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Individual- and Firm-level Determinants of Management Accountants' Digital Competence

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Abstract
Propose an instrument to capture digital competence in Mas and identify the most relevant individual- and firm-level factors associated with the digital competence of MAs.
Method: We survey 109 MAs to develop and validate a 10-item digital competence scale, following the methodological steps of scale development (items generation, scale construction, dimensionality assessment, reliability, and validity) and data analysis (exploratory and confirmatory factor analysis). We also examine individual (position, experience, generation, gender, education) and firm-level (data analytics department, tech affinity, size, digital transformation) variables.
Results: Our results show that individual factors are significantly associated with MAs' digital competence. Specifically, digital competence declines with age but is higher among MAs who hold a controller position and those with greater interest in technology. Also, we find that MAs' digital competence is negatively associated with the presence of an independent data analytics department within the organization.
Contributions: This article offers several contributions. First, it advances management accounting literature on digitalization by showing that individual characteristics play a key role in enhancing digital competence within the accounting and finance function. Second, it provides a methodological contribution by introducing a novel scale to measure management accountants' digital competence. Finally, it offers practical insights, suggesting that independent data analytics departments may actually hinder MAs' development of digital competence.
Keywords: digital competence, management accountants, individual factors, firm-level characteristics, survey.

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1 Introduction

The main purpose of this paper is to identify both individual- and firm-level determinants of the digital competence of management accountants (MAs). Organizations are increasingly investing in technology to improve their operations and decision-making processes (Kiron, Prentice, & Ferguson, 2014; Davenport & Ronanki, 2018; Broccardo et al., 2025). This is no different in the accounting and finance function. In fact, the accounting and finance function is undergoing significant digital transformation with the advent of artificial intelligence systems, machine learning, big data, and other advancements (Quattrone, 2016; Appelbaum, Kogan, Vasarhelyi, & Yan, 2017; Araujo Wanderley & Horton, 2024; Fähndrich & Pedell, 2025). Developing digital competence in accountants has been recognized as a priority for the profession by both academics and regulators (Rodrigues & Miranda, 2025; Brasil, 2024).

As a result of this digital shift, MAs are required to develop their digital competence to keep pace with these changes and leverage the vast amounts of data available to support operational and strategic business decisions (Bhimani & Willcocks, 2014; Moll & Yigitbasioglu, 2019; Arkhipova et al., 2024). However, there is still limited knowledge about how MAs are responding to these digital demands, possibly because the concept of digital competence for MAs is still evolving. Consequently, there is no validated instrument to measure the degree of digital competence among MAs. Therefore, the first specific goal of this paper is to propose an instrument to capture digital competence in MAs, based on characteristics suggested by professional institutions, such as Institute of Management Accountants (IMA) and Chartered Institute of Management Accountants (CIMA).

Being able to measure the degree of digital competence in MAs is important for helping organizations make several decisions, such as selecting professionals with higher digital competence, training those who lack it, or allocating professionals with higher levels of digital competence to tasks involving greater interaction with technology. However, simply measuring digital competence does not indicate which factors are associated with higher levels of it. For instance, prior studies suggest that individual factors, such as age and education level, are important enabling conditions for the level of digital competence (Hargittai, 2010; Van Laar, Van Deursen, Van Dijk, & De Haan, 2017). Additionally, firm-level characteristics such as size and digital familiarity are also highlighted as relevant enabling conditions (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Vial, 2021). Therefore, the second specific goal of this paper is to identify the most relevant individual- and firm-level factors associated with the digital competence of MAs.

We collect survey data from 109 MAs to develop a novel scale to capture digital competence, following the methodological steps of scale development (items generation, scale construction, dimensionality assessment, reliability, and validity) and data analysis (exploratory and confirmatory factor analysis) to refine and validate a 10-item scale. We also measure several individual-level (position, experience, generation, gender, and education) and firm-level (data analytics department, tech affinity, size, and digital transformation) variables.

Our results show that individual factors are significantly associated with MAs' digital competence. Specifically, digital competence declines with age but is higher among MAs who hold a controller position and those with greater interest in technology. At the firm level, we do not find a significant association between firm size and MAs' digital competence. Interestingly, however, we find that MAs' digital competence is negatively associated with the presence of an independent data analytics department within the organization. Furthermore, the negative association between age and digital competence is stronger for MAs who do not hold a controller position.

