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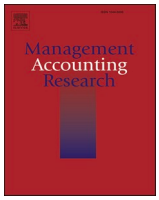

Digitalization of the finance function: Automation, analytics, and finance function effectiveness

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ABSTRACT

Contemporary digital technologies provide new opportunities for organizing work within the finance function. In this study, we examine two digital technologies that are particularly relevant to the operation of finance functions – automation and analytics. We argue that variation in the use of these technologies is related to the interplay between firm-level digitalization strategy and the objectives of the finance function. Drawing on prior literature, we distinguish between two finance function objectives: an efficiency objective and a business partnering objective. Based on survey responses from 137 finance function professionals and complementary insights from 11 interviews, we show that the use of digital technologies within the finance function is associated with both firm-level digitalization strategy and the specific objectives of the finance function. Specifically, we find a positive interaction between an emphasis on firm digitalization strategy and an efficiency objective on the use of both automation and analytics. In contrast, digitalization strategy and a business partnering objective have positive but independent effects on the use of analytics. We also find that finance functions that simultaneously use automation and analytics have lower effectiveness, which might be a result of resource constraints. Overall, our paper adds to our understanding of the drivers and consequences of digitalization in the finance function.

1. Introduction

Digitalization has emerged as one of the primary strategic priorities in organizations (Caputo et al., 2021; Kraus et al., 2022; Menz et al., 2021; Niemand et al., 2021). Technologies associated with digitalization have potentially significant consequences for how management accounting and control practices are carried out within the finance function (Fähndrich, 2023; Knudsen, 2020; Korhonen et al., 2021; Möller et al., 2020). Two technologies that are particularly important for the operation of the finance function are automation and analytics. Automation technologies execute business processes by following a series of structured workflows, such as automation of invoice processing and automated reporting (Kokina and Blanchette, 2019; Korhonen et al., 2021; Plattfaut and Borghoff, 2022), while analytics encompasses tools and techniques that enable organizations to make sense of big data and derive meaningful insights for decision-making, such as interactive dashboards and simulation modelling (Fehrenbacher et al., 2022; Labro et al., 2023; Li et al., 2018; Spraakman et al., 2021). While practitioner literature argues that automation and analytics have substantial benefits for finance functions in general, there is significant variation in their use in practice (Deloitte, 2021; Gartner, 2021). The purpose of this study is to examine how a firm-level digitalization strategy interplays with the objectives of the finance function in driving the use of digital technologies, and with what effects.

The technologies used by the finance function are likely to be dependent on the broader strategic objectives of the firm. Organizational strategy is an important determinant of the choice and design of accounting and control systems (Chenhall and Langfield-Smith, 1998). As such, we expect that the emphasis an organization places on digitalization strategy will be positively associated with digital technology use

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in the finance function. We also expect that the objectives of the finance function are important for understanding the types of digitalization technologies that are used. Prior research shows that contemporary finance functions have two main objectives – an efficiency objective and a business partnering objective – but that the emphasis on these objectives varies across firms, and importantly, this has implications for how the finance function operates (e.g., Chang et al., 2014; Hartmann and Maas, 2010; Lambert and Sponem, 2012; Maas and Matějka, 2009; van Slooten et al., 2024). As automation and analytics require substantial resource investment (e.g., IT, staffing, skill development) (Eilifsen et al., 2020; Plattfaut and Borghoff, 2022), we expect that finance functions will emphasize the use of digital technologies that relate more closely to their dominant objective.

Importantly, we expect the effects of firm-level digitalization strategy and finance function objectives to *interact* in shaping digitalization in the finance function. If the organization does not place a high emphasis on pursuing digitalization, it will be more difficult for the finance function to obtain the resources to undertake investment into the technologies that are aligned to its functional objective. Similarly, the effect of organizational digitalization on the choice of technologies used will be dependent on the objectives of the finance function. For instance, if the finance function focuses on providing routine reporting, standardizing processes, and ensuring compliance, automating tasks to render them more efficient is likely to be more relevant than advanced analytics, but the extent to which automation is used will also be dependent on the firm's emphasis on digitalization as a strategic priority.

Additionally, we examine how the use of digital technologies impacts the effectiveness of the finance function. Effectiveness here denotes the extent to which the finance function contributes to overall organizational performance, such as by measuring and monitoring business performance and providing relevant information for decision-making (Chang et al., 2014). Since the use of (advanced) analytics is typically targeted at providing insights for the business (Labro et al., 2023; Li et al., 2018), we expect that increased use of these technologies will be associated with higher finance function effectiveness. In comparison, automation technologies are focused on generating efficiency improvements in the finance function (Plattfaut and Borghoff, 2022). At the same time, they may also free up resources that can be used to deliver more effective business support, leading to higher finance function effectiveness. We also expect that automation and analytics will operate interdependently through reinforcing effects on finance function effectiveness (Bedford, 2020). Automation processes can improve the quality and timeliness of data that feed into analytics, while analytics helps to identify areas for optimization that automation technologies can improve.

We test our predictions using survey data obtained from finance function professionals in 137 European firms. We complement our statistical analysis with 11 interviews with finance professionals that help us interpret our survey-based findings. Our results show that digitalization strategy and a business partnering objective are positively but independently associated with an increased use of analytics in the finance function. However, we find a positive interaction between firm digitalization strategy and an efficiency objective on the use of both automation and analytics. Given that we find no independent association between an efficiency objective and the use of automation in the finance function, our results suggest that higher automation use only occurs when there is sufficient pressure (or legitimacy) to do so in the form of an organization-wide digital imperative. In terms of consequences, we find that that the use of analytics is positively associated with finance function effectiveness, although no association is found for automation use. Interestingly, we find that the joint use of automation technologies and analytics *reduces* (rather than increases) finance function effectiveness. Based on follow-up interviews, we interpret this negative interaction effect as being the result of resource trade-offs. As many finance functions are in the early stages of experimenting with digital technologies, attempting to emphasize both automation and analytics may come at the expense of overall finance function effectiveness, at least in the short term. This suggests that the nature of the interdependence between analytics and automation is conditional on the digitalization maturity of the finance function.

Our study contributes to the literature by showing that the interplay between a firm's digitalization strategy and departmental objectives is associated with variation in what digital technologies are used in the finance function. This extends the limited amount of prior literature on the determinants of automation and analytics (Bergmann et al., 2020; Krieger et al., 2021; Lem, 2024; Plattfaut and Borghoff, 2022), by demonstrating that objectives at both the firm level and functional level are important considerations for understanding variation in the types of digital technologies used. Furthermore, while previous research has focused on the impact of specific digital technologies on firm performance (Chen and Srinivasan, 2024; Lem, 2024; Müller et al., 2018), our study provides evidence on the outcomes of the joint use of automation and analytics in the finance function. Contrary to the expectation that automation use and analytics use reinforce the benefits of one another, we find that they have a negative association with finance function effectiveness. Follow-up interviews provide several potential explanations for this finding, including resource constraints that arise during early-stage technology adoption within the finance function.

The remainder of the paper proceeds as follows. The next section provides a review of the literature and hypotheses development, followed by a description of our data collection approach and variable measurement. In section four we present our empirical results. The final section offers a discussion of the results and our conclusions.

2. Theoretical development

In this section, we develop our theoretical expectations, which are summarized in Fig. 1. Our main constructs of interest are the use of two types of digitalization practices in the finance function: automation and analytics. We first discuss the reasons why firms mobilize these two digitalization practices. Thereafter, we discuss the impact of these practices on finance function effectiveness.

2.1. Variation in finance function digitalization

Digitalization within the finance function is a broad notion that potentially comprises a multitude of different technological practices. However, prior literature points to two practices that are particularly relevant to the finance function: automation and analytics. Automation focuses on digital tools, techniques, and processes that enable the finance function to standardize and automate repetitive tasks and routinized processes (Kokina and Blanchette, 2019; Plattfaut and Borghoff, 2022). Analytics use relates to digital technologies that enable the finance function to increase their capacity to gather, process, visualize, and disseminate information that provides business-relevant insights to decision-makers (Bergmann et al., 2020; Fehrenbacher et al., 2022; Schnegg and Möller, 2022).

Prior research has examined several factors at the organizational level associated with the adoption and use of digital technologies on tasks associated with the finance function, such as budgeting and financial reporting (Bergmann et al., 2020; Lem, 2024). In this study, we argue that understanding variation in the use of digital technologies requires consideration of the *joint impact* of factors at both the organization and functional levels. Specifically, we consider the interaction between the strategic objectives of the firm and the objectives of the finance function. Prior research demonstrates that organizational strategy shapes the choice and design of accounting and control systems (Chenhall and Langfield-Smith, 1998; Sandino, 2007). Research also shows that firm-wide strategic initiatives, such as 'lean', diffuse into the finance function (Fullerton et al., 2013; Kennedy and Widener, 2008; Nielsen and Kristensen, 2020). As such, the adoption of a digitalization

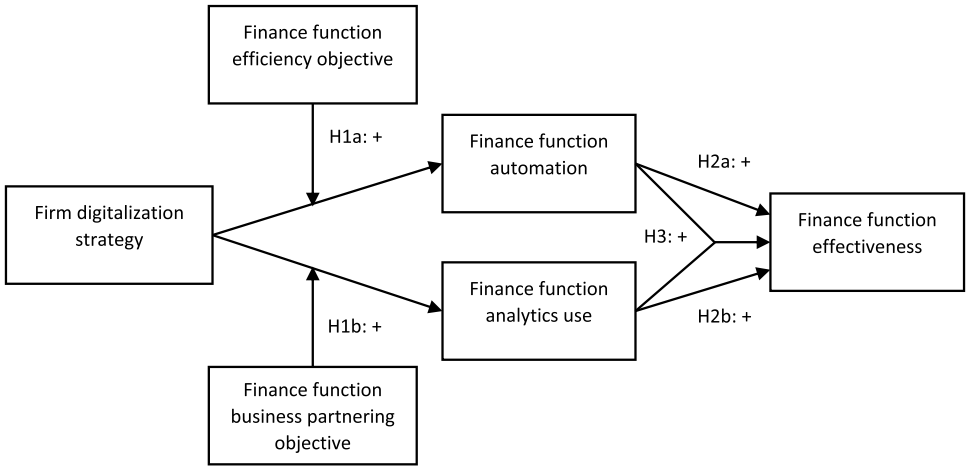

Fig. 1. Hypothesized relations.

strategy at the firm level is likely to spread across firm layers, including the finance function.

