Information & Management 61 (2024) 103888

Contents lists available at ScienceDirect

Information & Management

journal homepage: www.elsevier.com/locate/im

Determinants and consequences of routine and advanced use of business intelligence (BI) systems by management accountants

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ARTICLE INFO

Keywords:
business intelligence
management accounting
system use
IS success model
advanced use

ABSTRACT

There is limited evidence on why decision makers extend beyond routine use toward more advanced use of Business Intelligence (BI) systems. This study developed an extended DeLone and McLean information system success model hypothesizing the effects of system, data, information, and service quality, along with self-efficacy and task complexity, on routine and advanced use of BI. Task complexity was also considered as moderating the effects of use on individual performance. Data was collected from a sample (N = 362) of management accountants using BI systems. Results confirmed system, data, information, and service quality as important, and indicated that routine use is less likely under conditions of task complexity and does not rely on user self-efficacy to the same degree as advanced use. Using routine BI features was also not found to improve user performance to the same extent as advanced use. The study has contributed new theoretical insights into BI use and offered new conceptual and operational definitions of routine and advanced use of BI, with implications for practice in contexts such as management accounting.

1. Introduction

Business Intelligence (BI) systems are a class of information systems combining tools and infrastructure (e.g., OLAP, data warehouses, dashboards, and query tools) for data management, analysis, and reporting [3,32,116]. BI portals provide decision makers an interactive interface to manipulate, analyze, and visualize historical and current data and perform dynamic reporting, forecasting, prediction, and trend and drill-down analysis, among other uses [119]. According to Forrester [38], the global market for BI software is estimated to grow to nearly $40 billion by 2027, driven by a deepening data culture, advances in data visualization and big data analytics tools, and augmented intelligence. Most major vendors offer BI software tools (e.g., Microsoft, SAP, Oracle, and SAS), with specialist solutions emerging for sectors such as finance, healthcare, manufacturing, retail, energy, transportation, and public administration, among others. In the management accounting context, BI can provide for the predictive and integrated management control and analytics needed to improve financial and non-financial decision making [10,12,36,47,84,101]. However, the realization of benefits from BI depends on the manner and extent to which these systems are used in practice [130]. Unfortunately, management accountants often discontinue BI use after implementation and perform their work outside of BI systems using stand-alone tools like Excel [36,47,122]. This practice is unlikely to change given limited evidence linking BI use to performance and work outcomes [7,102,121–123]. Some have argued that BI outputs are not easy to use and make the work of management accountants more complex [34]. Users can find it challenging to migrate budgeting, forecasting, key performance indicators, activity-based management, performance reporting, and product costing to BI systems [36,102]. Additionally, some managers may use only basic BI features, choosing not to opt for and experiment with more advanced features [84]. These routine users tend to use BI systems more like a database without developing dashboards or making use of advanced analytics tools [46,47]. Past studies indicate that basic or routine use of pre-built BI reports is unlikely to bring sufficient benefits, and suggest that users support their work through more advanced features, such as self-service tools, interactive visualization, and predictive analytics [49,74]. To the best of our knowledge, past studies have not confirmed the relative effects of routine and advanced user behaviors on individual performance in a BI context. The purpose of our study is to address the questions regarding what motivates management accountants to make use of BI systems implemented in their

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https://doi.org/10.1016/j.im.2023.103888
Received 9 September 2022; Received in revised form 18 October 2023; Accepted 10 November 2023
Available online 11 November 2023

organizations, what motivates them to move beyond routine use of basic features toward more advanced use, and what consequences arise as a result of routine and advanced use for their job performance.

To address these questions, the study draws on the DeLone and McLean [29] information system success model, along with other studies (e.g., [49,74]), to develop a BI success model for management accounting. The DeLone and McLean model is focused on the multi-dimensional nature of IS success, incorporating both antecedents and consequences of user behavior, which is the purpose of our study. Despite the sophistication of information systems increasing, the model remains relevant by including a set of elements that consistently matter for IS success, such as information and system quality, use, and outcomes [64,81,91]. Moreover, the model is easily extended so that it can be contextualized to specific IS domains [41,71,89,110]. Through our extensions, we make a fourfold contribution. First, we contribute new constructs to distinguish between routine and advanced use of BI. This is important because management accountants may benefit most from advanced types of use as compared to routine use [4,7]. Second, we contextualize the IS success model by introducing data quality as an additional factor motivating use behavior and thus is among the most important prerequisites for BI benefits [118,129]. Third, we consider individual management accountants' self-efficacy for BI use and the complexity of their decision tasks as additional determinants of use, and the latter as a potential moderator of the relationship between use and performance. Individual factors such as these are too frequently omitted from IS success studies [64] but can be more important than organizational influences on an individual's decision to use complex IS systems and to the design of interventions such as training [14,77,104]. Fourth, the study compares the relative effects of routine versus advanced use on performance outcomes. The way in which BI is used is likely to determine the extent of benefits realized, and new advances in BI provide impetus to explore how advanced features provide added support for management accounting performance [34,84,121]. The empirical work involved a large sample survey of management accountants in South African public and private sector organizations who are users of BI systems from SAP, Oracle, and SAS, among others. By examining both the determinants and consequences of BI use in the accounting context, BI systems can be better designed and managed to meet the expectations of these users to facilitate their complex decision-making tasks and improve their performance.

The remaining sections of this article present the literature review, outline the theoretical background and develop the study's research model and hypotheses, and describe the research methods before presenting empirical findings and implications of results for research and practice.

2. Background Literature

Organizations expect to realize numerous benefits from BI system implementation [61]. However, 50 % to 80 % of these implementations

Table 1
Previous Studies on Individual BI Use and Success.

Study	Study Focus	Theory	Key Findings
Hou [53]	Study of end user computing satisfaction (EUCS), system usage, and individual performance of BI users in Taiwan	EUCS model	EUCS leads to increased BI usage and improved individual performance, and BI usage leads to higher levels of individual performance.
Huang et al. [57]	Behavioral intentions to use a data mining tool	Extended TAM model	Perceived usefulness and perceived ease of use explain user intentions.
Tona et al. [115]	Study of BI users in a public organization	IS success model	Use and user satisfaction significantly influence individual impact, but satisfaction does not predict use and vice versa. System and information quality are significant predictors of user satisfaction, but only system quality influences use.
Li et al. [74]	Post-acceptance BI usage behaviors of employees in Chinese telecom companies	Motivation theory	Extrinsic motivation (usefulness) had stronger impacts on routine use, whereas intrinsic motivation had stronger effects on innovative use. Personal innovativeness moderated relationships between motivation and use.
Popovič et al. [96]	Study of how information sharing values affect the IS success dimensions of systems and information quality	IS success model	Information-sharing values moderate the effects of information quality on BI information use intentions, but system quality does not influence BI information use.
Gaardboe et al. [39]	Study of BI success among end users in 12 public hospitals in Denmark	IS success model	System and information quality were associated with user satisfaction, which in turn related to individual impact. Use was not associated with individual impact.
Mudzana and Maharaj [83]	Study of top, middle, and operational management BI users	IS success model	User quality (skill) emerged as an important BI success factor influencing satisfaction.
Visinescu et al. [124]	Exploratory study of relationships between BI use, problem space complexity, information quality, and decision quality	Management support system framework	Level of BI use, information quality, and problem space complexity all influence perceived decision quality.
Hou [54]	Study of end user computing satisfaction (EUCS) and BI continuance intentions	EUCS	Higher levels of EUCS can lead to increased BI continuance intention.
Gonzales and Wareham [43]	Study of 104 BI users in quasi-voluntary contexts from multiple firms	IS success model	This study compares the original DeLone and McLean model to Seddon's respecified model. Satisfaction was highly significant for individual impact, but little support was found for a relationship between individual impact and system dependence.
Montero [82]	Study of how information quality and system quality relate to BI use among 109 senior executives in the US	IS success model	Information and system quality relate to information use, with maturity factors as moderators.
Kapo et al. [65]	Partial IS success model investigating BI satisfaction and use	IS success model	User satisfaction leads to increased frequency and duration of BI use and to individual user performance.
Jaradat et al. [62]	Study of factors influencing BI adoption intentions	Technology organization environmental theory and IS success model	Information and system quality determine BI usage intentions, along with perceptions of compatibility and relative advantage.
Trieu et al. [118]	Importance of organizational resources to extended use of BI	Theory of extended use	System qualities allow for more transparent interaction with BI, whereas representational fidelity has indirect effects on decision-making effectiveness through informed action.
Trieu [117]	Study of complementary organizational resources important to BI use	Cybernetic theory	Organizational data culture and data quality are important factors promoting individual dependence on and use of BI.

are estimated to fail worldwide [72,86,106]. Several studies have thus explored organizational-level influences on BI outcomes [3]. These works have drawn attention to the importance of management support and provision of resources [35,129], BI maturity [95], capabilities such as system integration [60], and BI system and data quality [116]. However, despite the importance of individual use to BI success and the realization of BI benefits, there are few studies on individual use of BI tools (see Table 1).