These results offer several contributions. First, we provide a theoretical contribution to the management accounting literature by demonstrating that individual characteristics may be more important in enhancing the digital competence of the accounting and finance function than firm-level characteristics or initiatives. Second, our study makes a methodological contribution by developing a novel scale to measure the digital competence of MAs, based on attributes identified by professional associations. Finally, our results contribute to practice by suggesting that the presence of an independent data analytics department may actually hinder the development of digital competence among MAs.

2 Theoretical background and hypotheses development

2.1 Digital competence of Mas

Information Technology (IT) has been a driving force in the accounting and finance function since the implementation of Integrated Information Systems in the 1990s (Rom & Rohde, 2007). In the following decades, new digital tools based on Robotic Process Automation (RPA), Big Data, Business Intelligence (BI), Artificial Intelligence, and others have become accessible (Aguiar et al., 2021). These tools, aimed at achieving greater efficiency and improved outcomes, require knowledge beyond finance and accounting, extending to areas such as IT and data science (Steens et al., 2024).

Digitalization enables the accounting and finance function to operate more strategically (Appelbaum et al., 2017; Rieg, 2018), positioning it with greater prestige (Horton et al., 2020) while reducing manual tasks (ACCA, 2016). This elevated role, known as the "Business Partner", is linked to strategic decision-making, in contrast to the traditional "Bean Counter" role—a narrow-focused professional with limited contributions to the organization (Heinzelmann, 2019).

The transition of the MA from a "bean counter" to a "business partner" has been widely discussed in the literature (Graham et al., 2012), despite a lack of empirical evidence in practice (Horton et al., 2020). While this shift towards the business partner profile has been slow, it is expected to accelerate as new technologies are adopted by MAs (Bhimani & Willcocks, 2014; Boerner et al., 2025; van Slooten et al., 2024). In addition to the academic literature, consulting reports and industry publications promote the use of digital tools (Eklund et al., 2018; Lawson & Hatch, 2020), while professional associations emphasize the need for developing new competencies to master these tools (AICPA & CIMA, 2019; IMA, 2019).

To remain relevant in the digital era, MAs must master new knowledge, skills, and capabilities, including domains such as strategy, planning and performance, reporting and control, business and operations, leadership, ethics and values, and technology and data analytics. The last domain is also referred to as digital competence and has been highlighted as a priority by professional bodies, academics, and regulators (AICPA & CIMA, 2019; Brasil, 2024; Rodrigues & Miranda, 2025). This study focuses on the skills and competencies related to technology and analytics. Accordingly, our main purpose is to identify both individual- and firm-level determinants of MAs' digital competence.

2.2 Hypotheses

We develop hypotheses predicting individual- and firm-level determinants of MAs' digital competence. We first predict the direct relationship between each determinant variable and MAs' digital competence, and then also consider potential interactive relationships between pairs of determinant variables and MAs' digital competence.

2.2.1 Individual-level

Individual characteristics have been suggested as predictors of digital competence (e.g., Lee, Jeong Cho, Xu, & Fairhurst, 2010; Laakkonen et al., 2024). In particular, we incorporate three demographic factors to examine their association with MAs digital competence, including age, current organizational position, and level of interest in technology.

We first propose that older MA professionals may perceive themselves as "too old" to learn new technologies, due to diminished cognitive capabilities during the learning process and lower self-efficacy related to cognitive functioning (Lee et al., 2010). Accordingly, our first hypothesis predicts a negative association between MAs' digital competence and age.

H1: The level of MAs' digital competence is negatively associated with age.

As controllers often engage more intensively with digital systems and data analysis, MAs in the position of controller are facing increasing demands to change their task profiles from bean counter to business partner due to the growing volume and variety of data (Granlund & Taipaleenmäki, 2005; van Slooten et al., 2024). Consequently, they need to combine business partner skills with an understanding of data analytics so that the use of digital technologies enables them to position themselves strongly as management partners in the future (Leitner-Hanetseder, Lehner, Eisl, & Forstenlechner, 2021). Hence, our second hypothesis predicts a positive association between MAs' digital competence and their current organizational position as controller.

H2: The level of MAs' digital competence is positively associated with the current position of controller.