At the level of the finance function, we distinguish between two objectives. Most finance functions conduct a broad range of activities, including invoice processing, bookkeeping, financial reporting, consolidation, planning and budgeting, and performance measurement. Many of these are core activities with clearly defined requirements (sometimes by regulation), with the main question being *how* they should be performed. As many of these activities involve routine tasks, a key objective of finance functions is to standardize and automate them to minimize the resources they consume (Chang et al., 2014; Maas and Matějka, 2009). We refer to this as an "efficiency objective", in the sense that the finance department seeks to improve existing processes in terms of making them more resource efficient. The finance function also offers various forms of decision-making support for business units and their managers, such as in the form of calculative analyses, forecasts, specific reports, or expert advice. This set of tasks is commonly summarized under the umbrella notion of "business partnering" (e.g., Siegel et al., 2003). Being a business partner implies placing an emphasis on decision-making advice and value-adding support of operational management. While efficiency and business partnering are not mutually exclusive objectives (Chang et al., 2014), finance functions are observed to vary in the emphasis they place on one relative to the other (Maas and Matějka, 2009).

These two objectives – efficiency and business partnering – are likely to influence the adoption of digitalization practices within the finance function. If there is a focus on the efficiency objective, then we expect that the finance function will invest resources towards digital tools and skill development aimed at greater automation. This inclination towards automation is driven by the recognition that automation standardizes tasks, reduces the need for manual labour, and ultimately enhances the efficiency of the finance function. If the emphasis is on the business partnering objective of the finance function, then investments into analytics use are more likely. This expectation stems from the recognition that analytics use enriches decision-support, through enhancing data analysis, forecasting, and communication capacity to help both the senior management team and operational-level managers.[1]

Importantly, we expect that digitalization strategy and finance function objectives not only have independent effects but also reinforce each other. This is consistent with prior literature that has emphasized the need to consider how organizational strategy is interrelated with the objectives of functional units, such as information technology departments (Brown and Magill, 1994; Matt et al., 2015). While a clear digitalization agenda at the firm level is likely to create impetus for the finance function to increase the use of digital technologies, the relative effect of digitalization strategy on automation or analytics will be dependent on the objectives of the finance function. Similarly, the effect of finance function objectives on automation and analytics will be impacted by the extent to which the firm emphasizes digitalization as a strategic priority, as this creates pressure, legitimacy and increases the likelihood of obtaining additional resources for digitalization efforts. In the absence of such a strategy, we would expect less intensity in the finance function's efforts to digitalize, even if their own objectives may suggest a particular digitalization focus. Given these arguments, we posit the following two hypotheses:

H1a. *A finance function's efficiency objective and a firm's digitalization strategy have a positive interaction effect on automation of the finance function.*

H1b. *A finance function's business partnering objective and a firm's digitalization strategy have a positive interaction effect on analytics use in the finance function.*

2.2. The effect of finance function digitalization

It is well-known that the finance function has (or should have) moved beyond their traditional reporting responsibilities to become more business-oriented by helping managers identify actions that contribute to organizational value (Burns and Baldvinsdottir, 2005; Maas and Matějka, 2009). Accordingly, finance function effectiveness refers to the extent to which finance function provides decision-making and control information to support value-adding performance management activities such as continuous business improvement, driving cost reduction, and identifying growth opportunities (Chang et al., 2014). We expect that an increase in both automation and analytics use will contribute to finance function effectiveness.

Automation technologies, such as robotic process automation, are focused on generating greater efficiency (Plattfaut and Borghoff, 2022). In their multiple case study, Kokina and Blanchette (2019) find that organizations benefit most from automating tasks that are labour-intensive, repetitive, high-volume, structured, rules-based, and have digital inputs. While the programmability of finance function work varies (Korhonen et al., 2021), many of the traditional transaction and reporting-based tasks share these characteristics. Applying automation increases efficiency by reducing time spent on manual tasks, lowering error rates, and improving process documentation and report quality. One potential spillover effect of automation could be a reduction in

[1] We acknowledge that finance function objectives may also change in response to the capabilities that are built up through adoption of digital technologies (e.g., Boerner et al., 2024).

finance function personnel. However, research suggests that it can also enable existing personnel to increase the attention given to more value-adding activities, such as business support. That is, when traditional tasks are automated, the finance team's time can shift to the support of operational managers and other value-adding tasks (Kokina and Blanchette, 2019; Kokina et al., 2021), which further contributes to finance function effectiveness. Hence, we predict that:

H2a. *Automation of the finance function is positively associated with finance function effectiveness.*

Analytics enables the processing of data to produce information and insights that are valuable to decision-makers (Ritter and Pedersen, 2020). In the finance function, analytics encompasses the use of advanced quantitative techniques such as statistical and analytical models, simulation, visualization, and cognitive computing (e.g., artificial intelligence) to analyze large amounts of data (Ritter and Pedersen, 2020; Srinivasan and Swink, 2018). Analytics use enables firms to increase their information-processing capacity (Galbraith, 1973; Tushman and Nadler, 1978), including the gathering of data from a wider array of sources as well as the ability to transform data into information and communicate this information more efficiently and effectively to improve organizational decision-making (Lem, 2024; Ritter and Pedersen, 2020; Srinivasan and Swink, 2018). In the finance function, analytics can be used to inform business decisions such as revenue generation, cost containment, and product development strategies (Bhimani and Willcocks, 2014). For example, Bergmann et al. (2020) observe that the use of analytics in the budgeting process enhances satisfaction due to time and resource savings and higher forecasting accuracy. As the finance function is the primary support for both decision-making and control, we predict that a greater use of analytics will increase the effectiveness of the finance function:

H2b. *Analytics use in the finance function is positively associated with finance function effectiveness.*

We also expect that automation and analytics use have interdependent effects. Specifically, we expect automation and analytics to operate as "reinforcing" complements (Bedford, 2020, pp. 2–3), such that each strengthens the impact of the other on finance function effectiveness. Automation, through digital tools such as robotic process automation, can improve the timeliness of available data and reduce the number of errors in it, both of which are essential elements of data quality (see Kokina et al., 2021). Improved data quality increases the potential for analytics to generate valuable insights (Redman, 2018), thereby enhancing the effectiveness of the finance function. Conversely, analytics can provide insights on processes within the finance function, providing opportunities to optimize and improve them through automation (van der Aalst et al., 2018).

Automation and analytics can also have synergies, leading to a better use of the firm's scarce resources. Automation frees up (human) resources that can be used elsewhere in the finance function (Korhonen et al., 2021). The freed-up resources can be redeployed through various means (e.g., training, time to experiment, acquire new skills) to better realize the potential of analytics to enhance the effectiveness of the finance function. Through enhanced data quality and the better use of scarce resources, we expect automation and analytics use to be complements in relation to finance function effectiveness:

H3. *Finance function automation and analytics use are complements and have a joint positive association with finance function effectiveness.*

3. Research method

3.1. Sample selection and data collection

Data were collected using a survey.[2] As digitalization and associated changes to the finance function are relatively recent phenomena, the survey method allows us to "map current practices in the field" and examine them in their natural setting (Speklé and Widener, 2018, p. 3). The survey was administered through an online questionnaire. Respondents were identified in several ways. First, we cooperated with a practitioner journal focusing on executives in finance and control, with a weblink to the survey distributed to their readers. Second, the survey link was distributed amongst IMA Europe members. Finally, we obtained access to finance executives through students in a part-time executive programme in accounting and control in two additional waves.[3] In total, the survey was accessible to respondents in each of these four waves from July 2021 until May 2022. Once finance professionals indicated that they were willing to participate, they received an email with a link to the survey. Within three weeks, potential respondents received up to two reminders.

We received 206 completed responses. We retained responses from finance professionals who have worked for at least one year in the firm and who have worked in firms that are at least three years old (as younger firms tend to have less established finance functions) and have a minimum of 50 full-time employees. We removed respondents who were not part of the finance function or the organization itself (e.g., external auditors, consultants, and interim professionals). The above-described process resulted in a usable sample of 137 observations from unique firms, comprising 32 responses sourced through the practitioner journal, 17 through IMA Europe, and 88 from the executive programme. We test for differences between early and late respondents within each source of survey data. Parametric and non-parametric tests suggest that there is unlikely to be any significant bias between these respondents.[4,5]

Because we collect dependent and independent variables from the same source, we carefully considered the common method bias (Speklé and Widener, 2018). Following Podsakoff et al. (2003), we took several steps to alleviate potential biases. Specifically, 1) we targeted respondents that are likely to have the required knowledge, 2) we varied item anchors and response formats, 3) we separated the measurement of dependent and independent variables, 4) we assured respondents of strict confidentiality and anonymity, and 5) we paid careful attention to

[2] The study complies with the ethical standards of one of the authors' academic institution and received a positive evaluation from the research ethics committee of the academic institution.