The operationalization of individual user behaviors has also been limited mostly to user intentions [57] or broad measures of frequency and duration of BI use [53]. Notwithstanding these limitations, there has been some effort to understand the determinants and consequences of user behavior by drawing on the IS success model [43], theories of end-user computing satisfaction [54], extended use [118], and TAM [57]. Yet, extant research has not reached consensus on the role of various factors in promoting BI use.

System-related factors such as system quality and ease of use are significant determinants of BI intentions and user satisfaction in some studies [39,57,62]. Technical and design quality should allow for more transparent interaction with BI to support decision-making efficiency [118]. However, the importance of BI system quality has not always been supported [96].

Mixed results have also been reported with respect to data and information qualities as determinants of BI use and outcomes. Some conclude information quality is a generally important determinant of organizational BI performance [116], but others could not confirm significant effects of information quality on individual BI use [43,115]. Data quality has been considered highly important to BI success at the organizational level of analysis [116,129] and only recently was found important to individual BI use [117]. Poor data can constrain the value individual users get from BI, and data and information quality are considered especially important to BI benefits in a management accounting context [66,128]. Yet, their roles in motivating use of more advanced BI features have not been determined. Service quality is another important consideration for use of complex IS [56]. However, few BI studies have considered the factor of service quality [43], and none outline its importance to adopting more advanced or extended levels of BI use.

Furthermore, job-related factors and decision tasks of users might interact with IS success factors in the BI context but have been infrequently examined [3]. The job relevance of BI is important because users want to improve their task efficiency and work goals through the tool [57], and usage intentions can thus depend on user perceptions about BI's compatibility with their work [61]. Few studies consider user-related factors such as competencies and skills required for effective utilization of BI systems [3], and particularly toward sophisticated uses such as running custom queries, predictive analytics, or visualization tools. In addition, user satisfaction has been found to also influence the duration and frequency of BI use [54,65]. However, the importance of user satisfaction to more extended conceptualizations of BI use has not been confirmed.

Some recent studies confirm that organizations can improve profitability and reduce risks through BI implementation [134], but the link between BI use and outcomes at the individual level has not always been confirmed. For example, although BI use was found highly significant for individual user performance in some studies [53,118], others have not confirmed the link between BI use and individual job performance [39,43,44], or have found BI use associated with poor decision quality in some instances [124]. Distinguishing the effects of routine versus advanced use behaviors on individual performance outcomes may be important to explaining these inconsistent findings. Our research addresses these multiple gaps in the study of BI use through the development of our research model and hypotheses presented next.

3. Research model and hypotheses

Our BI system success model is depicted in Fig. 1. The model defines system quality, information quality, and service quality as important attributes in an individual user's evaluation of a system leading to actual use of the system and to user satisfaction [5,19,28,126,132]. System quality refers to the usability, availability, reliability, and response time of the system as experienced by its users, whereas information quality reflects the content and format of the system's outputs to ensure they are useful, relevant, and understandable to users in their decision making [29,40]. Service quality reflects the support users receive when using the IS, such as the ability for a support team to respond reliably and timeously to user queries [29]. Recent work has also drawn attention to the importance of data quality in IS success [23,43]. Data quality reflects the completeness and integrity of the underlying data captured and stored in a system [80,116], and is specifically relevant in the BI context [60,117]. User satisfaction is the affective response of the user toward the system, such as whether it is found enjoyable or frustrating to use [11,103]. Use and user satisfaction then have consequences for user performance [59,90,120], such as perceived contribution to individual problem solving, decision making, and productivity [53,58,92,99,109]. However, the measurement of use has been oversimplified in many IS success studies [90], and we therefore distinguish between routine and advanced system use. Fig. 1 also depicts our incorporation of user self-efficacy, along with the direct and moderating effects of task complexity on the links between BI use and performance.

3.1. Routine and advanced BI use

Researchers have too often adopted unidimensional conceptualizations of system use, such as the frequency or duration of use [19,53,59]. These may be suitable where use is a proxy for implementation success but are less useful where use is considered a causal agent for explaining the diverse downstream impacts of an IT system [31]. Users are known to engage in different use-related activities [8], and through their experience and learning some achieve a deeper embedding of a system into their work [25]. A richer multi-dimensional conceptualization of use is thus required, such as the extent to which an application is used in different types of work tasks [31] or the extent to which different features of an application are employed [63]. These measures better capture the content and scope of system use and recognize that users of the same system can make use of different features to different degrees [111]. Past work has considered it useful to distinguish users in the post-acceptance stage by their use of a system's basic routine features versus more advanced features and functional potential. Examples include the distinctions between typical versus extended use [55], exploitation versus exploration [13], routine versus innovative use [73], and extended versus exploratory use [105]. These distinctions recognize that not all users achieve comprehensive and sophisticated use of complex systems [55]. In the BI context, the concepts of routine and advanced use were introduced by Li et al. [74] as two qualitatively distinct BI usage behaviors with the former focused on standard, low risk uses in routine activities, whereas the latter emphasized use of more advanced and extended features in support of emergent tasks. These different uses can occur at an employee's discretion, in parallel or at different times in support of work [74]. Thus, whereas some managers may use the BI system to access only basic queries and standard reports on past performance, others may use the same system in more advanced ways, such as using programmable or customized features to identify the drivers of performance, make predictions, or create future forecasts [7,98,103]. As illustrated in Table 2 (see also Gartner [42]), routine and advanced use are thus also distinguishable by the sophistication of the analytic features employed [50]. Importantly, these two uses may have different implications for user outcomes [49], with those using BI in more advanced ways more likely to experience the system as improving their performance [1,10,101,113]. Moreover, it is not sufficiently tested

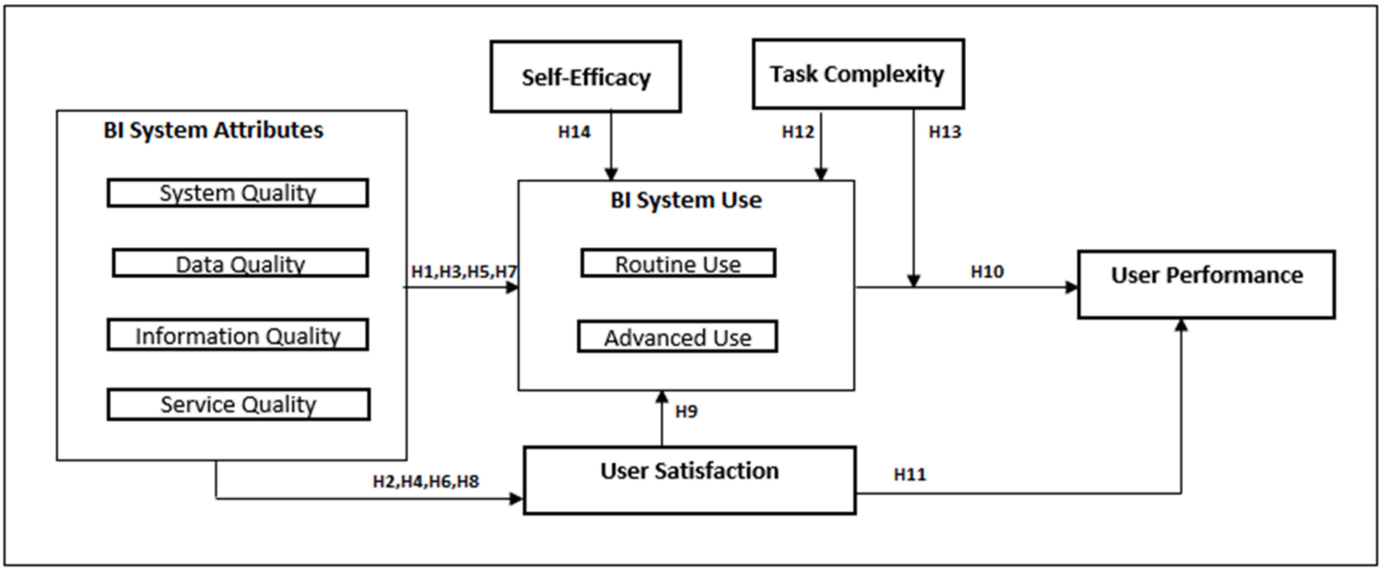

Fig. 1. Research model.

which system attributes are more relevant to advanced use as compared to routine use. Thus, we incorporate both routine and advanced use behaviors in our research model.

3.2. System quality

System quality plays a significant role in influencing system use and user satisfaction [28,95,130,39,90]. This is because it minimizes the required effort to access functionality and enhances efficiency of the system [15,24]. In the BI context, a more usable IS system assists users to use more of the system's functionality to search for information and generate needed reports [130]. Past studies support that when a BI system is easy to use and has better response times, the use of the system improves [39,108]. Therefore, it is hypothesized that:

H1a. Perceptions of system quality will have a positive impact on both routine and advanced use of BI systems by management accountants.

Users are likely to associate advanced use of system features with higher effort expectancy, and a system's ease of use has been found to be the most important factor influencing more advanced uses of an enterprise system [55]. Problems with system performance and usability are more likely, on average, to influence engagement with a system's more complex features. Easier-to-use BI systems are likely to encourage users to explore advanced features to obtain more benefits [97], and stable BI systems are needed to encourage more innovative use of BI in decision making [74]. System quality is thus considered especially important for encouraging more advanced BI system use. Therefore, it is hypothesized that:

H1b. Perceptions of system quality will have a stronger impact on advanced use than on routine use.