Interest refers to a psychological state or predisposition to engage repeatedly with certain objects or ideas over time (Hidi & Renninger, 2006). As a motivational factor, interest plays a key role in driving engagement and influencing performance outcomes, such as the development of digital competence when the object of interest is technology. Overall, people interested in technology are typically more familiar with technology and possess skills to use it better (Rantala, Taipale, Oinas, & Karhinen, 2022). Therefore, our third hypothesis predicts a positive association between MAs' digital competence and their interest in technology.

H3: The level of MAs' digital competence is positively associated with tech interest level.

2.2.2 Firm-level

In addition to individual characteristics, we also expect that firm-level variables influence digital competence (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Vial, 2021). Specifically, we consider two firm-level characteristics to examine their association with MAs' digital competence: the presence of an independent data analytics (DA) department and the firm's size.

A DA department is an organizational unit responsible for managing data-related resources, developing analytical models, and delivering data-driven insights to support operational and strategic decision-making across business functions. It typically includes professionals such as data scientists, data engineers, and data analysts (Stobierski, 2021). The department centralizes analytics expertise, infrastructure, and governance to facilitate the effective use of data (Davenport & Harris, 2007; Wang, Kung, & Byrd, 2018; Vial, 2021). While there is limited direct empirical research on the relationship between the existence of a DA department and MAs' digital competence, we argue that when firms establish independent DA departments, the responsibility for advanced data analysis may become centralized within that function. As a result, MAs may have fewer opportunities or less need to develop their own digital competence related to analytics. Therefore, our fourth hypothesis predicts a negative association between MAs' digital competence and the existence of an independent DA department.

H4: The level of MAs' digital competence is negatively associated with the firm having an independent DA department.

Large companies typically have more resources, capabilities, infrastructure, and incentives to invest in digital technologies and training that support the development of employees' digital competence, whereas small and medium-sized companies often lack the necessary internal resources and capabilities for this endeavour (e.g., Li, Su, Zhang, & Mao, 2018; Fähndrich & Pedell, 2025). Therefore, our fifth hypothesis predicts a positive association between MAs' digital competence and firm size, as larger firms are more likely to invest in digital technologies, data infrastructure, and employee training, providing greater opportunities for MAs to develop digital skills.

H5: The level of MAs' digital competence is positively associated with the firm size.

2.2.3 Moderating Hypotheses

In addition to examining the relationships between individual variables, at either the individual or firm level, and MAs' digital competence, we also consider that these variables may interact in shaping MAs' digital competence. In particular, given the importance of age as a determinant of digital competence development (e.g., Hauk, Hüffmeier, & Krumm, 2018), we examine whether holding the position of controller and the MA's level of interest in technology moderate the relationship between age and MAs' digital competence.

Becoming a controller is a key milestone in the career progression of finance professionals. As MAs grow older, if they have not yet attained the position of controller, their expectations of reaching this role may diminish as their perception of future time horizons shrinks (e.g., Carstensen, 2006). This, in turn, can reduce their motivation to invest in developing new competencies, such as digital competence, due to reduced promotion prospects. Therefore, our sixth hypothesis predicts that the negative association between MAs' age and their digital competence will be stronger when the professional has not attained the position of controller.

H6: The negative association between MAs' digital competence and age is higher when the MA does not hold a current position of controller.

Interest has been acknowledged as a key driver of learning and competence development, such that individuals with low interest are less likely to invest cognitive resources in learning, particularly as challenges increase, such as age-related barriers (e.g., Hidi & Renninger, 2006). In addition, age has been found to negatively correlate with technology acceptance, with this relationship being moderated by individual factors like interest (e.g., Hauk et al., 2018). Therefore, when interest is low, older individuals are more likely to experience reduced digital competence due to lower engagement, effort, and self-efficacy. Accordingly, our seventh and final hypothesis predicts that the negative association between MAs' age and their digital competence will be stronger when their interest in technology is lower.

H7: The negative association between MAs' digital competence and age is higher when the MA does not have higher levels of interest in technology.

2.2.4 Summary

Table 1
Hypotheses and expected relationships

Hypothesis	Determinant	Relationship with MAs' Digital Competence	Expected Signal
H1	Age	Direct	Negative (–)
H2	*Current position of controller*	Direct	Positive (+)
H3	Interest in technology	Direct	Positive (+)
H4	Firm has independent DA department	Direct	Negative (–)
H5	Firm size	Direct	Positive (+)
H6	*Interaction: Age x Controller position*	Moderation of H1	*Stronger negative when not a controller*
H7	Interaction: Age x Interest in technology	Moderation of H1	Stronger negative when interest is low

Table 1 summarizes the hypotheses, indicating whether a direct or moderating association is predicted, as well as the expected direction of the association with MAs' digital competence.