[3] Given our diverse group, respondents could select whether they answered the survey in English or in Dutch; other languages were not available. One of the team members translated the English survey to Dutch; to detect potential changes in the meaning of survey items stemming from their translation into Dutch, the translation was verified by two other team members (also native speakers). No major differences due to translation were found; minor differences were discussed amongst the team members before the survey translation was finalized.

[4] We cannot test for non-response bias as we do not know the characteristics of the target population to which our invitation to participate in the survey was sent to. However, we are not aware of any systematic bias in our final set of respondents that would limit generalizability of our results. Our convenience sample appears appropriate to testing theoretical predictions, which is the purpose of this study (see Speklé and Widener, 2018).

[5] Given that we collect our data in different waves, we cannot test for differences in early versus late respondents over time for the whole sample. Within each wave, we compare the first and last 20 per cent of surveys received (representing early versus late respondents), and compare characteristics across the subgroups on several dimensions (size, digitalization strategy, age of the firm). Our results are mostly non-significant ($p < 0.1$). The exception is that firm age is significant at $p = 0.08$ for the Mann-Whitney U-test, with late respondents being somewhat younger relative to early respondents.

item wording.

We also assess common method bias empirically. First, we conduct Harman's single factor test. The unrotated solution from a principal components analysis shows nine components with an Eigenvalue exceeding one. The first component explains 31.75 per cent of the total variance, well below the generally accepted threshold of 50 per cent. Second, we incorporate a theoretically unrelated marker variable into the structural model used for our main test of hypotheses. We use a measure for "fantasizing", which is defined as the extent to which one has a vivid imagination (Malhotra et al., 2006).[6] Incorporating this measure as an additional antecedent to all endogenous variables does not have a material influence on our results. Overall, these analyses suggest that common method bias is not a significant concern.

The demographics of our final sample are shown in Table 1. The most common industries relate to manufacturing, construction, finance, and logistics, while just under half (48 %) the sample employ 500 or more employees. Most firms have their primary operations located either in the Netherlands (65 %) or elsewhere in Europe (18 %). The most common respondent positions are financial or business controllers (48 %), finance managers (15 %), or chief financial officers (13 %). Other positions include director of finance, cost controller, manager of finance and operations, and head of financial reporting and control. Respondents had held their position for an average of 2.57 years, while average firm tenure was 3.32 years.

Table 1
Firm and respondent demographics.

Industry	**No.**	**%**
Traditional manufacturing	19	14 %
Construction and building	15	11 %
Financial and insurance activities	15	11 %
High-tech manufacturing	10	7 %
Transportation and storage	10	7 %
Human health and social work	8	6 %
Wholesale and retail trade	7	5 %
Real estate activities	6	4 %
Public government, defense and social security	6	4 %
Utilities	5	4 %
Information and communication	4	3 %
Accommodation and food service activities	3	2 %
Professional, scientific and technical activities	3	2 %
Environment, culture, recreation	2	1 %
Other	24	18 %
Total	137	
Firm size	**No.**	**%**
50 — 99	23	17 %
100 — 499	47	35 %
500 — 999	11	8 %
1000 — 2499	18	13 %
2500 — 4999	12	9 %
5000 — 9999	6	4 %
> = 10000	19	14 %
Total[1]	136	
Location of primary operations		
Netherlands	89	65 %
Europe (excl. Netherlands)	24	18 %
Worldwide	10	7 %
United States	8	6 %
Other	6	4 %
Total	137	
Respondent position		
Chief financial officer	18	13 %
Controller	66	48 %
Finance manager	21	15 %
Other	32	23 %
Total	137	

[1] One observation missing.

Following the analysis of our survey data, we interviewed five survey respondents who indicated they would be willing to further discuss their answers. In addition, we interviewed another six finance professionals, identified from personal networks and working in various industries, to further inform our research (see Appendix A for a list of interviewees). The average length of these 11 interviews was about 45 min. In Section 4.3, we draw on the interview data to help interpret and contextualize our quantitative findings.

3.2. Variable measurement

Where possible, constructs are measured using existing validated instruments (Bedford and Speklé, 2018a). Where no prior construct measures were available, or when existing instruments needed to be adapted to the specific focus of this study, we followed contemporary approaches to construct measurement (Bedford and Speklé, 2018b; MacKenzie, Podsakoff.,2011). This included paying careful attention to the construct definitions, construct dimensionality, measurement model, and whether items captured the conceptual domain of the construct. Following this process, all multi-item constructs were conceptualized as unidimensional and operationalized using reflective measurement models. We pretested the survey instrument with three academics with relevant expertise and four finance function managers, to assess the face validity of our measures, with a particular focus on newly developed or adapted items. This process resulted in several minor changes to item wording. Survey items and response scales are outlined in Appendix B.

Firm digitalization strategy (DIGSTRAT) is measured using five questions that reflect the extent to which a firm has formulated and implemented a strategy that leverages digital resources (Bharadwaj et al., 2013). We use two items with minor changes to wording from Lu and Ramamurthy (2011) and Niemand et al. (2021). We also include one item adapted from Ravichandran (2018), related to investment into digital technologies, to ensure we fully capture the conceptual meaning of digitalization strategy as being realized in the firm.

To measure the objectives of the finance function we asked respondents to indicate the importance of a set of objectives. Four items related to a focus on *efficiency* (EFFICIENCY) and five items indicated a focus on *business partnering* (PARTNER). Most items were adapted from prior studies examining finance function objectives (Chang et al., 2014; Maas and Matějka, 2009). We added a few additional items related to finance function efficiency, to ensure conceptual coverage of the construct. These items are based on practitioner literature related to the role of the finance function (Agrawal et al., 2020; PwC, 2017).

No prior instrument was available to assess the extent of *automation* (AUTOMATION) in the finance function. Automation refers to the extent to which digital tools are being used to automate tasks and processes (Kokina and Blanchette, 2019). Item construction was guided by this definition as well as literature on automation in practice. Practitioner literature emphasizes using digital tools to automate routine activities and eliminate repetitive tasks that are currently done manually, as well as to streamline and standardize processes (Gibson et al., 2020; KPMG, 2019; PwC, 2020). Four items were then constructed to reflect the extent of automation of the finance function.

To measure *analytics use* in the finance function (ANALYTICS), we draw on five items from the scale of Srinivasan and Swink (2018), which has been validated several times in the literature (e.g., Dubey et al., 2021). The items reflect a firm's use of analytical tools and techniques to gain insights from available data to inform decision-making (Ritter and Pedersen, 2020; Srinivasan and Swink, 2018). We made minor wording

[6] Respondents are asked the extent to which they agree or disagree on a five-point scale with the following statements: 1) I daydream a lot, 2) when I go to the movies I find it easy to lose myself in the film, 3) I often think of what might have been (Malhotra et al., 2006).

changes to some of the items to better align the measure to the specific context of the finance function.

Finance function effectiveness (FF_EFFECTIVENESS) refers to the extent to which the finance function provides decision-making and control information to support value-adding activities in the organization (Chang et al., 2014). To measure this construct, we adapt four items from the instrument of Chang et al. (2014). These items related to provision of relevant information, monitoring business performance, business improvement, and alignment with business requirements. We consider these items to be general reflections of the overall effectiveness of the finance function in most organizations.

We include several control variables to account for specific industry-, firm-, and function-level effects. We control for industry effects through two dummy variables. The first takes the value of one if the firm is in the finance sector (and zero otherwise), while the second takes the value of one if the firm is involved in manufacturing (and zero otherwise). Given that a large number of the firms in our sample have their primary operations located in the Netherlands, we included a dummy variable (NETHERLANDSHQ) taking the value of 1 if the firm headquarters is in the Netherlands. We also control for firm size (SIZE) using an eight-point scale that measures entities' revenues (Kroos et al., 2022).[7] Finally, we control for *finance function digital skills* (SKILLS), as this may influence the extent to which the use of analytics and the extent of automation are translated into finance function effectiveness. We measure digital skills in the finance function using the three-item scale developed by Chakravarty et al. (2013).

3.3. Measurement model validation and descriptive statistics

Tests of hypotheses are conducted using partial least squares (PLS) analysis. We use PLS as it accounts for measurement error and is suitable for testing associations with relatively small sample sizes (Hair et al., 2014). PLS also computes a measurement model simultaneously with the structural model, allowing for assessments of construct validity and reliability.

We first examine item cross-loadings for all reflectively measured constructs. As shown in Table 2, all items, except two, load above 0.7 on the theoretically expected constructs. The exceptions are an item for PARTNER (0.625) and an item for EFFICIENCY (0.681). As the loadings are still at an acceptable level, and dropping them makes no substantive difference to the structural model results, both are retained. Descriptive statistics, along with reliability and average variance extracted (AVE) statistics are shown in Table 3, while correlations are reported in Table 4.[8]

Reflectively measured constructs are assessed for convergent validity using average variance extracted (AVE) scores. All AVE scores exceed the recommended minimum threshold of 0.5, indicating that the majority of item variance is attributable to the shared construct rather than error. Discriminant validity is established by using the square root of the AVE. As reported along the diagonal of the correlation matrix in Table 4, all values exceed the correlations of the respective rows and columns, demonstrating discriminant validity (Chin, 1998). We also calculate the heterotrait-monotrait (HTMT) ratio of correlations. In non-tabulated results, the maximum HTMT ratio is 0.76, which is below the recommended threshold of 0.90, providing further support for construct discriminant validity. Constructs are then assessed for reliability by examining composite reliability scores. All scores are above 0.7, indicating acceptable levels of reliability.[9]

4. Findings

4.1. Structural model results

The results of the structural model are reported in Table 5. Significant path coefficients are constructed from bootstrapping using 5000 subsamples (Hair et al., 2014).