System quality also plays a significant role in influencing user satisfaction [28,29,90]. Poor-quality systems that are not stable or easy to use increase the cognitive effort and time required of users and thus detract from overall user experience and satisfaction [90]. Management accountants are thus more likely to enjoy using a system that is easier to use [82]. Past studies support the impact of system quality on user satisfaction [100,104,132], including in a BI context [39]. Therefore, it is hypothesized that:

H2. Management accountant perceptions of system quality have a positive impact on user satisfaction.

Table 2
Summary of routine and advanced use (adapted from Gartner [42]).

Routine Use	Advanced Use
Executing existing BI standards reports (i.e., cost center reports)	Use of self-help service tools embedded on the BI to analyze information without the assistance of the IT practitioner
Executing existing BI built queries (i.e., sales volume)	Use of interactive visualization to transform information to a visual form, allowing the user to understand information better
Performing basic analysis (i.e., ratio analysis)	Use of predictive analytics to leverage on current and historic data to predict the future (i.e., forecast)
Extracting raw data from BI tools and preparing reports in Excel (i.e., general ledger)	Use of drill-down functionality that allows the user to go deeper into the information to be analyzed
Running ad-hoc reports (i.e., monthly financial report measuring cash flow)	Use of dashboards that allows displaying key performance indicators in a visual format
Cleansing data (i.e., eliminating redundant profit centers)	Use of the BI query functionality to develop customized reports that meet the need of the user
	Use of trend analysis to understand current and future movement using time series data
	Use of scenario planning to perform 'what-if' scenarios and make better decisions on the best possible future scenario

3.3. Data quality

BI systems integrate data from underlying transactional systems through various extract and load operations. To promote user trust in BI, it is important that these operations are viewed as successful, and that data being manipulated within the BI tool is complete, accurate, and consistent [26,116]. Data quality ensures that individual management accountants can confidently rely on data records and use the BI system in executing their tasks, such as scenario planning, analytics, costing, predictions, dashboard reports, and agile visualizations [82]. Thus:

H3a. Perceptions of data quality will have a positive impact on both routine and advanced use of BI systems by management accountants.

Management accountants are more likely to use BI innovatively if data stored is trusted to be of good standard [116]. In the absence of quality data, users are likely to lose interest in the system and may default to using it only for the most basic uses as advanced reporting cannot be relied on [23,60]. Users may be reluctant to expend extra effort in generating visualizations, running predictions, and using other complex analytical features if they are not convinced that underlying data records are up-to-date, complete, and accurate. Users more confident in data quality in source systems are more likely to report using BI to its fullest potential [117]. Thus:

H3b. Perceptions of data quality will have a stronger impact on advanced use than on routine use.

Users are also less likely to use or be satisfied with a system where underlying data is not considered suitable and of good standard [19]. Poor-quality data is likely to result in dissatisfaction and frustration with the system [116]. Users will also likely be more satisfied when they can spend more time on core functions rather than preparing data or questioning and fixing data-related errors [82]. Therefore, it is hypothesized that:

H4. Management accountant perception of data quality has a positive impact on user satisfaction.

3.4. Information quality

Accurate and relevant information output depends on high levels of underlying data quality [7,88]. Information outputs not underpinned by reliable and complete data records have limited value for business processes and decision making [26]. Data quality problems have been among the top problems impacting the confidence of users in BI reports (Gartner [42,116]). Users are thus unlikely to form positive perceptions of information quality if they have poor perceptions of data quality [117,127]. Therefore:

H5a. Perceptions of data quality will have a positive impact on perceptions of information quality.

Accurate and relevant information output is likely to further influence BI use [87,98]. When better quality information is produced by the BI system, a user may feel more empowered in their decision making and be motivated to use the system to support their work [95]. Management accountants are thus more likely to turn to BI solutions if it satisfies their information needs. Therefore, it is hypothesized that:

H5b. Perceptions of information quality will have a positive impact on both routine and advanced use of BI systems by management accountants.

The quality of outputs produced by the BI system can encourage the use of more advanced features of the BI system to obtain more benefits [74]. Users may be especially encouraged to access features beyond basic reporting when they believe they can more easily interpret and make sense of the output [97]. However, users will likely be reluctant to explore advanced features such as predictive analytics if resultant outputs are poorly formated and difficult to apply in decision making. Limitations in routine reports are likely to be easier to overcome. Given that interpretation of advanced outputs is more likely to be affected by problems with format and usability, we can hypothesize that:

H5c. Perceptions of information quality will have a stronger impact on advanced use than on routine use.

Accurate and relevant information output is likely to improve user satisfaction [87,98]. However, poor-quality information outputs will add to user frustration. If information is irrelevant, inaccurate, and outdated, users may doubt the integrity and the ability of the BI system. Poor information quality may frustrate the user experience as they struggle to interpret and work with the information outputs. Past studies support information quality as a determinant of satisfaction in both BI [39,43] and non-BI contexts [100,132]. Management accountants' satisfaction should thus be improved with better-quality information produced by BI [95]. Therefore, it is hypothesized that:

H6. Management accountant perceptions of information quality have a positive impact on user satisfaction.

3.5. Service quality

The availability of IS support services may assist users to gain confidence and help reduce or eliminate potential usage problems [114]. Proper support given to users may even result in them using a system more innovatively. Service quality can also be important in the BI context where IS support teams assist users in operating advanced functions such as interactive visualizations and predictive analytics [87,96]. Therefore, it is hypothesized that:

H7a. Perceptions of service quality will have a positive impact on both routine and advanced use of BI systems by management accountants.

Without service support, a user is less likely to move beyond the more basic levels of use. Proper support allows users to explore additional features of the system, such as developing queries, enhancing dashboards, and interactive visualizations. If BI users are not assisted in using the complex functionality, they are less likely to make more extensive use of the system [80]. Service quality is thus considered especially important for promoting advanced use. Hence:

H7b. Perceptions of service quality will have a stronger impact on advanced use than on routine use.

Providing high-quality service and system support is recognized as important for user satisfaction [29]. Employees are likely to be overall more satisfied with a system in their workplace if they feel supported by a responsive, reliable, and capable team providing services to ensure system availability [6]. However, poor service quality can frustrate user trust and decrease satisfaction [112]. Service quality should also impact on user satisfaction in the BI context, with the relationship supported in prior studies [44]. Therefore, it is hypothesized that:

H8. Management accountant perceptions of service quality have a positive impact on user satisfaction.

3.6. Use, user satisfaction, and individual performance

User satisfaction is a strong determinant of usage behaviors in the post-adoption stage [9]. A decrease in usage is an early indication of declining user satisfaction [29], but if a user enjoys a system and find it works the way they want, they are more likely to use it [31]. In the BI context, user satisfaction with system attributes has been found to increase use [53]. Past studies also support that increased user satisfaction can lead to greater use in contexts such as knowledge management [132], employee portals [120], student information systems [100], and mobile banking [114]. Hence, we hypothesize that:

H9a. User satisfaction will have a positive impact on advanced and routine use of BI systems.

Satisfaction is likely to be a particularly salient determinant of advanced use because users must be highly motivated to extend beyond routine use toward more advanced use [73]. Satisfied users are more likely to commit to learning and applying advanced system functionality in their tasks [55]. Satisfaction is an important determinant of discretional use behaviors [59,64], which is often the case for use of a system's advanced features. Routine use may reflect a normative compliance and be less influenced by the internal affective state of users [125]. Hence:

H9b. User satisfaction will have a stronger impact on advanced use than on routine use.

Use has implications for the realization of benefits [29], with use behaviors influencing downstream impacts in a system-to-value chain

[31]. Past studies support the logic of individual job performance benefits as outcomes of use [53,64,114,120]. We can then hypothesize that high levels of BI system usage should lead to improved job performance [53]. BI use can support management accountants to extract standard reports and track performance against target, including cost and profit center reports, variance, and ratio analysis [80]. It can also provide functions to support them in forecasting, costing, scenario planning, key performance indicator monitoring, and trend analysis, among other uses [47]. BI use relieves management accountants from manipulating data on spreadsheets [85,112], allowing them to spend more time analyzing reports and making decisions [97]. Therefore:

H10a. Advanced and routine use of BI systems will have a positive impact on the performance of management accountants.

Users are likely to accrue additional benefits in the post-adoptive stage by enriching their use of system features [63]. Moving from typical or standard use to advanced use allows users to exploit and extend more of a system's features and functional potential to contribute to their job performance [55,111]. Advanced use can facilitate a newly expanded scope of managerial accounting work [7], assisting management accountants to answer more questions from available data to allow for realization of more benefits from the tool. Thus:

H10b. Advanced use will have a stronger impact on the performance of management accountants than will routine use.

User satisfaction reflects a judgment about whether system capabilities match work requirements, and if such estimate of the match is correct, then a positive association between user satisfaction and individual impact is likely [59]. Prior studies have supported the positive impact of user satisfaction on individual performance [59,120], and a recent meta-analysis supports user satisfaction as a strong and conclusive determinant of net benefits perceptions [81]. Users more satisfied with their BI solution have also been found to report improved job accuracy and performance [53]. Therefore, it is hypothesized that:

H11. User satisfaction with BI has a positive impact on individual performance of management accountants.