3 Method

3.1 Data collection and sample

We conducted a descriptive, cross-sectional survey (Van der Stede et al., 2005) using a questionnaire administered virtually through the Google Forms platform between December 2022 and March 2023. The target population consisted of management accounting professionals at various levels of seniority, with the MA as the key respondent. Convenience sampling was used as a practical approach for hypothesis testing (Speklé and Widener, 2018), as the sample included a diverse range of firm sizes and respondent profiles.

The questionnaire link was shared with two target groups: (i) participants affiliated with a higher education institution offering postgraduate programs in accounting and finance, and (ii) professionals identified via LinkedIn. An invitation letter outlined the study's objectives, provided assurances of confidentiality, and mentioned the benefit of receiving an executive report. Respondents were required to agree to these terms before completing the survey. At the higher education institution, four rounds of invitations were sent to current and former students of MBA (Master of Business Administration) and master's programs. Across all rounds, 900 individuals were contacted, resulting in 30 valid responses—a response rate of 3.33%. On LinkedIn, 689 professionals with relevant experience in management accounting were contacted directly, yielding 80 valid responses—a response rate of 11.61%. One response was excluded because the participant indicated a legal rather than a management accounting background. The final sample comprised 109 valid responses.

3.2 Variables measurement

The **dependent variable**, **MA digital competence**, was developed for this study following procedures grounded in the literature on scale development (e.g., Boateng et al., 2018; Hinkin, 1998), as well as applications of these procedures (e.g., Biesecker et al., 2017; Braun & Hadwich, 2016). The development process was conducted in three main stages (Table 2). Based on the frameworks of the IMA and the Chartered Global Management Accountant (CGMA), an initial set of items was created to represent four dimensions of digital competence: (i) Information Technology, (ii) Data Governance, (iii) Data Analytics, and (iv) Data Visualization. Item generation followed an inductive approach (Hinkin, 1998), using specifications derived from interviews, discussion panels, and official documents from the IMA and CGMA. A content validity assessment was performed using the Content Validity Coefficient (CVC) (Hernandez-Nieto, 2002). Six subject-matter experts in management accounting and technology evaluated each item for clarity, pertinence, and relevance. All items achieved CVC scores above the 0.80 threshold, indicating strong content validity, and therefore, no item was eliminated at this stage.

Table2
Scale development stages

Stage	Passos
1. Item Development	1.1. Domain identification and initial item generation. 1.2. Content validity evidence analysis.
2. Scale Development	2.1. Questionnaire pre-test 2.2. Questionnaire administration 2.3. Item reduction 2.4. Factor extraction
3. Scale Evaluation	3.1. Dimensionality assessment 3.2. Reliability assessment 3.3. Validity assessment

Source: Adapted from Boateng et al. (2018)

Next, we proceeded with the scale development, conducted in two main steps. First, the questionnaire was pretested with four participants (two undergraduate and two graduate accounting students). No semantic or comprehension issues were reported. Second, an Exploratory Factor Analysis (EFA) was performed using polychoric matrices and the Robust Diagonally Weighted Least Squares (RDWLS) estimation method (Asparouhov & Muthén, 2010), with factor retention guided by Parallel Analysis (Timmerman & Lorenzo-Seva, 2011).

The EFA followed a three-step iterative process: (i) determination of the number of factors, (ii) removal of items with factor loadings below 0.70 (a stringent cutoff; Comrey & Lee, 1992), and (iii) evaluation of fit indices and the reliability of the final solution. This process resulted in a 13-item solution, which was further analyzed using Item Response Theory (IRT) with the Graded Response Model (GRM) (De Ayala, 2008).