Recall that $H1_a$ and $H1_b$ are concerned with the joint effects of digitalization strategy and finance function objectives on finance function digitalization. $H1_a$ argues that DIGSTRAT and EFFICIENCY will have a positive interaction effect on AUTOMATION. Results from Model 2 show that the interaction of DIGSTRAT and EFFICIENCY has a significant positive association with AUTOMATION, suggesting that firm-level digitalization strategy and an efficiency objective in the finance function reinforce each other in driving the use of automation technologies in finance. In terms of the main effects, DIGSTRAT has a significant positive effect on AUTOMATION, while the effect of EFFICIENCY is non-significant. In other words, automation activities in the finance function are either driven jointly by the emphasis on a clear digitalization strategy and an efficiency objective in the finance function, or independently by a greater strategic focus on digitalization, but not by an emphasis on an efficiency objective alone. This suggests that the pressure or legitimacy of a firm-wide digitalization agenda seems to be a necessary condition for greater emphasis on automation in the finance function.

Regarding $H1_b$, the interaction effect of DIGSTRAT and PARTNER on ANALYTICS is not significant (Model 2: $b = -0.015$, $p =$ n.s.). Hence, $H1_b$ is not supported. Looking at the main effects, we find a significant and positive main effect of both DIGSTRAT and PARTNER on ANALYTICS. In other words, DIGSTRAT and PARTNER have positive, independent effects on ANALYTICS, but do not reinforce each other. We do, however, find a positive and significant interaction effect of DIGSTRAT and EFFICIENCY on ANALYTICS (Model 2: $b = 0.190$, $p < 0.05$). This suggests that a greater emphasis on analytics use is associated with firms that jointly focus on both digitalization strategy and the efficiency objective of the finance function.

$H2_a$ predicts that automation of the finance function is positively associated with finance function effectiveness. No support is found for this hypothesis, with the association between AUTOMATION and FF_EFFECTIVENESS non-significant (Model 2: $b = -0.003$, $p =$ n.s.). We do find support for $H2_b$, with a positive and significant association observed between ANALYTICS and FF_EFFECTIVENESS (Model 2: $b = 0.465$, $p < 0.01$).

Finally, we expect that AUTOMATION and ANALYTICS have a joint positive association with FF_EFFECTIVENESS (H3). Our results show a significant but negative association (Model 2: $b = -0.222$, $p < 0.01$). This finding suggests that an increased emphasis on automation reduces the benefits derived from analytics use on the effectiveness of the finance function, and vice versa. We discuss potential explanations for this finding in Section 4.3. Findings regarding our hypotheses are summarized in Table 6.

4.2. Robustness checks

We conduct several robustness checks on our main results. First, we drop the first item from the measure of ANALYTICS. The item relates to data visualization and business intelligence, which may be considered as more rudimental compared to more recent data analytics practices. Dropping this item has no effect on our main results.

[7] SIZE ranges between 1 and 8, according to whether revenue (in euros) ranges from 10 to 50 million, 50–100 million, 100–250 million, 250–500 million, 500 million to 1 billion, 1–5 billion, 5–15 billion, or is higher than 15 billion.

[8] Item-level descriptive statistics are shown for AUTOMATION and ANALYTICS in Appendix C.

[9] We also calculated Cronbach's alphas, which were greater than 0.79 for all construct measures.

Table 2
Measurement model cross loadings.

	DIGSTRAT	AUTOMATION	ANALYTICS	EFFICIENCY	PARTNER	FF_EFFECTIVENESS	SKILLS
DIGSTRAT1	**0.828**	0.495	0.425	0.162	0.358	0.444	0.426
DIGSTRAT2	**0.897**	0.471	0.384	0.105	0.221	0.327	0.505
DIGSTRAT3	**0.823**	0.463	0.496	0.173	0.348	0.361	0.537
DIGSTRAT4	**0.891**	0.472	0.366	0.112	0.307	0.397	0.482
DIGSTRAT5	**0.908**	0.493	0.410	0.163	0.340	0.387	0.536
AUTOMATION1	0.396	**0.824**	0.569	0.216	0.247	0.368	0.502
AUTOMATION2	0.476	**0.883**	0.626	0.190	0.321	0.385	0.595
AUTOMATION3	0.461	**0.884**	0.565	0.155	0.292	0.374	0.524
AUTOMATION4	0.563	**0.882**	0.557	0.260	0.347	0.464	0.506
ANALYTICS1	0.415	0.563	**0.730**	0.211	0.401	0.486	0.514
ANALYTICS2	0.431	0.536	**0.864**	0.285	0.453	0.516	0.551
ANALYTICS3	0.334	0.524	**0.866**	0.301	0.377	0.516	0.461
ANALYTICS4	0.420	0.544	**0.845**	0.258	0.427	0.548	0.520
ANALYTICS5	0.355	0.551	**0.767**	0.220	0.384	0.394	0.521
EFFICIENCY1	0.113	0.208	0.278	**0.826**	0.310	0.263	0.145
EFFICIENCY2	0.205	0.242	0.269	**0.823**	0.317	0.270	0.163
EFFICIENCY3	0.010	0.043	0.188	**0.681**	0.298	0.163	0.042
EFFICIENCY4	0.136	0.191	0.226	**0.782**	0.293	0.258	0.097
PARTNER1	0.267	0.242	0.414	0.296	**0.751**	0.478	0.391
PARTNER2	0.359	0.277	0.389	0.317	**0.813**	0.464	0.322
PARTNER3	0.346	0.382	0.440	0.316	**0.883**	0.449	0.394
PARTNER4	0.166	0.218	0.324	0.261	**0.735**	0.315	0.237
PARTNER5	0.228	0.188	0.342	0.289	**0.625**	0.198	0.347
FF_EFFECTIVENESS1	0.370	0.320	0.509	0.195	0.386	**0.858**	0.425
FF_EFFECTIVENESS2	0.375	0.340	0.484	0.272	0.404	**0.869**	0.409
FF_EFFECTIVENESS3	0.414	0.485	0.587	0.357	0.531	**0.849**	0.521
FF_EFFECTIVENESS4	0.358	0.420	0.490	0.239	0.407	**0.862**	0.512
SKILLS1	0.503	0.539	0.593	0.237	0.380	0.488	**0.851**
SKILLS2	0.488	0.558	0.463	0.139	0.340	0.452	**0.882**
SKILLS3	0.506	0.505	0.586	0.033	0.442	0.494	**0.887**

DIGSTRAT = firm digitalization strategy, AUTOMATION = finance function automation, ANALYTICS = finance function analytics use, EFFICIENCY = finance function efficiency objective, PARTNER = finance function business partnering objective, FF_EFFECTIVENESS = finance function effectiveness, SKILLS = finance function digital skills.

Table 3
Descriptive, reliability and average variance extracted statistics.

	Mean	**Median**	**StdDev**	**Min**	**Max**	**CR**	**AVE**
DIGSTRAT	4.94	5.40	1.36	1.0	6.8	0.94	0.76
AUTOMATION	2.69	2.75	0.91	1.0	5.0	0.93	0.76
ANALYTICS	2.38	2.20	0.91	1.0	5.0	0.91	0.67
EFFICIENCY	3.76	3.75	0.66	2.0	5.0	0.86	0.61
PARTNER	3.66	3.60	0.72	1.4	5.0	0.88	0.59
FF_EFFECTIVENESS	3.15	3.17	0.74	1.0	5.0	0.92	0.74
SKILLS	2.94	3.00	0.78	1.0	4.7	0.91	0.76
FIN_IND	0.11	0.00	0.312	0.0	1.0	—	—
MAN_IND	0.21	0.00	0.408	0.0	1.0	—	—
NETHERLANDSHQ	0.65	1.00	0.477	0.0	1.0	—	—
SIZE	4.32	3.00	2.02	2.0	8.0	—	—

Notes:
1) DIGSTRAT = firm digitalization strategy, AUTOMATION = finance function automation, ANALYTICS = finance function analytics use, EFFICIENCY = finance function efficiency objective, PARTNER = finance function business partnering objective, FF_EFFECTIVENESS = finance function effectiveness, SKILLS = finance function digital skills, FIN_IND = dummy variable taking the value of 1 if the firm is in the finance industry, MAN_IND = dummy variable taking the value of 1 if the firm is in the manufacturing industry, NETHERLANDSHQ = dummy variable taking the value of 1 if the firm headquarters is located in the Netherlands, SIZE = firm size.
2) CR = composite reliability, AVE = average variance extracted.

Second, some respondents work for firms in the public and not-for-profit sectors ($n = 8$). These firms may face different regulatory and competitive pressures to other firms in our sample. No changes to the tests of hypotheses are found when these observations are excluded.

Third, we examine whether environmental factors influence finance functions' automation and analytics use. In particular, environments where technology has higher and more frequent impacts and where there is greater competition may be associated with higher levels of digitalization in the finance function. Technological turbulence is measured with three items used by Zhou and Wu (2010) that were originally developed by Jaworski and Kohli (1993). The level of competitive pressures in the use of digital technologies is measured using the three-item measure from Sun et al. (2020). Adding either variable to our structural model produces no substantive changes to our interpretation of hypothesis tests. We also examine whether the business strategy of the firm influences our results. We include a single-item measure from van der Stede.(2000) that assesses the percentage of revenues that are derived from products with either a cost leadership or differentiation strategy. We find that business strategy has minimal influences on our reported results, and no significant associations with finance function digital technologies or effectiveness.

Fourth, we examine whether firms that place no emphasis on digitalization strategy or have not yet adopted any digital practices influence reported results. This applies only to a single firm in our sample.