3.7. Task complexity

Task-technology fit theory highlights the additional importance of work task characteristics in moving a user to rely more heavily on certain features of an information system [30,45]. Task characteristics may thus be important to understanding why IS success occurs [92]. Complex tasks are more ambiguous and uncertain and involve a higher cognitive load [70], with few established routines and knowledge available for arriving at decision outcomes [45]. Through information provision, information systems, such as BI systems, reduce the cognitive load and uncertainty associated with decision tasks [135]. Task complexity can thus inspire the use of IS systems to improve performance [20,75,90]. Users with more complex tasks will have more motivation to embrace more advanced system features than users facing fewer complex tasks [74]. Management accountants with responsibilities such as understanding causes of variances and quantifying effects of decisions on profitability are facing ambiguous decisions with high cognitive load and would be more reliant on the analytical and information support of a BI tool. They are likely to have a greater dependence on BI features as task complexity increases. Therefore:

H12a. Management accountant task complexity will have a positive impact on advanced and routine BI system use.

H12b. Management accountant task complexity will have a stronger impact on advanced use than on routine use.

We can also suggest that the link between use and performance will be stronger among individuals who have higher task complexity than among users with lower levels of task complexity [76]. If a user with high task complexity is able, via the use of a BI system, to locate more useful information to support them in decision making, then their individual performance is likely to increase [75]. Thus, individual performance is improved when system use facilitates the user to make more complex decisions [78]. However, a user facing low task and decision complexity may not necessarily require the same level of system use and information support to perform in their job. Advanced BI features provide the added analytical capability for users to make better decisions under conditions of greater uncertainty. It follows then that advanced use will have more benefit for users facing more complex decision tasks. The moderating effect of task characteristics on the relationship between use and performance has been supported in prior enterprise and decision support system studies [16,21]. Therefore, we can also hypothesize that:

H13a. Management accountant task complexity will moderate the relationship between BI system use and user performance.

H13b. Management accountant task complexity will have a stronger moderating effect for advanced use than for routine use.

3.8. Self-efficacy

Self-efficacy is a user's belief in their ability to execute behaviors, such as using a BI system to enhance their individual performance [51]. Users with low levels of self-efficacy will be less likely to use a system, and especially less likely to extend their use to more advanced system features. Users with more confidence are likely to experiment with more novel BI system features without requiring much additional support. Training aims to develop skills and competence to help less experienced users find ways to use a system in performing their work and introduce them to more advanced features [5,132]. Self-efficacy is thus likely to influence system usage behaviors. Therefore:

H14a. Individual self-efficacy will have a positive impact on both routine and advanced use of BI systems by management accountants.

H14b. Individual self-efficacy will have a stronger impact on advanced use than on routine use.

4. Methods

4.1. Measures

The research instruments were adopted from the work of DeLone and McLean [29], among others. Individual items are reflected in Appendix A. System quality was measured as six items reflecting system availability, ease of use, response time, and stability [29,132]. Data quality was measured using three items reflecting perceived completeness and correctness of records [23,53]. Information quality was measured as seven items reflecting the accuracy, understandability, relevance, and usefulness of outputs [28,29]. Service quality was measured as five items reflecting responsiveness, helpfulness, and user confidence in support services [92]. All items were measured on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree).

Routine use was operationalized as the use of the BI system by management accountants to support normal or regular tasks through extraction of pre-built standard reports and existing queries. Advanced use was operationalized as the use of the BI system by management accountants to support planning, budgeting, analytics, dynamic forecasting, costing, and reporting tasks through use of more advanced BI system features such as self-service tools, interactive visualization, predictive analytics, and drill-down functionality [74]. The final set of 8 items reflecting routine and 12 items reflecting advanced use (Table 4) were developed from the literature (Table 2) and subsequently refined through an initial exploratory study with 10 experts and BI users. These interviews asked about user experiences with the main features of BI systems and categorized these features between routine and advanced features. Use of the routine and advanced features by the management accountant in support of their work was measured using a 6-point scale (1 = never to 6 = very often).

User satisfaction was measured through five items reflecting the extent to which the system meets expectations and is overall enjoyable and pleasant to use [53,131]. Individual performance was measured using seven items reflecting job performance, productivity, and effectiveness in decision making and problem identification [53,58].

Task complexity was measured using eight items reflecting the ambiguity, uncertainty, and knowledge requirements of tasks [45]. Self-efficacy was measured using three items reflecting confidence in ability to use BI tools [14,51]. All measures were on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree), with task complexity items reverse scored. Experience was measured as number of years the users has been using the BI system. Training reflected whether or not the user received formal training before using the BI system [5].

To improve content and face validity, a pre-test was first conducted using another 10 BI system practitioners and academic experts who reviewed the instrument. Thereafter, pilot testing was conducted using a convenience sample of 20 management accountants who were BI users. Recommendations were used to enhance the final instrument. These included extension of routine use instruments by adding data cleansing and executing existing queries, whereas on advance use instruments, the following were added: optimization, agile visualization, and interactive visualization.

4.2. Sample

Data collection was restricted to individual management accountants in South Africa using BI systems as part of their work. This required the sampling of management accountants within South African organizations that have already implemented a BI system for active use [33], including both public and private sectors where BI and analytics systems have widely diffused [22]. Therefore, the non-probability sampling frame was constructed to include management accountants who are users of BI systems across both public and private organizations. To sample the private sector, the Financial Mail [37] ranking of the 200 largest leading companies in South Africa was consulted. This list includes organizations in sectors such as finance, manufacturing, and telecommunications, among others, and ranks them based on their total asset value. In addition, 196 public entities listed by National Treasury in South Africa were included [93]. Management accountants from a total of 396 organizations were sampled. For each organization, the chief financial officer (CFO) or an equivalent manager was first contacted. In most cases, they provided information on the head of management accounting unit who was then contacted to request specific details of individual management accountants who could be approached to participate in the study. These individual management accountants were then invited directly as potential respondents or were forwarded the questionnaire by the organizational contact, depending on the organization's preference. The survey ran for 12 weeks, with an estimated 1000 individual management accounts invited directly or indirectly to participate. Using this snowball sampling approach, responses were received from 365 individual management accountants using BI systems in the targeted organizations. Respondents were not offered an incentive to participate, but they could request a copy of the final report.

Given the high number of responses, there was no need to send reminders. The high response also reduced threats to validity of conclusions arising from non-response bias. Moreover, early (within the first 5 days) and late respondents (in the last 5 days) were compared using *t*-tests, and no differences in responses were observed, further reducing concern over non-response bias. Three responses were eliminated as they were missing data items, resulting in a useable sample of 362 observations with sufficient data for meaningful statistical analysis. In addition, 17 respondents preferred not to state their BI experience yet did respond on their BI system in use. A *t*-test showed no significant differences on variables of interest between the small group who did not stipulate their BI experience and the other respondents, and therefore these responses were retained. The demographic profile of respondents is presented in Table 3.

Table 3 suggests an even number of male and female respondents, over half with more than 11 years of experience in management accounting and just over 40 % holding a senior management position. Most of the respondents have a professional affiliation with the Chartered Institute of Management Accountants (CIMA) or a CA (SA) designation. Approximately half of the respondents have between 6 and 15 years of user experience with BI, but most have not attended formal training. Users were requested to select the BI tool currently used in their work as a management accountant and refer to it when answering questions. The most popular BI system appears to be SAP BusinessObjects, followed by Microsoft's Power BI.

A mean split on the advanced use scale (mean = 5.06) was used to identify high advanced users (above the mean) and low advanced users (below the mean). Based on their mean scores, users in the high advanced subgroup ($n = 258$) were, on average, using advanced features often or very often, whereas those in the low advanced subgroup ($n == 104$) used such features more rarely or not at all. Chi-square tests reveal no significant differences at the $p < 0.05$ level between the two subgroups on age, gender, professional membership, industry sector, or experience. It is noteworthy that nearly 50 % of the low advanced user subgroup had over 11 years exposure to BI, suggesting that years of use is not necessarily sufficient for advanced use. The two subgroups differed significantly on training attendance ($\chi^2 = 7.612$, $p < 0.05$), but interestingly most advanced users (60.9 %) had no formal training. This suggests a potential paucity in formal training options on advanced features and a tendency for more advanced users to be self-taught. The three most frequently used advanced features in the pooled sample were predictive analytics (mean = 5.33, std dev = 1.05), drill-down functionality (mean = 5.22, std dev = 1.32), and creating dashboards (mean = 5.19, std dev = 1.18). However, the use of advanced features was independent of BI software with similar proportions of users in each subgroup making use of the various packages. The routine use scale (mean = 4.13, std dev = 1.30) comprised items representing use of basic features such as standard pre-built reports and queries. High advanced users scored significantly higher ($t = 4.77$, $p < 0.001$) on their use of these basic routine features (mean = 4.33, std dev = 1.24) compared to low advanced users (mean = 3.62, std dev = 1.30), suggesting that advanced users tend to make more use of all BI features.