Finally, we proceeded with the scale evaluation. A Confirmatory Factor Analysis (CFA) was conducted using the RDWLS estimation method (DiStefano & Morgan, 2014; Li, 2016) to test the unidimensional structure. Fit indices included normed Chi-square (χ^2/df), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) (Kline, 2015; Brown, 2006). Through iterative modifications based on modification indices, redundant items were removed, resulting in a final scale with 10 items. Unidimensionality was confirmed through the Unidimensional Congruence (UniCo), Explained Common Variance (ECV), and Mean of Item Residual Absolute Loadings (MIREAL) indices, all supporting a strong unidimensional structure. The scale demonstrated excellent reliability: Composite Reliability (CR) = 0.956, Cronbach's Alpha = 0.955, and McDonald's Omega = 0.955. Additionally, the Average Variance Extracted (AVE) was 68.65%, indicating high internal consistency and precision. Evidence of construct validity based on relationships with other variables was assessed using Pearson correlations and multiple regression analysis. In particular, having studied programming or Structured Query Language (SQL) significantly increased the digital competence score, supporting convergent validity. Standard tests confirmed that regression assumptions were met, including normality (Shapiro-Francia), absence of multicollinearity, and homoscedasticity (Breusch-Pagan and White tests). The final Digital Competence Scale for MAs comprises 10 items, rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Items are ordered by factor loading from highest to lowest (Table 3).

Table 3
Digital competence measurement scale

Item	Description
1	I am capable of developing a data analysis project aimed at an organizational objective, from planning to implementation.
2	I am able to independently design dashboards that are relevant to my target audience.
3	I can evaluate a new dataset and select appropriate analysis techniques and necessary data treatments.
4	I am capable of building prescriptive models to improve organizational performance.
5	I am able to develop complete data pipelines to integrate them into organizational processes, suggesting necessary adaptations to these processes.
6	I am capable of identifying when new data needs to be generated in specific areas of the business for which I am responsible for conducting analyses.
7	I have sufficient proficiency in software tools to create data visualizations (e.g., charts, diagrams, and dashboards) based on available data.
8	I am able to transform unstructured data so that it fits into established analysis models, using digital automation tools for this purpose.
9	I am fully capable of proposing solutions based on data analysis for business problems.
10	I have the skills to handle large datasets—larger than what a spreadsheet can process—and generate analyses from these datasets.

The **independent variables** include age, current position of controller, interest in technology, existence of an independent DA department, and firm size. Respondents indicate their **age** in years. They also indicate their **current position** in the company by selecting one of the following options: Controller, Accountant, Accounting Department Staff, Administrative Director, Finance Director, or Other. We create a dummy variable coded '1' if the respondent selected Controller, and '0' otherwise. **Interest in technology** is measured by asking respondents to indicate their general level of interest in technology using a 5-point Likert scale, where '1' indicates "no interest" and '5' indicates "very high interest". These three variables (age, controller position, and interest in technology) are mean-centered. Mean centering is commonly used when interpreting interactions in regression models to reduce multicollinearity and to aid interpretation (Aiken & West, 1991).

To measure the **existence of a DA department**, we ask respondents whether their company has a department, separate from the finance department, that is responsible for data analytics, even if it also performs other functions. **Firm size** is measured by asking respondents how many employees their company has, using the following categories: (i) Fewer than 50; (ii) 50 to 999; (iii) 1,000 to 9,999; (iv) 10,000 to 19,999; (v) 20,000 to 99,999; and (vi) 100,000 or more. Based on these categories, we group firms into three size classifications: small (options i and ii), medium (option iii), and large (options iv, v, and vi).

We also include four **control variables**: firm technology affinity, firm digital transformation implementation, gender, and education. Respondents rate their company's overall affinity with technology using a 5-point Likert scale, where '1' indicates "no affinity" and '5' indicates "very high affinity". Prior studies acknowledge that a firm's digital transformation maturity shapes how employees develop digital skills (e.g., Vial, 2021).

Respondents also rate their company's level of digital transformation implementation using a 5-point Likert scale, where '1' indicates "no initiatives" and '5' indicates "fully implemented". Prior research suggests that the extent of digital technology implementation within firms shapes how MAs develop digital competencies, adapt their roles, and utilize data analytics (e.g., Moll & Yigitbasioglu, 2019).

Respondents also indicate their gender. A digital gender gap has been acknowledged in prior studies, suggesting that males tend to have higher levels of digital competence than females (e.g., Fatehkia, Kashyap, & Weber, 2018). Finally, respondents indicate their highest level of education, with the following options: Bachelor's degree, Specialization degree, Master's degree, and PhD. Education has also been recognized as a potential determinant of individual digital competence (e.g., Hauk, Hüffmeier, & Krumm, 2018).