Table 4
Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) DIGSTRAT	0.87										
(2) AUTOMATION	0.55	0.87									
(3) ANALYTICS	0.48	0.67	0.82								
(4) EFFICIENCY	0.17	0.24	0.31	0.78							
(5) PARTNER	0.37	0.35	0.50	0.39	0.77						
(6) FF_EFFECTIVENESS	0.44	0.46	0.61	0.31	0.51	0.86					
(7) SKILLS	0.57	0.61	0.63	0.16	0.45	0.55	0.87				
(8) FIN_IND	0.12	0.13	0.01	0.01	0.05	0.15	0.11	—			
(9) MAN_IND	−0.15	−0.05	−0.01	0.06	0.10	0.05	0.02	−0.18	—		
(10) NETHERLANDSHQ	−0.10	−0.02	−0.07	−0.12	−0.03	−0.16	−0.07	−0.18	−0.26	—	
(11) SIZE	0.14	0.15	0.30	0.10	0.26	0.21	0.20	0.07	0.07	−0.26	—

Notes:
1) DIGSTRAT = firm digitalization strategy, AUTOMATION = finance function automation, ANALYTICS = finance function analytics use, EFFICIENCY = finance function efficiency objective, PARTNER = finance function business partnering objective, FF_EFFECTIVENESS = finance function effectiveness, SKILLS = finance function digital skills, FIN_IND = dummy variable taking the value of 1 if the firm is in the finance industry, MAN_IND = dummy variable taking the value of 1 if the firm is in the manufacturing industry, NETHERLANDSHQ = dummy variable taking the value of 1 if the firm headquarters is located in the Netherlands, SIZE = firm size.
2) The square-root of the average variance extracted is shown along the diagonal of the correlation matrix.
3) All correlations equal to or greater than 0.18 are significant at $p < 0.05$ (two-tailed).

Table 5
Results from the PLS structural model.

	Dependent variables					
	Model 1: Without interaction terms			Model 2: With interaction terms		
Independent variables	AUTOMATION	ANALYTICS	FF_EFFECTIVENESS	AUTOMATION	ANALYTICS	FF_EFFECTIVENESS
DIGSTRAT	0.489	0.337	0.125	0.460	0.326	0.106
	(7.082)***	(4.824)***	(1.341)	(6.189)***	(4.644)***	(1.133)
EFFICIENCY	0.119	0.133	—	0.114	0.134	—
	(1.372)	(1.776)*		(1.340)	(1.840)*	
PARTNER	0.106	0.288	—	0.122	0.303	—
	(1.126)	(3.809)***		(1.330)	(4.207)***	
DIGSTRAT * EFFICIENCY	—	—	—	0.148	0.190	—
				(1.964)**	(2.561)***	
DIGSTRAT * PARTNER	—	—	—	—0.105	—0.015	—
				(1.428)	(0.223)	
AUTOMATION	—	—	—0.036	—	—	—0.003
			(0.412)			(0.035)
ANALYTICS	—	—	0.438	—	—	0.465
			(4.358)***			(3.792)***
AUTOMATION * ANALYTICS	—	—	—	—	—	—0.222
						(2.427)***
SKILLS	—	—	0.206	—	—	0.198
			(1.964)*			(1.935)*
AUTOMATION * SKILLS	—	—	—	—	—	0.023
						(0.207)
ANALYTICS * SKILLS	—	—	—	—	—	0.141
						(1.280)
FIN_IND	0.270	—0.182	0.374	0.313	—0.112	0.320
	(1.355)	(0.674)	(1.986)*	(1.685)*	(0.439)	(1.641)*
MAN_IND	0.091	—0.022	0.164	0.053	—0.072	0.142
	(0.473)	(0.134)	(0.923)	(0.273)	(0.429)	(0.797)
NETHERLANDSHQ	0.176	0.045	—0.142	0.183	0.104	—0.171
	(1.060)	(0.276)	(0.912)	(1.121)	(0.662)	(1.097)
SIZE	0.058	0.171	—0.007	0.064	0.154	—0.008
	(0.774)	(2.288)**	(0.094)	(0.823)	(2.071)**	(0.110)
Adjusted R-square	36.5 %	31.7 %	41.3 %	32.7 %	39.0 %	42.8 %

Notes:
1) DIGSTRAT = firm digitalization strategy, AUTOMATION = finance function automation, ANALYTICS = finance function analytics use, EFFICIENCY = finance function efficiency objective, PARTNER = finance function business partnering objective, FF_EFFECTIVENESS = finance function effectiveness, SKILLS = finance function digital skills, FIN_IND = dummy variable taking the value of 1 if the firm is in the finance industry, MAN_IND = dummy variable taking the value of 1 if the firm is in the manufacturing industry, NETHERLANDSHQ = dummy variable taking the value of 1 if the firm headquarters is located in the Netherlands, SIZE = firm size.
2) *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$ (one-tailed for hypothesized associations, two-tailed otherwise).

Dropping this observation has minimal effect on the reported results.

Fifth, financial organizations may be more likely to digitalize their finance functions than those in other industries (e.g., traditional manufacturing; see Plekhanov et al., 2023). To rule out the possibility that firms in the financial sector are driving our results, we exclude these observations and rerun the analysis. No significant changes to our results

Table 6
Summary of hypothesis tests.

Hypotheses		Findings
$H1_a$	A finance function's efficiency objective and a firm's digitalization strategy have a positive interaction effect on automation of the finance function.	Supported
$H1_b$	A finance function's business partnering objective and a firm's digitalization strategy have a positive interaction effect on analytics use in the finance function.	Not supported
$H2_a$	Automation of the finance function is positively associated with finance function effectiveness.	Not supported
$H2_b$	Analytics use in the finance function is positively associated with finance function effectiveness.	Supported
H3	Finance function automation and analytics use are complements and have a joint positive association with finance function effectiveness.	Not supported (opposite association)

are observed.

Sixth, we incorporate two variables on organizational outcomes, revenue growth and firm financial performance, into the model. These variables control for the possibility that higher growth or more financially successful organizations will have finance functions with higher digitalization. Revenue growth is a single item that asks respondents what the average percentage growth in revenues were over the past three years.[10] Firm financial performance is measured using four items taken from Henri (2006) and Chapman and Kihn (2009). Respondents indicated the performance relative to their competitors over the past three years in terms of sales volume, market share, profit, and return on investment. Tests of hypotheses remain unchanged with the inclusion of either variable, with the only additional path found to be significant being a positive association between firm financial performance and finance function automation ($p < 0.05$).

Seventh, we control for potential bias that might arise from using three different sources for survey data. Two dummy variables are included – the first taking a value of one if the respondent source is from IMA Europe (and zero otherwise), and the second taking a value of one if the respondent is obtained via the practitioner journal (and zero otherwise). Although the control variable for IMA Europe has negative and significant associations with ANALYTICS and FF_EFFECTIVENESS ($p < 0.01$), there are no changes to the direction or significance of hypothesized paths.

Finally, given that there has been some discussion in the literature regarding the robustness of PLS-SEM results, we replicate our model in OLS regressions. Variables are measured using average scores of the same items used in the main structural path model reported in Section 4.1. In untabulated results, we find that all hypothesized associations in the OLS regressions had the same sign as those in the structural path model, and there were no substantive changes in the statistical significance of tests of hypotheses. Overall, these robustness checks suggest that our main results are relatively robust.

4.3. Results from follow-up interviews

After completing the initial statistical analysis, we contacted several respondents (finance professionals) from our sample to provide context to our main empirical results. Five participants agreed to follow-up interviews to elaborate on their responses to the survey. In a second round, we interviewed six finance professionals, who were contacted through personal networks and who had experienced varying levels of digitalization in their firms and departments. One or two researchers conducted each of the 11 interviews (see Appendix A for an overview of the interviewees).

First, regarding the connection between firm-level digitalization strategy, finance function objectives, and the two digitalization practices within the finance function (i.e., $H1_a$ and $H1_b$), various interviewees confirm our findings. For example, one of the interviewees (who works in a large technology company) noted that the finance function is responsible for reducing costs within the unit to increase the firm's margin. She commented that the "strong focus on reducing costs makes it actually easier to automate activities within the finance function" (Interviewee 8), suggesting that finance function objectives drive the choice of technology. Other interviewees explained that finance function objectives can change over time, and in turn, influence the use of digitalization practices. For example, one of the interviewees mentioned that "using automation, we have realized 30–40 per cent productivity improvements within finance – we now focus more on analytics" (Interviewee 6). Similarly, another interviewee indicated that they seek to build "coalitions of the willing" to gather support for specific strategic investments in digitalization practices within finance (Interviewee 11).

Alternatively, when digitalization is *not* a priority at the firm level, finance function professionals with an entrepreneurial spirit may develop local finance digitalization initiatives. Examples of digitalization initiatives mentioned by interviewees include data-driven forecasting, the connection of various data sources to carry out business analytics, the quick identification of trends, and the automation of repetitive tasks. However, broader adoption of such digitalization initiatives in the finance function may be hindered when finance does not get a "green light" from top management. One interviewee exemplified this point by complaining that "top management is not such a fan of [digitalization-related] change; they just like to build ships" (Interviewee 4).[11] These comments suggest that the adoption of digitalization practices in the finance function can be hindered when digitalization is not explicitly formalized in a firm-level strategy and promoted by top management.

Second, regarding $H2_a$ and $H2_b$, our interviewees expect both automation and analytics to increase the effectiveness of the finance function. For example, analytics can increase the effectiveness of the finance function as it helps to forecast and manage projects: "we use operational data to forecast the cost to completion of our projects – we trust that our algorithm provides us [with] proper solutions" (Interviewee 11). Similarly, another respondent indicated that "previously, if management wanted to know something, you needed a deep dive into the projects. Nowadays, you can use data to identify issues for management; so quicker insights at a deeper level, with less time" (Interviewee 2). Automation is often associated with becoming more efficient; one interviewee mentioned that "we can get most benefits from automation" (Interviewee 4), and "as far as the financial processes and financial data are concerned, the focus is on automation and especially on optimizing costs" (Interviewee 8).