5. Results

5.1. Measurement model testing

The dimensionality of the constructs was confirmed through an initial exploratory principal components analysis with varimax rotation. The results (Table 4) did not suggest that any items needed to be dropped as all factor loadings were above 0.60 and average variance extracted values were all above 0.50 (Table 4). Moreover, as per Harman's one factor test, the first factor did not account for a majority of variance, only 14.5 %, suggesting no concerns over common method bias [67,94]. In addition, we considered the marker variable approach to test for common method bias [79]. We selected self-reported experience in management accounting as a marker because it is likely to be subject to a similar disproportionate response or acquiescence bias as other variables, such as levels of BI use and performance. However, it is not expected to be theoretically or statistically related to other model variables. When the marker variable was included as an additional determinant of the dependent variables, the significance of path coefficients did not change, providing further assurance that common method bias was not substantial [79]. Cronbach's alpha was used to measure internal consistency of the multi-item scales and found to be greater than 0.70 for

Table 3
Demographics and descriptive statistics of respondents.

Descriptive statistics	Category	Pooled sample	Low advanced user subgroup	High advanced user subgroup
Sample size		362 (100 %)	104 (100 %)	258 (100 %)
Median age range		36–40 years	36–40 years	36–40 years
Gender	Male	139 (38.4 %)	35 (33.7 %)	104 (40.3 %)
	Female	159 (43.9 %)	53 (51.0 %)	106 (41.1 %)
	Prefer not to say	64 (17.7 %)	16 (15.4 %)	48 (18.6 %)
Median experience in management accounting		11–15 years	11–15 years	11–15 years
Years of experience using BI systems	<2 years	43 (11.9 %)	10 (9.6 %)	33 (12.8 %)
	2–5 years	60 (16.6 %)	10 (9.6 %)	50 (19.4 %)
	6–10 years	93 (25.7 %)	26 (25.0 %)	67 (26.0 %)
	11–15 years	91 (25.1 %)	36 (34.6 %)	55 (21.3 %)
	>16 years	58 (16.0 %)	15 (14.4 %)	43 (16.7 %)
	Prefer not to say	17 (4.7 %)	7 (6.7 %)	10 (3.9 %)
Current BI system being used by your organization	SAP BusinessObjects	127 (35.1 %)	34 (32.7 %)	93 (36.0 %)
	Microsoft Suite, Power BI	56 (15.5 %)	18 (17.3 %)	39 (15.1 %)
	Clear Analytics (Excel based)	39 (10.8 %)	9 (8.7 %)	30 (11.6 %)
	Oracle	37 (10.2 %)	11 (10.6 %)	26 (10.1 %)
	SAGE	35 (9.7 %)	11 (10.6 %)	23 (8.9 %)
	SAS	32 (8.8 %)	13 (12.5 %)	19 (7.4 %)
	Other*	36 (10.0 %)	8 (7.7 %)	28 (10.9 %)
Attended training for this BI system	Yes	112 (30.9 %)	43 (41.3 %)	69 (26.7 %)
	No	206 (56.9 %)	49 (47.1 %)	157 (60.9 %)
	Prefer not to say	44 (12.2 %)	12 (11.5 %)	32 (12.4 %)
Sector of current employment as a management accountant	Finance	51 (14.1 %)	13 (12.5 %)	38 (14.7 %)
	Utilities and Energy	44 (12.2 %)	15 (14.4 %)	29 (11.2 %)
	Service	37 (10.2 %)	7 (6.7 %)	30 (11.6 %)
	Telecoms	32 (8.8 %)	4 (3.8 %)	28 (10.9 %)
	Pharmaceutical	30 (8.3 %)	12 (11.5 %)	18 (7.0 %)
	Retail	28 (7.7 %)	6 (5.8 %)	22 (8.5 %)
	Accounting	27 (7.5 %)	9 (8.7 %)	18 (7.0 %)
	Public sector	25 (6.9 %)	9 (8.7 %)	16 (6.2 %)
	Manufacturing	24 (6.6 %)	10 (9.6 %)	14 (5.4 %)
	Logistics	22 (6.1 %)	8 (36.4 %)	14 (5.4 %)
	Airline	22 (6.1 %)	5 (4.8 %)	17 (6.6 %)
	Mining	20 (5.5 %)	6 (5.8 %)	14 (5.4 %)
Current management level	Junior and entry management	53 (14.7 %)	18 (17.3 %)	36 (13.9 %)
	Middle management	83 (22.9 %)	27 (26.0 %)	56 (21.7 %)
	Senior management	151 (41.7 %)	41 (39.4 %)	109 (42.2 %)
	Specialist	60 (16.6 %)	16 (15.4 %)	44 (17.1 %)
	Executive management	15 (4.1 %)	2 (1.9 %)	13 (5.0 %)
Professional qualification	CIMA	199 (55.0 %)	54 (51.9 %)	145 (56.2 %)
	SAICA, CA (SA)	135 (37.3 %)	46 (44.2 %)	89 (34.5 %)
	Other	27 (7.5 %)	4 (3.8 %)	24 (9.3 %)
Routine use	Mean (std dev)	4.13 (1.30)	3.62 (1.30)	4.33 (1.24)
Advanced use	Mean (std dev)	5.06 (1.02)	3.84 (1.14)	5.55 (0.29)

* Other BI systems in use included QlikView, IBM Cognos, and MicroStrategy, among others.

all constructs. This provides support for convergent validity and reliability of our scales. To confirm discriminant validity, we compared inter-construct correlations with the square root of AVE of each construct. The square roots of AVE of each construct are presented along the diagonal of Table 5. These are shown as larger than the inter-construct correlations (i.e., constructs share more variance with their own items than with other constructs in the model). In addition, the HTMT ratios were calculated, and results indicate that the ratios are less than 0.85 [52]. Therefore, discriminant validity was confirmed.

A further confirmatory factor analysis test of the measurement model was undertaken using AMOS. The maximum-likelihood method was adopted. Although the ratio of X^2 / DF = 12 is slightly higher than the recommended level, other fit indices were reasonable [GFI = 0.790; NFI = 0.854; CFI = 0.924; IFI = 0.925; RMSEA = 0.050; DF = 1297; TLI = 0.919; and RFI = 0.844] with the factor loadings between 0.633 and 0.931. Taken together, results confirm the reliability, convergent, and discriminant validity of the measured constructs.

A Mann-Whitney comparison of users in the high advanced use subgroup with those in the low advanced use subgroup reveals significant differences across all model variables, except self-efficacy (Table 6). The mean rank for users classified as high advanced users was higher on

Table 4
PCA Results and item reliability.

Variable	Items	Factor loadings	AVE	Cronbach's Alpha
System Quality	The BI system is always up and running.	0.751	0.643	0.915
	The BI system is easy to navigate.	0.830		
	The response time of the BI system is acceptable.	0.821		
	The BI system is easy to use.	0.813		
	The BI system is user friendly.	0.863		
	The BI system is stable.	0.782		
Data Quality	Data input records in the system are always complete.	0.837	0.620	0.830
	Data records in the system are never missing.	0.845		
	Data records in the system are always correct.	0.847		
Information Quality	Information output by the BI system is presented in a useful format.	0.878	0.720	0.947
	Information output by the BI system is accurate.	0.844		
	Information output provided by the BI system is easy to understand.	0.850		
	Information output provided by the BI system meets my needs.	0.847		
	Information output provided by the BI system is relevant.	0.891		
	Information output produced by the BI system is complete with no need to rely on other systems.	0.850		
	Information output provided by BI systems is important and helpful for my work.	0.839		
Service Quality	My organization's BI system support team is always helpful to me.	0.838	0.659	0.906
	My organization's BI system support team is responsive within reasonable time.	0.856		
	My organization's BI system support team is committed to resolving my system challenges.	0.869		
	My organization's BI system support team responds to my request promptly.	0.798		
	With the support that I have received, I believe I can now use the BI system with confidence.	0.848		
User Satisfaction	I enjoy using the BI system.	0.872	0.754	0.939
	I would recommend the BI system to other management accountants.	0.898		
	The BI system works the way I want it to work.	0.888		
	It is pleasant to use the BI system.	0.900		
	Overall, I am satisfied with the BI system.	0.863		
Individual Performance	Using the BI system improves my job performance.	0.809	0.566	0.901
	Using the BI system increases my work productivity.	0.781		
	Using the BI system enhances my effectiveness in my job.	0.727		
	Using the BI system improves my decision-making quality.	0.761		
	Using the BI system helps me identify potential problems faster.	0.711		
	Using the BI system assists me in making decisions quicker.	0.783		
	Using the BI system assists me in spending less time in meetings.	0.789		
Self-Efficacy	I could use more advanced features of a BI tool with only the built-in help functions for assistance.	0.833	0.763	0.906
	I am confident in my ability to use the more advanced features of a BI tool.	0.831		
	I am confident in my ability to use a BI system to predict the future performance of the organization.	0.810		
Task Complexity	The work that I perform is routine.	0.904	0.685	0.945
	My co-workers perform the same job in the same way most of the time.	0.919		
	The duties that I perform are repetitious.	0.907		
	My co-workers perform repetitive activities in doing their jobs.	0.904		
	There is a clearly known way to do the major types of work I normally encountered.	0.909		
	There is a clearly defined body of knowledge of subject matter that can guide me in doing my work.	0.931		
	There is an understandable sequence of steps that can be followed in doing my work.	0.905		
	I can actually rely on established procedures and practices in doing my work.	0.906		
Routine Use	Running existing reports	0.823	0.687	0.946
	Executing existing queries	0.810		
	Performing basic analysis	0.846		
	Extracting data from BI tools and preparing reports in Excel	0.860		
	Accessing standard reports	0.820		
	Running ad-hoc reporting	0.812		
	Abstraction of raw data	0.824		
	Cleansing data	0.800		
Advanced Use	Self-service tools	0.786	0.674	0.961
	Interactive visualization	0.804		
	Predictive analytics reports	0.888		
	Drill-down functions	0.883		
	Creating dashboards	0.832		
	Constructing my own queries	0.875		
	Setting performance management targets	0.855		
	Trend analysis	0.842		
	Scenario planning	0.633		
	Predictive modeling	0.768		
	Agile visualizations	0.730		
	Optimization	0.855		

all four system attributes, and in BI contribution to performance. These users also ranked significantly higher in task complexity.