3.3 Data analysis method

Robust standard errors are used to produce consistent estimates even when the residuals are heteroskedastic or non-normally distributed (White, 1980; Wooldridge, 2010). We estimate models both with and without control variables. Additionally, we run parsimonious models including one interaction term at a time rather than both interaction terms simultaneously. This approach helps avoid inflating multicollinearity, which can make it difficult to isolate the unique effect of each interaction and results in a more complex, harder-to-interpret model (Aiken, West, & Reno, 1991). The basic regression model is specified as follows:

$$MAs\ Digital\ Competence = \alpha + \beta_1\ Idade + \beta_2\ Controlador + \beta_3\ InteresseTecnologia + \beta_4 DepartmentoAD + \beta_5 PorteEmpresa + \beta_6 Interação + \beta_7 Controles$$

4 Results

4.1 Descriptives

Table 4 presents descriptive statistics for the sample.

Panel A shows that, on average, MAs exhibit a digital competence score of 50.0, ranging from 24.1 to 64.7. The average age of MAs is 35.8 years, with 33.0% holding a controller position. The average level of interest in technology among MAs is 4.26.

Panel B indicates that 65.1% of the companies have an independent analytics department. The most common company size is fewer than 999 employees (44.0%), followed by firms with 1,000 to 9,999 employees (34.9%).

Panel B also shows that most MAs perceive their companies to have a high technology affinity (41.3%), followed by moderate (26.6%) and much (23.8%) affinity for technology.

Additionally, the majority of MAs perceive their companies as having significant progress in digital transformation (38.5%), followed by partial implementation (30.3%). Finally, Panel B reveals that, among the MA respondents, 55.1% are male, and 68.8% have completed specialization courses.

Table 4

Descriptive statistics for the main variables.

PANEL A					
Variables	N	Mean	Std. Dev.	Min.	Max.
Digital competence	109	50,00	10,05	24,07	64,67
Age	109	35,83	6,99	20,00	54,00
Position	109	0,33	0,47	0,00	1,00
Tech interest level	109	4,26	0,83	2,00	5,00
DA department	109	0,65	0,48	0,00	1,00
Firm size	109	1,77	0,78	1,00	3,00
Tech affinity	109	3,80	0,92	1,00	5,00
Digital transformation	109	3,58	0,97	1,00	5,00
Gender	109	0,55	0,50	0,00	1,00
Education	109	1,96	0,61	1,00	4,00

PANEL B	N.º	%
Position		
'0' Percentage of respondents (109) who do not hold a controller position	73	67,0
'1' Percentage of respondents (109) who hold a controller position	36	33,0
Tech interest level		
'2' Percentage of respondents (109) with low interest in technology	4	3,7
'3' Percentage of respondents (109) with moderate interest in technology	15	13,7
'4' Percentage of respondents (109) with high interest in technology	39	35,8
'5' Percentage of respondents (109) with much interest in technology	51	46,8
Independent analytics dept		
'0' Percentage of firms (109) without an independent analytics department	38	34,9
'1' Percentage of firms (109) with an independent analytics department	71	65,1
Firm size		
'1' Percentage of firms (109) with fewer than 999 employees	48	44,0
'2' Percentage of firms (109) with between 1,000 and 9,999 employees	38	34,9
'3' Percentage of firms (109) with more than 9,999 employees	23	21,1
Tech affinity		
'1' Percentage of firms (109) with no affinity for technology	1	1,0
'2' Percentage of firms (109) with low affinity for technology	8	7,3
'3' Percentage of firms (109) with moderate affinity for technology	29	26,6
'4' Percentage of firms (109) with high affinity for technology	45	41,3
'5' Percentage of firms (109) with much affinity for technology	26	23,8
Digital transformation		
'1' Percentage of firms (109) with no initiative for digital transformation	2	1,9
'2' Percentage of firms (109) in the initial stages of digital transformation	13	11,9
'3' Percentage of firms (109) in the partial implementation of digital transformation	33	30,3
'4' Percentage of firms (109) with significant progress in digital transformation	42	38,5
'5' Percentage of firms (109) with fully implemented digital transformation	19	17,4
Gender		
'0' Percentage of respondents (109) who are female	49	44,9
'1' Percentage of respondents (109) who are male	60	55,1
Education		
'1' Percentage of respondents (109) with an undergraduate degree	20	18,4
'2' Percentage of respondents (109) with a specialization degree	75	68,8
'3' Percentage of respondents (109) with a master's degree	12	11,0
'4' Percentage of respondents (109) with a doctoral degree	2	1,8