Regarding the interaction effect predicted in H3, interviewees made explicit that a certain "threshold level" of data quality needs to be in place before analytics could be meaningfully used. Interviewees argued that data quality can be enhanced through automation processes, and that high-quality data is a "boundary condition" for obtaining good results from analytics. As one of our interviewees put it bluntly:

> Within our firm we always say 'garbage in, garbage out'. So, it all starts with data management and reliable systems. And then analytics come in. By automating the normal [repetitive] stuff upfront, you can analyze it better later in the process […] Manual [non-

[10] Five-point scale with response options of < 0 %, 0–10 %, 11–20 %, 21–30 % and > 30 %.

[11] The company is active in the shipbuilding industry.

automated] work comes with many exceptions, and analytics does not like exceptions. (Interviewee 8)

This suggests that a positive interaction effect may only materialize when a certain minimum level of automation is in place.

The interviews provide several other insights as to why a positive interaction between automation and analytics use may only become visible over time. For instance, some interviewees indicated that the efficiencies of using automation indeed might save time, lead to an ending of "dull work" and ultimately a reduction of the workforce. At the same time, however, it is noted that those employees whose tasks are being automated are "not always well equipped" to carry out the new analytics-related tasks. As one interviewee explained: "Not everybody is capable of fulfilling a finance business partner role. It requires a different set of skills" (Interviewee 1). In some cases, staff are asked to do other tasks, even outside of the traditional finance function – one interviewee gave the example of his team members helping the legal department with repetitive tasks.

While these cases help explain the lack of a significant positive interaction in our main results, they do not explain why we observe a significant *negative* interaction. Some interviewees did, however, indicate why this might occur:

The big disadvantage of doing things [i.e., automation and analytics] simultaneously is that you ask too much from the same people. (Interviewee 10)

My first responsibility is to get rid of all the customization […] We can't afford the luxury of working on both [analytics and automation] at the same time [as that would be too costly]. (Interviewee 9)

These observations suggest that if there are resource constraints (in terms of money, time or a lack of digital skills) in the finance function, then attempting to focus simultaneously on automation and analytics may be associated with decreased effectiveness. Other interviewees commented that emphasizing both automation and analytics use at the same time could help the finance function learn quickly by "trial and error", but that this would come at the expense of effectiveness, at least in the short-term, as decisions will be based upon low(er) quality data. This finding is consistent with practitioner literature which suggests that while organizations capture both revenue benefits as well as cost reductions from technology-driven changes, they capture less of the value than initially expected (LaBerge, Zemmel.,2022). This "going back and forth" between different technologies is "not a straight line" (Interviewee 11) and may eventually result in certain technologies being abandoned as newer practices or process improvements emerge. However, the general belief shared by interviewees is that standardization and automation are a prerequisite for further adoption of more sophisticated digitalization practices, such as advanced analytics and artificial intelligence.

The negative interaction between automation and analytics on finance function effectiveness may reflect that, in practice, most finance functions are in the early stages of experimenting with, implementing and scaling up digital tools. While a negative interaction may thus be expected in the short-term, it may extend to later stages if new processes emerge that also require automation – leading to further re-calibration, continuous improvement, elimination of errors, and changes to governance structures. Compared to a focus on analytics only, such an additional ongoing concern with both automation and analytics may divert managerial attention and lead to less effective leveraging of digital technologies.

4.4. Additional analysis

Our analysis of the interview data suggests that automation and analytics use may be dependent on the maturity of the finance function in terms of digital investment and skills development. While we did not measure digital maturity or resource constraints in our survey instrument, we do measure the extent of digital skills of finance function staff. As a further test, we rerun our main analysis (reported in Table 5, Model 2) with the addition of a three-way interaction term between AUTOMATION, ANALYTICS and SKILL. In untabulated results, the interaction between AUTOMATION and ANALYTICS remains significant and negative ($b = -0.218$, $p < 0.01$), while the three-way interaction is positive but non-significant ($b = 0.079$, $p =$ n.s.).

5. Discussion and conclusion

Our findings contribute to the literature in several ways. First, our results add to the limited evidence on the use of digital technologies in the finance function (Bergmann et al., 2020; Lem, 2024) by examining the role of firm- and function-level objectives. Prior literature has pointed to the relevance of finance function objectives for understanding individual behaviors (e.g., Goretzki et al., 2018; Hartmann and Maas, 2010; Maas and Matějka, 2009; van Slooten et al., 2024). Our paper takes up the idea that finance function objectives matter, but applies this to understand variation in the use of digital technologies employed in the finance function. Moreover, we consider how the effects of functional objectives are interrelated with the wider strategic objectives of the firm. Specifically, as we find no independent association between an efficiency objective and the use of automation, a firm-wide digitalization agenda appears to be a necessary condition for higher use of automation technologies in the finance function. In contrast, firm digitalization strategy and a business partnering objective are found to be independently associated with analytics use, while the interaction effect is non-significant. Insights from our interviews suggest that finding an independent effect of the business partnering objective, but not the efficiency objective, could be related to differing degrees of entrepreneurial spirit. Departments scoring relatively higher on efficiency objectives may not have the same intrinsic interest in, and drive for, digitalization as departments that see themselves more as business partners (see also Niemand et al., 2021).

Second, we extend research on the performance consequences of digital technologies (e.g., Chen and Srinivasan, 2024; Lem, 2024; Müller et al., 2018). Our results show that analytics is positively associated with finance function effectiveness, but not automation. One reason for this non-significant result in the case of automation is that efficiency gains translate into cost savings (through headcount reduction) or the deployment of employees elsewhere in the organization (as indicated by one of the interviewees), rather than being directed towards increased finance function effectiveness (i.e., a reallocation of finance professionals to more value-added activities).

Moreover, we provide evidence on the interdependent effects of digital technologies. Contrary to expectations, we find a negative interaction effect between automation and analytics on finance function effectiveness. We suggest several possible explanations. First, given that finance functions tend to be resource constrained (Goretzki and Pfister, 2023), attempting to implement both technologies simultaneously can lead to a scenario where the deployment of one technology limits the effective utilization of the other. Second, the concurrent implementation of automation and analytics may create role ambiguities (Rautiainen et al., 2024; Yigitbasioglu et al., 2023), hindering the ability of the finance function to gain significant benefits from each technology (Tillema et al., 2022; van Slooten et al., 2024). Additionally, the complexity involved in integrating different digital technologies may result in misalignment between automated processes and the data needs of analytics, leading to data inconsistencies or errors (Lauterbach et al., 2020). The finance function may also lack the expertise required to navigate these integration challenges effectively (Kokina et al., 2021), further undermining the potential effectiveness of these technologies when combined. Consistent with this, some of our interviewees indicated that a shift in emphasis at different points in time is required to capitalize upon multiple technologies.

Our study is subject to several potential limitations. First, as the primary data in this study is obtained from a cross-sectional survey, causality is based only on theoretical arguments (Speklé and Verbeeten, 2014). In addition, our evidence is based on a convenience sample from several European countries. Even though we attempt to control for such effects, our results could be influenced by unobserved institutional factors or cultural differences. As our observations relate to organizational entities (rather than organizations as a whole), we are also unable to assess the representativeness of our sample in terms of industry. Given that we are testing theory, the representativeness of our sample is less of an issue than sample relevance (Speklé and Widener, 2018). In addition, while we include a range of control variables, we cannot rule out the effects of omitted variables. Finally, the relatively limited size of our sample makes subset analyses (for example, on the digital maturity of the organization or the finance function) difficult.

Our paper sheds light on how firm digitalization strategy interacts with finance function objectives to shape digitalization practices and the consequences of these choices for finance function effectiveness. Future research can extend our insights into firm- and function-level effects by focusing on individual-level effects. For instance, our paper suggests that automation initiatives in the finance function require a firm-wide digitalization impetus. While much accounting research shows how the numbers produced by finance create pressure on other departments, the finance department itself may also experience various sorts of tension or anxiety (Armstrong, 2002; Goretzki and Pfister, 2023). In particular, as automation initiatives may be an important reason for digital anxiety, our findings connect with Firk et al. (2024), who observed a considerable amount of digital anxiety in their study of the finance function in a large multinational firm. While they find that digital anxiety leads to lower work engagement, it can be reduced by measures such as digital training or good leadership. If not addressed, however, "[d]igital anxiety could thus unfold as a barrier to the digital transformation of the finance function" (ibid., p. 96). In and of itself, the finance function may be hesitant to drive automation, partly because it often goes along with the risk of staff reductions. Analytics use, in contrast, has less downside risk, and is therefore more likely to be driven by the finance department itself, which can enhance its value and recognition within the firm by deploying analytics for better decision support (de Araujo Wanderley, Horton.,2024). Future research may complement our findings by examining digital anxiety as well as other individual-level effects, such as how individuals react to a firm-wide digitalization agenda depending on their specific roles.

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Appendix A. Interviewed finance professionals

Interviewee	Interview date	Sector
Interviewee 1*	13–10–2023	Transportation
Interviewee 2*	23–10–2023	Services general
Interviewee 3*	26–10–2023	Manufacturing
Interviewee 4*	03–11–2023	Maritime
Interviewee 5*	03–11–2023	Retail
Interviewee 6	28–08–2024	Telecom
Interviewee 7	19–09–2024	Insurance
Interviewee 8	19–09–2024	Technology
Interviewee 9	23–09–2024	Agriculture
Interviewee 10	01–10–2024	Banking
Interviewee 11	07–10–2024	Construction

* This interviewee also participated in survey.