5.2. Structural model and hypothesis testing

The structural model was tested using AMOS with results reported in Table 7 indicating 17 out of 22 hypothesized paths were directly supported by the model being tested.

System quality ($p < 0.001$), data quality ($p < 0.01$), information quality ($p < 0.001$), and service quality ($p < 0.05$) were all found to have positive significance effects on routine use. Furthermore, system quality ($p < 0.001$), data quality ($p < 0.05$), information quality ($p < 0.001$), and service quality ($p < 0.01$) were all found to have positive significance influence on advanced use, with effect sizes larger for advanced use than routine use, thus supporting H1a, H1b, H3a, H3b, H5b, H5c, H7a, and H7b. To further confirm the effects, we ran

Table 5
Discriminant validity.

	Mean (S.D.)	SQ	DQ	IQ	SQa	US	IP	SE	TC	RU	AU
SQ	5.32 (1.14)	**0.800**									
DQ	5.40 (1.13)	0.147**	**0.787**								
IQ	5.08 (1.36)	0.132*	0.111*	**0.848**							
SQa	5.29 (1.13)	0.150**	-0.022	0.044	**0.811**						
US	3.24 (1.42)	0.122**	0.138**	0.065	-0.085	**0.872**					
IP	5.65 (0.98)	0.277**	0.081	0.160**	0.084	0.155**	**0.750**				
SE	5.53 (1.26)	-0.016	-0.028	-0.095	0.034	-0.082	-0.003	**0.874**			
TC	5.09 (1.64)	0.165**	0.141**	-0.038	-0.001	0.119**	0.015	-0.017	**0.827**		
RU	4.13 (1.30)	0.197**	0.147**	0.177**	0.137**	0.068	0.271**	0.045	0.047	**0.829**	
AU	5.06 (0.98)	0.234**	0.163**	0.255**	0.139**	0.130**	0.279**	0.115*	0.138**	0.309**	**0.816**

** significant at the 0.01 level (2-tailed), * significant at the 0.05 level (2-tailed).

Table 6
High advanced use versus low advanced use.

Variable	High Advanced Use Subgroup ($n ==$ 258)		Low Advanced Use Subgroup ($n ==$ 104)		Significance of Mann-Whitney U
	mean (std dev)	mean rank	mean (std dev)	mean rank	
System Quality	5.626 (0.825)	209.10	4.561 (1.427)	113.02	***
Data Quality	5.656 (0.817)	199.92	4.769 (1.479)	135.80	***
Information Quality	5.192 (1.342)	195.97	4.775 (1.381)	145.60	***
Service Quality	5.714 (0.563)	215.44	4.260 (1.460)	97.31	***
User Satisfaction	3.519 (1.513)	194.91	2.496 (0.100)	148.22	***
Individual Performance	5.766 (0.886)	195.78	5.356 (1.125)	146.07	***
Self-Efficacy	4.818 (1.569)	186.82	4.522 (1.628)	168.31	n/s
Task Complexity	5.741 (0.976)	216.40	4.334 (1.292)	94.92	***

*** $p < 0.001$; n/s = not significant.

additional multiple regressions with bootstrap resampling to determine the overlap, if any, among confidence intervals. As shown in Table 8, we confirm no overlapping confidence intervals for effects of DQ and IQ providing added support to H3b and H5c. Although there is some overlap in confidence intervals for the effects of SQ and SQa, the overlap is not more than 50 % of the confidence interval range, thus giving us confidence to support H1b and H7b that their effects are greater on advanced use than on routine use. We also considered data quality to have additional indirect effects on BI use through effects on information quality. The effect of data quality on information quality is significant, supporting H5a.

H2 and H4 were supported, as system and data quality are significant for satisfaction (Table 7). Information quality did not have a significant effect on user satisfaction. Therefore, H6 is rejected. This is surprising given the purpose of BI systems and is discussed further in the following. Service quality was found to have a negative influence on user satisfaction, and therefore H8 was also rejected. We discuss possible reasons for this unexpected finding in the next section.

User satisfaction had a direct positive influence on advanced use of the BI system but no direct positive influence on routine use, hence H9a is partially supported but H9b is fully supported as advanced use was hypothesized as more relevant to user satisfaction. The advanced use of BI has a direct positive influence on the performance of management accountants. The routine use of the BI system similarly has a direct positive influence on performance. Thus, H10a is supported, as both types of use have independent direct effects on the performance of management accountants, but advanced use has a larger effect, which supports H10b. To further confirm 10b, we similarly ran a multiple regression with bootstrap resampling to determine any overlap in confidence intervals. Results showed that the 95 % confidence intervals associated with the regression coefficient for routine use (0.118–0.256) did not overlap those of advanced use (0.567–0.668). User satisfaction also has a significant effect on individual performance of management accountants, hence H11 is supported. Users who are satisfied with their BI system are also more likely to believe it contributes to their work performance.

Task complexity was modeled as a direct determinant of routine and advanced use. It was found to exert positive significant effects on advanced use but not on routine use, thus providing partial support for H12a and support for H12b. Self-efficacy has a positive significant influence on advanced use of the BI system. However, there is no significant influence on routine use of the BI system, thus supporting H14b. Experience and training were omitted from the final model as they exhibited no significant relationship with use, confirming self-efficacy as a more relevant individual factor.

Overall, the model explained 27.4 % of the variance in user satisfaction ($R^2 = 0.274$), 40.7 % of the variance in advanced use ($R^2 = 0.407$), 19.9 % of the variance in routine use ($R^2 = 0.199$), and 52.2 % of the variance in individual performance ($R^2 = 0.522$). The final model fit indicates a significant X^2 ($p = 0.001$) and X^2/DF = 11 is slightly higher than the recommended range with good fit indices [GFI = 0.768; NFI = 0.882; CFI = 0.930; IFI = 0.914; RMSEA = 0.052; TLI = 0.925; RFI = 0.839].[1]

[1] For completeness, we tested an alternate specification of the IS success model as proposed by Seddon [107] and considered in studies such as those of Sabherwal et al. [104] and Wu and Wang [132]. This model included paths from system attributes to individual performance perceptions and reversed the causality between individual performance and satisfaction and individual performance and use. This respecification of the DeLone and McLean model was not a better fit to our data [GFI=0.963; NFI=0.711; CFI=0.759; IFI=0.782; RMSEA=0.101; DF=10; TLI=0.528; RFI=0.782].

Table 7
Results of the hypothesized model (direct effects).

Hypothesis	Path	Estimate	S.E.	C.R.	p-value	Supported
H1a, H1b	SQ —> RU	0.210	0.057	3.692	***	Yes
	SQ —>AU	0.287	0.072	3.996	***	
H2	SQ —> US	0.202	0.087	2.316	0.02	Yes
H3a, H3b	DQ —> RU	0.129	0.046	2.794	0.004	Yes
	DQ —>AU	0.352	0.168	2.101	0.034	
H4	DQ —> US	0.268	0.113	2.381	0.013	Yes
H5a	DQ —> IQ	0.135	0.063	2.129	0.033	Yes
H5b, H5c	IQ —> RU	0.199	0.046	4.320	***	Yes
	IQ —>AU	0.593	0.132	4.494	***	
H6	IQ —>US	0.141	0.180	0.780	0.433	No
H7a, H7b	SQa —> RU	0.157	0.078	2.027	0.035	Yes
	SQa —> AU	0.228	0.088	2.599	0.008	
H8	SQa —> US	-0.128	0.064	-2.005	0.045	No
H9a, H9b	US —> RU	0.165	0.368	0.448	0.720	No
	US —> AU	0.651	0.289	2.253	0.026	Yes
H10a, H10b	RU —> IP	0.255	0.071	3.590	***	Yes
	AU —> IP	0.679	0.158	4.304	***	
H11	US —> IP	0.653	0.208	3.137	***	Yes
H12a, H12b	TC —> AU	0.059	0.031	1.934	0.050	Yes
	TC —> RU	0.007	0.038	0.181	0.876	No
H14a, H14b	SE —> RU	0.083	0.168	0.496	0.591	No
	SE —> AU	0.381	0.161	2.372	0.014	Yes

*** ($p < 0.001$). SQ = system quality; DQ = data quality; IQ = information quality; SQa = service quality; US = user satisfaction; RU = routine use; AU = advanced use; IP = individual performance; SE = self-efficacy; TC = task complexity.

