider dashboards to be flexible in terms of interaction
PE	PE1	Using dashboards would make my job easier
	PE2	I would find dashboards useful in my work
	PE3	Using dashboards improves my work performance
SI	SI1	Colleagues who influence my behavior would appreciate it if I used dashboards
	SI2	Colleagues who are important to me would appreciate it if I used dashboards
	SI3	In general, my organization supports the use of dashboards
UB	UB1	On average, I use dashboards
AGE		Categories: 0 = 18–24 year, 1 = 25–34 year, 2 = 35–44 year, 3 = 45–54 year, 4 = 55–64 year, 5 = > 65 yr
EXPERIENCE		Categories: 0 = never, 1 = < 1 month, 2 = 1–6 months, 3 = 6–12 months, 4 = 1–3 year, 5 = > 3 yr



Appendix 2 Example for dashboards used in questionnaire: Microsoft Power BI. (source <https://powerbi.microsoft.com/de-de/guidedtour/power-platform/power-bi/2/1>)

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Declarations

Conflict of interest The author has no financial or proprietary interests in any material discussed in this article.

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