Appendix B. Survey items

Survey items	Scale
Firm digitalization strategy	
Please indicate to what extent you agree with the following statements about your entity 1. We have a clearly defined digitalization strategy 2. We invest a lot in new digital technologies to support various organizational processes 3. We have established new business models, products, or services on the basis of our digital competencies 4. We have a climate that is supportive of using digital technologies 5. We constantly seek new ways to enhance the effectiveness of digital technologies use	(1) Strongly disagree / (2) Disagree / (3) Somewhat disagree / (4) Neither agree nor disagree / (5) Somewhat agree / (6) Agree / (7) Strongly agree
Finance function efficiency objective	
How important are the following objectives for the finance function of your entity? 1. Increasing efficiency of the finance function 2. Standardizing processes in the finance function 3. Ensuring resources of the finance function are fully utilized 4. Reducing time spent on routine tasks in the finance function	(1) Not at all important / (2) Slightly important / (3) Moderately important / (4) Very important / (5) Extremely important
Finance function business partnering objective	
How important are the following objectives for the finance function of your entity? 1. Providing insights and advice to business managers 2. Influencing operational decision-making 3. Developing strategic objectives and business models	(1) Not at all important / (2) Slightly important / (3) Moderately important / (4) Very important / (5) Extremely important

(*continued on next page*)

(*continued*)

Survey items	Scale
4. Aligning activities across the organization to drive value generation	
5. Driving major changes in the organization	
Finance function automation	
Please indicate to what extent the following statements apply to the work of the finance function in your entity	(1) Not at all / (2) To some extent / (3) To a moderate extent / (4) To a high extent / (5) To a very high extent
1. We deploy tools (e.g., Robotic Process Automation software) for automating routine processes	
2. We have installed tools to eliminate manual work for repetitive activities	
3. We use digital technologies to standardize processes	
4. There is a high level of automation and standardization	
Finance function analytics use	
Please indicate to what extent the following statements apply to the work of the finance function in your entity	(1) Not at all / (2) To some extent / (3) To a moderate extent / (4) To a high extent / (5) To a very high extent
1. We use data visualization and business intelligence techniques (e.g., dashboards) to analyze and report past information	
2. We use advanced analytical techniques (e.g., optimization, simulation, regression) to predict future performance (e.g., sales forecasts, profitability scenarios)	
3. We develop and use statistical and analytical models to inform decision-making	
4. We analyze large amounts of data (e.g., from customers, suppliers, competitors) with the help of analytical tools and models	
5. We use cognitive computing techniques (e.g., artificial intelligence, machine learning, deep learning, neural networks) to improve decision-making	
Finance function digital skills	
Please answer to what extent the finance function of your entity	(1) Not at all / (2) To some extent / (3) To a moderate extent / (4) To a high extent / (5) To a very high extent
1. Provides the resources and opportunities for employees to obtain data analytics skills	
2. Hires new employees that already have data analytics skills	
3. Has the right skills and expertise to take advantage of data analytics	
Finance function effectiveness	
How effective is the finance function of your entity in achieving the following?	(1) Not at all effective / (2) Slightly effective / (3) Moderately effective / (4) Very effective / (5) Extremely effective
1. Providing relevant information to business decision-makers	
2. Measuring and monitoring business performance	
3. Continuous business improvement	
4. Aligning finance with business requirements	

Appendix C. Descriptive statistics for automation and analytics use scale items

	Mean	Median	StdDev	Min	Max
Finance function automation					
1. We deploy tools (e.g., Robotic Process Automation software) for automating routine processes	2.41	2	1.15	1	5
2. We have installed tools to eliminate manual work for repetitive activities	2.77	3	1.04	1	5
3. We use digital technologies to standardize processes	2.82	3	1.01	1	5
4. There is a high level of automation and standardization	2.75	3	1.01	1	5
Finance function analytics use					
1. We use data visualization and business intelligence techniques (e.g., dashboards) to analyze and report past information	3.19	3	1.17	1	5
2. We use advanced analytical techniques (e.g., optimization, simulation, regression) to predict future performance (e.g., sales forecasts, profitability scenarios)	2.20	2	1.11	1	5
3. We develop and use statistical and analytical models to inform decision-making	2.26	2	1.08	1	5
4. We analyze large amounts of data (e.g., from customers, suppliers, competitors) with the help of analytical tools and models	2.52	2	1.22	1	5
5. We use cognitive computing techniques (e.g., artificial intelligence, machine learning, deep learning, neural networks) to improve decision-making	1.74	1	1.02	1	5

Data availability

The data that has been used is confidential.

References

Agrawal, A., Eklund, S., Waite, J., Woodcok, E., 2020. Finance 2030: four imperatives for the next decade. McKinsey Co.

Armstrong, P., 2002. The costs of activity-based management. Account. Organ. Soc. 27 (1-2), 99–120.

Bedford, D.S., 2020. Conceptual and empirical issues in understanding management control combinations. Account. Organ. Soc. 86, 101187.

Bedford, D.S., Speklé, R.F., 2018a. Constructs in Survey-Based Management Accounting and Control Research: An Inventory from 1996 to 2015. J. Manag. Account. Res. 30 (2), 269–322.

Bedford, D.S., Speklé, R.F., 2018b. Construct validity in survey-based management accounting and control research. J. Manag. Account. Res. 30 (2), 23–58.

Bergmann, M., Brück, C., Knauer, T., Schwering, A., 2020. Digitization of the budgeting process: determinants of the use of business analytics and its effect on satisfaction with the budgeting process. J. Manag. Control 31 (1), 25–54.

Bharadwaj, A., El Sawy, O.A., Pavlou, P.A., Venkatraman, N.V., 2013. Digital business strategy: toward a next generation of insights. MIS Q. 471–482.

Bhimani, A., Willcocks, L., 2014. Digitisation, 'Big Data' and the transformation of accounting information. Account. Bus. Res. 44 (4), 469–490.

Boerner, X., Wiener, M., Guenther, T.W., 2024. Controllership effectiveness and digitalization: shedding light on the importance of business analytics capabilities and the business partner role. Manag. Account. Res. 66, 100904.