Table 8
Results of regression analysis.

	95 % Confidence Interval (lower bound)	95 % Confidence Interval (upper bound)
IQ —> RU	0.105	0.210
IQ —>AU	0.240	0.491
DQ —> RU	0.084	0. 123
DQ —>AU	0.155	0.326
SQ —> RU	0.113	0.208
SQ —>AU	0.199	0.272
SQa —> RU	0.108	0.157
SQa —>AU	0.149	0.225

To test the moderating effect of task complexity (H13a–H13b), we calculated interaction terms between task complexity and the two use constructs. As per recommendation [2], the variables were centered prior to analysis. Performance was then modeled as a function of advanced and routine use; task complexity; and the interactions between advanced use and task complexity as well as routine use and task complexity.

We considered the model's goodness of fit, the significance of the path coefficients, and the sign of the path to reach conclusions about moderation [48]. The results (Table 9) indicate that the complexity of the management accountant's tasks increases their opportunity to use the BI system innovatively to support their management accounting function ($p < 0.001$). Task complexity also has a moderating effect on routine use and performance ($p < 0.05$). The relationship between use and performance is moderated by task complexity, but the moderating effect is weaker for routine use, supporting both H13a and H13b. This confirms that the more complex the tasks of management accountants, the stronger will be the effect of advanced use on performance. This supports the importance of using the advanced features of the BI system to improve performance under conditions of greater task complexity.

Table 9
Results of the moderating effects model.

Hypothesis		Estimate	S.E.	C.R.	p-value	Supported
H13a, H13b	IN_RU —> IP	0.103	0.050	2.032	0.042	Yes
	IN_AU —> IP	0.200	0.047	4.255	***	Yes
	TC —> IP	0.219	0.056	3.921	***	Yes
	RU —> IP	0.154	0.043	3.538	***	Yes
	AU —> IP	0.229	0.056	4.069	***	Yes

*** ($p < 0.001$). IP = individual performance; TC = task complexity; RU = routine use; AU = advanced use; IN_RU = interaction effect (routine use x task complexity); IN_AU = interaction effect (advanced use x task complexity).

6. Discussion

The purpose of this study was to address the questions as to what motivates management accountants to make use of BI systems implemented in their organizations, what motivates them to move beyond routine use and toward more advanced use, and identification of the consequences of routine and advanced use for their job performance. To answer the questions, we extended the DeLone and McLean IS success model and tested our hypotheses with data collected from 362 respondents.

Empirical testing found that both routine use and advanced use are important to performance, but advanced use has a stronger path coefficient. Routine use relies only on basic features such as drawing mostly on pre-specified reports and queries [49,69], which contributes less to individual performance outcomes and quality of decision making. However, advanced use was found to be crucial to supporting management accountants in their job performance, confirming some expectations from prior literature [18,49,74,112]. Advanced use requires management accountants to use advanced features such as predictive analytics, interactive visualizations, drill-down functions, dashboard reporting, optimization, query construction tools, and predictive modeling [50,85,112]. Management accountants who do not use these BI system features are less likely to experience improved productivity and quality of decision making. Individual investments of time and intellectual effort to learn to use more advanced features does appear to produce extended benefit. These individual effects could in turn lead to improved organizational outcomes, but empirical examination of such organizational level effects must be confirmed by future research.

On the question as to what motivates management accountants to make use of BI systems, our results indicate that BI use depends on several system attributes along with individual user attributes and task characteristics. It appears that users with higher levels of self-efficacy were associated with more advanced use but not with routine use. Improving user self-efficacy for use of advanced BI features is thus essential to improving realization of benefits from BI. We also found the paths from task complexity to advanced use and routine use were both significant, but the effect size for routine use was lower. Users facing less complex tasks may only need standard features and functions, whereas users facing more complex tasks will rely on more advanced features and be more creative in their BI usage to find solutions to their more complex decision problems. In addition, we hypothesized that the relationship between BI use and individual user performance may be stronger among individuals who have higher task complexity than among those with lower levels of task complexity [27,74,75]. In the moderator tests, task complexity was found to have a positive significant moderating effect on both routine use and advanced use and performance. However, the moderating effect of task complexity was stronger for advanced use, suggesting that users who face more complex tasks are more likely to benefit from advanced use. In a complex task environment, the volume of information being processed overwhelms the capacity of users [45], requiring more advanced use of BI systems to achieve higher performance outcomes. Users who face complex tasks but rely only on routine use features are unlikely to improve their performance.

For system attributes, we show that management accountants expect BI systems to be available, easy to navigate, easy to use, user friendly, and stable, which motivates their use and user satisfaction with these systems. The quality of data is also an essential system success factor in the BI context [116]. Accurate and complete records help users trust BI tools for executing not just routine tasks but also experimenting with more novel and advanced features. Efforts to improve data quality should thus continue to be encouraged [68]. Results also confirmed that greater BI usage can be promoted through the design and format of information outputs, ensuring they are easy to understand and consistent for users. Service quality also influenced both routine and advanced use of BI. Good-quality support services help users gain confidence in using BI and result in more advanced use.

We found user satisfaction to contribute positively to improvements in individual performance. When a system supports the complex demands of users, then benefit perceptions are shaped by user satisfaction [81]. User satisfaction can be sustained by maintaining the system's ease of use and continuing to ensure that data is of a high quality. Surprisingly, the hypothesis linking information quality to user satisfaction was not supported. Information quality appears to be essential to motivate system usage but is not necessarily important to user satisfaction. It might be that information quality is a hygiene factor in BI systems [17]. For instance, it might be observable that poor-quality information outputs lead to dissatisfaction but good-quality information outputs do not necessarily lead to satisfaction. Users expect high-quality outputs that meet their information needs [133], but poor information quality would lead to dissatisfaction given the threat posed to management accounting functions [102]. Future work may wish to consider dissatisfaction as conceptually distinct from satisfaction within the IS success framework. Moreover, service quality appeared to reduce user satisfaction significantly. This was not expected, but the finding could mean that users who often tend to rely on the BI support services are generally less satisfied. Complex systems, even if well supported by a responsive team, may not necessarily be found enjoyable to use and may not work the way users want, and users may resent needing to access support. Thus, greater provision of support services may be a response to difficulties with a system and low user satisfaction, a phenomenon also deserving consideration in future work.

6.1. Theoretical contribution and implications

Our work contributes to existing research on how IS systems are used to attain performance outcomes (e.g., [118]). We confirm that benefits for managerial decision making from complex IS systems, such as BI, are less likely to arise when use is restricted to only basic features (see also [81]). Advanced use behavior is shown as a more relevant IS success measure with implications for individual performance outcomes, as argued by DeLone and McLean [29] and suggested elsewhere [31]. Our concepts of routine versus advanced use should be applicable to studies in other utilitarian IS contexts, such as ERP, CRM, and groupwork systems, along with studies of individual productivity tools and mobile apps, such as for self-service banking.

Following suggestions of Petter et al. [92] and Jeyaraj [64], we also considered additional IS success factors, namely self-efficacy and task complexity. We have determined that routine use is less likely under conditions of task complexity and does not rely on self-efficacy to the same extent as advanced use. We also show that IS success depends not only on system attributes but also on the nature and complexity of the job for which that system is used. Task complexity motivates use and influences the consequences of use for job performance. Factors such as individual self-efficacy and task complexity have not been considered in other recent studies of BI use [118]. It has been argued that the inclusion of potential moderators has been too frequently ignored in prior research on IS success [64], and we were able to address this through our consideration of task complexity as a moderator. Future work must continue to include job factors such as task complexity in the IS success model.

6.2. Implications for practice

From a practical perspective, users facing more complex tasks report using more advanced BI features. BI support programs must then be designed around the task complexity of users. By differentiating between the types of use, we were able to show advanced use as a critical success factor in the BI context for supporting management accountants in their job performance. Specifically, management accountants are more likely to perform if they are able to use the advanced features of a BI system, and performance further increases when task complexity is supported by advanced use. If users are unable to use the advanced features of the BI system, they would normally be using only standard features in routine support of their work that contributes less to their individual performance outcomes. This is likely to undermine the overall return on organizational investments into BI solutions. Supporting management accountants to use systems in more creative and advanced ways in their work is thus a necessary and important intervention for practice and the profession. Training programs and other interventions that enhance user self-efficacy can be effective in promoting more advanced use. In addition, BI developers must pay attention to system quality issues, such as ease of use and access, along with information output quality to promote more advanced use. If information outputs are poorly formated and difficult to interpret, then users are less likely to rely on more complex features, and this has implications for their performance. Data quality is distinct from output quality. Users must be convinced that data extraction and loading operations result in complete and reliable BI datasets for analysis. User satisfaction is an important measure of IS success. Anything that detracts from user satisfaction can have implications for system use and outcomes. Service quality is not sufficient to overcome limitations in system design, and users may resent the need to access support teams to make use of complex IS solutions.