Brown, C.V., Magill, S.L., 1994. Alignment of the IS functions with the enterprise: toward a model of antecedents. MIS Q. Dec. 371–403.
Burns, J., Baldvinsdottir, G., 2005. An institutional perspective of accountants' new roles – the interplay of contradictions and praxis. Eur. Account. Rev. 14 (4), 725–757.
Caputo, A., Pizzi, S., Pellegrini, M.M., Dabić, M., 2021. Digitalization and business models: Where are we going? A science map of the field. J. Bus. Res. 123, 489–501.
Chakravarty, A., Grewal, R., Sambamurthy, V., 2013. Information technology competencies, organizational agility, and firm performance: enabling and facilitating roles. Inf. Syst. Res. 24 (4), 976–997.
Chang, H., Ittner, C.D., Paz, M.T., 2014. The Multiple Roles of the Finance Organization: Determinants, Effectiveness, and the Moderating Influence of Information System Integration. J. Manag. Account. Res. 26 (2), 1–32.
Chapman, C.S., Kihn, L.-A., 2009. Information system integration, enabling control and performance. Account. Organ. Soc. 34 (2), 151–169.
Chen, W., Srinivasan, S., 2024. Going digital: implications for firm value and performance. Rev. Account. Stud. 29 (2), 1619–1665.
Chenhall, R.H., Langfield-Smith, K., 1998. The relationship between strategic priorities, management techniques and management accounting: an empirical investigation using a systems approach. Account. Organ. Soc. 23 (3), 243–264.
Chin, W.W., 1998. The partial least squares approach to structural equation modeling. Mod. Methods Bus. Res. 295 (2), 295–336.
de Araujo Wanderley, C., Horton, K.E., 2024. Digitalization tensions in the management accounting profession: Boundary work responses and their consequences. Br. Account. Rev., 101455
Deloitte, 2021. *Finance 2025 revisited (what we know now)*.
Dubey, R., Angappa, G., Stephen J, C., Samuel, F.W., David, R., Foropon, C., 2021. Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. Int. J. Prod. Res. 59 (1), 110–128.
Eilifsen, A., Kinserdal, F., Messier Jr, W.F., McKee, T.E., 2020. An exploratory study into the use of audit data analytics on audit engagements. Account. Horiz. 34 (4), 75–103.
Fähndrich, J., 2023. A literature review on the impact of digitalisation on management control. J. Manag. Control 34, 9–65.
Fehrenbacher, D.D., Ghio, A., Weisner, M., 2022. Advice utilization from predictive analytics tools: the trend is your friend. Eur. Account. Rev. 32 (3), 1–26.
Firk, S., Gehrke, Y., Wolff, M., 2024. Digital anxiety in the finance function: consequences and mitigating factors. J. Manag. Account. Res. 36 (1), 95–118.
Fullerton, R.R., Kennedy, F.A., Widener, S.K., 2013. Management accounting and control practices in a lean manufacturing environment. Account. Organ. Soc. 38 (1), 50–71.
Galbraith, J.R., 1973. Designing Complex Organizations. Addison-Wesley, Boston, MA.
Gartner, 2021. Digit. Future Financ. 10 CFO Oppor. Accel. Digit. Transform.
Gibson, A.B., Kaplan, B., Cutbill, D., 2020. From mirage to reality: bringing finance into focus in a digital world. Deloitte Cent. Controll. Retrieved from ⟨https://www2.deloitte.com/us/en/pages/advisory/articles/future-of-automation-in-finance.html⟩.
Goretzki, L., Lukka, K., Messner, M., 2018. Controllers' use of informational tactics. Account. Bus. Res. 48 (6), 700–726.
Goretzki, L., Pfister, J.A., 2023. The productive accountant as (un-)wanted self: realizing the ambivalent role of productivity measures in accountants' identity work. Crit. Perspect. Account. 95, 102504.
Hair, J., Hult, T., Ringle, C., Sarstedt, M., 2014. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Thousand Oaks, CA: Sage Publications, Inc.
Hartmann, F.G.H., Maas, V.S., 2010. Why business unit controllers create budget slack: involvement in management, social pressure, and machiavellianism. Behav. Res. Account. 22 (2), 27–49.
Henri, J.-F., 2006. Management control systems and strategy: a resource-based perspective. Account. Organ. Soc. 31 (6), 529–558.
Jaworski, B.J., Kohli, A.K., 1993. Market orientation: antecedents and consequences. J. Mark. 57 (3), 53–70.
Kennedy, F.A., Widener, S.K., 2008. A control framework: Insights from evidence on lean accounting. Manag. Account. Res. 19 (4), 301–323.
Knudsen, D.-R., 2020. Elusive boundaries, power relations, and knowledge production: a systematic review of the literature on digitalization in accounting. Int. J. Account. Inf. Syst. 36, 100441.
Kokina, J., Blanchette, S., 2019. Early evidence of digital labor in accounting: innovation with Robotic Process Automation. Int. J. Account. Inf. Syst. 35, 100431.
Kokina, J., Gilleran, R., Blanchette, S., Stoddard, D., 2021. Accountant as digital innovator: Roles and competencies in the age of automation. Account. Horiz. 35 (1), 153–184.
Korhonen, T., Selos, E., Laine, T., Suomala, P., 2021. Exploring the programmability of management accounting work for increasing automation: an interventionist case study. Account. Audit. Account. J. 34 (2), 253–280.
KPMG (2019). Automation of financial reporting and technical accounting. Retrieved from: ⟨https://assets.kpmg.com/content/dam/kpmg/uk/pdf/2019/09/automation-of-financial-reporting-and-technical-accounting.pdf⟩.
Kraus, S., Durst, S., Ferreira, J.J., Veiga, P., Kailer, N., Weinmann, A., 2022. Digital transformation in business and management research: an overview of the current status quo. Int. J. Inf. Manag. 63, 102466.
Krieger, F., Drews, P., Velte, P., 2021. Explaining the (non-) adoption of advanced data analytics in auditing: A process theory. Int. J. Account. Inf. Syst. 41, 100511.
Kroos, P., Schabus, M., Verbeeten, F.H., 2022. The relation between internal forecasting sophistication and accounting misreporting. J. Manag. Account. Res. 34 (1), 51–73.
LaBerge, L., Smaje, Zemmel, R., 2022. Three new mandates for capturing a digital transformation's full value. McKinsey & Company. McKinsey Global Publishing.
Labro, E., Lang, M., Omartian, J.D., 2023. Predictive analytics and centralization of authority. J. Account. Econ. 75 (1), 101526.
Lambert, C., Sponem, S., 2012. Roles, authority and involvement of the management accounting function: a multiple case-study perspective. Eur. Account. Rev. 21 (3), 565–589.
Lauterbach, J., Mueller, B., Kahrau, F., Maedche, A., 2020. Achieving effective use when digitalizing work: the role of representational complexity. MIS Q. 44 (3), 1023–1048.
Lem, K.W., 2024. Data analytics strategy and internal information quality. Contemp. Account. Res. 41 (2), 1376–1410.
Li, H., Dai, J., Gershberg, T., Vasarhelyi, M.A., 2018. Understanding usage and value of audit analytics for internal auditors: An organizational approach. Int. J. Account. Inf. Syst. 28, 59–76.
Lu, Y., Ramamurthy, K.R., 2011. Understanding the link between information technology capability and organizational agility: an empirical examination. MIS Q. 35 (4), 931.
Maas, V.S., Matějka, M., 2009. Balancing the dual responsibilities of business unit controllers: field and survey evidence. Account. Rev. 84 (4), 1233–1253.
MacKenzie, Podsakoff, Podsakoff, 2011. Construct measurement and validation procedures in MIS and behavioral research: integrating new and existing techniques. MIS Q. 35 (2), 293.
Malhotra, N.K., Kim, S.S., Patil, A., 2006. Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past research. Manag. Sci. 52 (12), 1865–1883.
Matt, C., Hess, T., Benlian, A., 2015. Digital transformation strategies. Bus. Inf. Syst. Eng. 57, 339–343.
Menz, M., Kunisch, S., Birkinshaw, J., Collis, D.J., Foss, N.J., Hoskisson, R.E., Prescott, J. E., 2021. Corporate strategy and the theory of the firm in the digital age. J. Manag. Stud. 58 (7), 1695–1720.
Möller, K., Schäffer, U., Verbeeten, F., 2020. Digitalization in management accounting and control: an editorial. J. Manag. Control 31, 1–8.
Müller, O., Maria, F., vom Brocke, J., 2018. The effect of big data and analytics on firm performance: an econometric analysis considering industry characteristics. J. Manag. Inf. Syst. 35 (2), 488–509.
Nielsen, H., Kristensen, T.B., 2020. Impact of lean operations on the roles of finance functions and their application of lean. Eur. Bus. Rev. 32 (4), 731–763.
Niemand, T., Rigtering, J.C., Kallmünzer, A., Kraus, S., Maalaoui, A., 2021. Digitalization in the financial industry: A contingency approach of entrepreneurial orientation and strategic vision on digitalization. Eur. Manag. J. 39 (3), *317*–326.
Plattfaut, R., Borghoff, V., 2022. Robotic process automation: a literature-based research agenda. J. Inf. Syst. 36 (2), 173–191.
Plekhanov, D., Franke, H., Netland, T.H., 2023. Digital transformation: a review and research agenda. Eur. Manag. J. 41 (6), 821–844.
Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y., Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. J. Appl. Psychol. 88 (5), 879903.
PwC (2017). Stepping up: How finance functions are transforming to drive business results. Retrieved from: ⟨https://www.pwc.com.au/consulting/assets/finance-effectiveness-benchmark-2017.pdf⟩.
PwC (2020). The PwC Finance Benchmarking Report 2019-20. Retrieved from: ⟨https://www.pwc.co.uk/finance/assets/pdf/uk-finance-effectiveness-benchmarking-report-2019-2020.pdf⟩.
Rautiainen, A., Scapens, R.W., Järvenpää, M., Auvinen, T., Sajasalo, P., 2024. Towards fluid role identity of management accountants: A case study of a Finnish bank. Br. Account. Rev. 56 (4), 101341.
Ravichandran, T., 2018. Exploring the relationships between IT competence, innovation capacity and organizational agility. J. Strateg. Inf. Syst. 27 (1), 22–42.
Redman, T.C., 2018. Can your data be trusted? In Harvard Business Review (Ed.). HBR guide to data analytics basics for managers. Harvard Business Review Press, pp. 71–78.
Ritter, T., Pedersen, C.L., 2020. Digitization capability and the digitalization of business models in business-to-business firms: past, present, and future. Ind. Mark. Manag. 86, 180–190.
Sandino, T., 2007. Introducing the first management control systems: evidence from the retail sector. Account. Rev. 82 (1), 265–293.
Schnegg, M., Möller, K., 2022. Strategies for data analytics projects in business performance forecasting: a field study. *Journal of Management*. Control 33 (2), 241–271.
Siegel, G., Sorensen, J.E., Richtermeyer, S.B., 2003. Are you a business partner? Strateg. Financ. 39–43.
Speklé, R.F., Verbeeten, F.H., 2014. The use of performance measurement systems in the public sector: effects on performance. Manag. Account. Res. 25 (2), 131–146.
Speklé, R.F., Widener, S.K.S.K., 2018. Challenging issues in survey research: discussion and suggestions. J. Manag. Account. Res. 30 (2), 3–21.
Spraakman, G., Sanchez-Rodriguez, C., Tuck-Riggs, C.A., 2021. Data analytics by management accountants. Qual. Res. Account. Manag. 18 (1), 127–147.
Srinivasan, R., Swink, M., 2018. An investigation of visibility and flexibility as complements to supply chain analytics: an organizational information processing theory perspective. Prod. Oper. Manag. 27 (10), 1849–1867.
Sun, S., Hall, D.J., Cegielski, C.G., 2020. Organizational intention to adopt big data in the B2B context: An integrated view. Ind. Mark. Manag. 86, 109–121.
Tillema, S., Trapp, R., Van Veen-Dirks, P.M.G., 2022. Business partnering in risk management: a resilience perspective on management accountants' responses to a role change. Contemp. Account. Res. 39 (3), 2058–2089.
Tushman, M.L., Nadler, D.A., 1978. Information processing as an integrating concept in organizational design. Acad. Manag. Rev. 3 (3), 613–624.
van der Aalst, W.M., Bichler, M., Heinzl, A., 2018. Robotic process automation. Bus. Inf. Syst. Eng. 60, 269–272.

van der Stede, W.A., 2000. The relationship between two consequences of budgetary controls: budgetary slack creation and managerial short-term orientation. Account. Organ. Soc. 25 (6), 609–622.
van Slooten, A.C.A., Dirks, P.M.G., Firk, S., 2024. Digitalization and management accountants' role conflict and ambiguity: a double-edged sword for the profession. Br. Account. Rev., 101460
Yigitbasioglu, O., Green, P., Cheung, M.-Y.D., 2023. Digital transformation and accountants as advisors. Account. Audit. Account. J. 36 (1), 209–237.
Zhou, K.Z., Wu, F., 2010. Technological capability, strategic flexibility, and product innovation. Strateg. Manag. J. 31 (5), 547–561.