6.3. Limitations and future research direction

Some limitations are noted in the study. First, data was collected from management accountants sampled from South African organizations, and results may therefore not be generalizable to all management accountants or to users in other BI system contexts. Future studies should extend empirical testing of our model to users in other contexts. Second, the data collected was cross-sectional, and therefore we rely on theoretical arguments in making causal inferences between the constructs. Longitudinal research designs would need to be employed in future studies to provide better evidence of causality, such as between advanced use and performance. Third, self-administered surveys are subject to methods bias. For example, a selection bias may exist where the decision of management accountants to participate in the study was not independent of their perceptions of the system, and this may compromise the external validity of the findings. However, we were able to collect data from a large number of individuals from multiple private and public sector organizations, all of whom use BI to greater or lesser extents in the performance of their work. Fourth, we asked participants to select and reflect in their responses on the BI tool they use in their work as management accountants. However, we did not distinguish between the mandatory or voluntary nature of use [131], and it is not impossible that users could have access to multiple systems and be advanced users of one tool but more limited users of another. This may have influenced how users responded to questions. Future work may wish to conduct case analysis of users within specific organizational settings where multiple systems are in operation. Fifth, in modeling the link between task complexity and use, we have drawn on theories such as task-technology fit, which consider use a function of task characteristics. However, we cannot rule out alternate causal explanations, such as where users with more experience in advanced BI use are assigned more complex tasks. Sixth, routine and advanced users may differ in ability to make informed judgments about the overall qualities of the BI system. If routine users are underestimating system qualities and avoiding advanced use, then different interventions may be warranted. Finally, we distinguished between high and low advanced users based on their use of features such as self-service tools, interactive visualization, predictive analytics, and drill-down functionality. Future research can make further efforts to assess the division between advanced versus routine users. Distinguishing routine from advanced users can assist organizations in optimizing their use of complex information systems, such as BI.

7. Conclusions

This study addressed questions regarding what motivates management accountants to make use of BI systems implemented in their organizations and the consequent effects of routine and advanced use for their performance. The study specifically distinguished routine from advanced use of BI system features and examined these within a DeLone and McLean IS success model. We extended IS success factors to include data quality, finding that system, data, information, and service quality influence both routine and advanced use behaviors. However, management accountants using only routine BI features were not found to benefit with improved performance to the same degree as those using more advanced system features of BI. User satisfaction is important to use and is influenced most by system and data quality. Results showed that advanced use is more likely under conditions of task complexity and requires greater user self-efficacy than routine use. Future IS success studies must include richer conceptualizations of system use, along with consideration for how task and individual factors influence IS success.

CRediT authorship contribution statement

Thanyani Norman Mudau: Conceptualization, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft. **Jason Cohen:** Writing – review & editing, Supervision, Conceptualization, Visualization. **Elmarie Papageorgiou:** Writing – review & editing, Supervision, Conceptualization, Visualization.

Appendix A. – Copy of research instrument (excluding demographic questions)

1 Please indicate the extent in which you agree with each of the following statements related to the BI system that you currently use in your work as a management accountant. Please indicate whether you Strongly disagree, Mostly disagree, Disagree, are Neutral, Agree, Mostly agree, or Strongly agree with each statement.

No.	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
SQ1	The BI system is always up and running.	1	2	3	4	5	6	7
SQ2	The BI system is easy to navigate.	1	2	3	4	5	6	7
SQ3	The response time of the BI system is acceptable.	1	2	3	4	5	6	7
SQ4	The BI system is easy to use.	1	2	3	4	5	6	7
SQ5	The BI system is user friendly.	1	2	3	4	5	6	7
SQ6	The BI system is stable.	1	2	3	4	5	6	7
DQ1	Data input records in the system are always complete.	1	2	3	4	5	6	7
DQ2	Data records in the system are never missing.	1	2	3	4	5	6	7
DQ3	Data records in the system are always correct.	1	2	3	4	5	6	7
IQ1	Information output by the BI system is presented in a useful format.	1	2	3	4	5	6	7
IQ2	Information output by the BI system is accurate.	1	2	3	4	5	6	7
IQ3	Information output provided by the BI system is easy to understand.	1	2	3	4	5	6	7
IQ4	Information output provided by the BI system meets my needs.	1	2	3	4	5	6	7
IQ5	Information output provided by the BI system is relevant.	1	2	3	4	5	6	7
IQ6	Information output produced by the BI system is complete with no need to rely on other systems.	1	2	3	4	5	6	7
IQ7	Information output provided by BI systems is important and helpful for my work.	1	2	3	4	5	6	7
SQa1	My organization's BI system support team is always helpful to me.	1	2	3	4	5	6	7
SQa2	My organization's BI system support team is responsive within reasonable time.	1	2	3	4	5	6	7
SQa3	My organization's BI system support team is committed to resolving my system challenges.	1	2	3	4	5	6	7
SQa4	My organization's BI system support team responds to my request promptly.	1	2	3	4	5	6	7
SQa5	With the support that I have received, I believe I can now use the BI system with confidence.	1	2	3	4	5	6	7
US1	I enjoy using the BI system.	1	2	3	4	5	6	7
US2	I would recommend the BI system to other management accountants	1	2	3	4	5	6	7
US3	The BI system works the way I want it to work.	1	2	3	4	5	6	7
US4	It is pleasant to use the BI system.	1	2	3	4	5	6	7
US5	Overall, I am satisfied with the BI system.	1	2	3	4	5	6	7
IP 1	Using the BI system improves my job performance.	1	2	3	4	5	6	7
IP 2	Using the BI system increases my work productivity.	1	2	3	4	5	6	7
IP 3	Using the BI system enhances my effectiveness in my job.	1	2	3	4	5	6	7
IP 4	Using the BI system improves my decision-making quality.	1	2	3	4	5	6	7
IP 5	Using the BI system helps me identify potential problems faster.	1	2	3	4	5	6	7
IP 6	Using the BI system assists me in making decisions quicker.	1	2	3	4	5	6	7
IP 7	Using the BI system assists me in spending less time in meetings.	1	2	3	4	5	6	7

(*continued on next page*)

(*continued*)

No.	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
SE1	I could use more advanced features of a BI tool with only the built-in help functions for assistance.	1	2	3	4	5	6	7
SE2	I am confident in my ability to use the more advanced features of a BI tool.	1	2	3	4	5	6	7
SE3	I am confident in my ability to use a BI system to predict the future performance of the organization.	1	2	3	4	5	6	7

2 Please indicate the extent in which you agree with each of the following statements related to the complexity of your work as a management accountant.

No.	Statements	Strongly disagree	Mostly disagree	Disagree	Neutral	Agree	Mostly agree	Strongly agree
TC1	The work that I perform is routine.	1	2	3	4	5	6	7
TC2	My co-workers perform the same job in the same way most of the time.	1	2	3	4	5	6	7
TC3	The duties that I perform are repetitious.	1	2	3	4	5	6	7
TC4	My co-workers perform repetitive activities in doing their jobs.	1	2	3	4	5	6	7
TC5	There is a clearly known way to do the major types of work I normally encountered.	1	2	3	4	5	6	7
TC6	There is a clearly defined body of knowledge of subject matter that can guide me in doing my work.	1	2	3	4	5	6	7
TC7	There is an understandable sequence of steps that can be followed in doing my work.	1	2	3	4	5	6	7
TC8	I can actually rely on established procedures and practices in doing my work.	1	2	3	4	5	6	7

3 Below are the basic functions of BI tools. Please indicate how often you have been using these basic functions. I use more basic features of the BI tool such as:

No.	Statements	Never	Very rarely	Rarely	Occasionally/Sometimes	Often	Very often
RU1	Running existing reports	1	2	3	4	5	6
RU2	Executing existing queries	1	2	3	4	5	6
RU3	Performing basic analysis	1	2	3	4	5	6
RU4	Extracting data from BI tools and preparing reports in Excel	1	2	3	4	5	6
RU5	Accessing standard reports	1	2	3	4	5	6
RU6	Running ad-hoc reporting	1	2	3	4	5	6
RU7	Abstraction of raw data	1	2	3	4	5	6
RU8	Cleansing data	1	2	3	4	5	6

4 Below are the advanced features of BI tools. Please indicate how often you regularly use more advanced features of your BI tool. I use advanced features of the BI tool such as:

No.	Statements	Never	Very rarely	Rarely	Occasionally/Sometimes	Often	Very often
IU1	Self-service tools	1	2	3	4	5	6
IU2	Interactive visualization	1	2	3	4	5	6
IU3	Predictive analytics reports	1	2	3	4	5	6
IU4	Drill-down functions	1	2	3	4	5	6
IU5	Creating dashboards	1	2	3	4	5	6
IU6	Constructing my own queries	1	2	3	4	5	6
IU7	Setting performance management targets	1	2	3	4	5	6
IU8	Trend analysis	1	2	3	4	5	6
IU9	Scenario planning	1	2	3	4	5	6
IU10	Predictive modeling	1	2	3	4	5	6
IU11	Agile visualizations	1	2	3	4	5	6
IU12	Optimization	1	2	3	4	5	6

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