4.1.1 Correlations

Table 5 presents the correlation table. We observe that the digital competence score is lower for older MAs, while it is higher for MAs in the controller position and those with higher levels of interest in technology. Additionally, older MAs tend to be employed in smaller firms. It is also worth noting that MAs in the controller position are predominantly male. Furthermore, the presence of an independent DA department is associated with larger firms, as well as with firms that have higher levels of affinity for technology and progress in digital transformation.

Table 5
Correlation table

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Digital competence	1,00									
(2) Age	-0,19*	1,00	-							
(3) Position	0,24**	0,08	1,00							
(4) Tech interest level	0,30***	0,04	0,02	1,00						
(5) DA department	-0,15	0,00	0,02	-0,10	1,00					
(6) Firm size	0,11	-0,17*	-0,02	0,19**	0,31***	1,00				
(7) Tech affinity	0,01	0,10	-0,02	0,06	0,32***	0,25**	1,00			
(8) Digital transformation	0,08	0,04	-0,04	0,12	0,30***	0,21**	0,61***	1,00		
(9) Gender	0,29	-0,03	0,28***	0,10	-0,04	0,04	0,04	0,03	1,00	
(10) Education	0,06	0,27***	0,01	-0,09	-0,01	-0,02	0,05	-0,03	0,25***	1,00

This table presents Pearson correlations.
*, **, and *** indicate two-tailed statistical significance for the correlation at the 10%, 5%, and 1%, respectively.

4.1.2 Regression results

Table 6 presents the regression results for the digital competence score using robust standard errors, based on the 109 respondents described in Table 1. Columns (1), (3), and (5) show the results without control variables, while columns (2), (4), and (6) include control variables. Columns (1) and (2) do not include interaction terms, while columns (3) and (4) present the results with an interaction term between MAs' age and position. Finally, columns (5) and (6) include an interaction term between MAs' age and interest in technology.

We first observe that age has a negative and significant association with MAs' digital competence in all models. This is consistent with H1 and supports the idea that younger MAs are associated with higher levels of digital competence. We also observe that the MAs' position has a positive and significant association with digital competence in all models. This supports H2, which suggests that MAs holding a controller position have higher levels of digital competence. Additionally, we find support for H3, predicting that the level of MAs' digital competence is positively associated with their level of interest in technology. In all models, the results show a positive and significant association between digital competence and interest in technology.

Table6
Regression results

Model	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Digital competence	Digital competence	Digital competence	Digital competence	Digital competence	Digital competence
Age	-0,29*** (-2,46)	-0,33*** (-2,62)	-0,29*** (-2,54)	-0,34*** (-2,69)	-0,29*** (-2,43)	-0,34*** (-2,57)
Position	5,46*** (3,21)	4,62*** (2,65)	5,33*** (3,14)	4,59*** (2,69)	5,43*** (3,14)	4,62*** (2,62)
Age * Position	–	–	0,34* (1,53)	0,33* (1,44)	–	–
Tech interest level	3,29*** (2,86)	3,12*** (2,76)	3,20*** (2,76)	3,06**** (2,71)	3,28*** (2,84)	3,12*** (2,74)
Age * Tech interest level	–	–	–	–	0,03 (0,24)	-0,01 (-0,10)
DA department	-3,17* (-1,66)	-3,44** (-1,77)	-3,25** (-1,69)	-3,56** (-1,82)	-3,15* (-1,64)	-3,44** (-1,76)
Firm size	0,99 (0,74)	0,69 (0,49)	0,99 (0,74)	0,68 (0,48)	1,01 (0,75)	0,68 (0,48)
Control variables?	Não	Sim	Não	Sim	Não	Sim
N	109	109	109	109	109	109
Adjusted R^2	0,213	0,264	0,225	0,275	0,213	0,264

Notes: This table presents the results for regressing respondents' digital competence on respondents' age, position, tech interest level, their interactions, as well as firms' presence of independent analytics department and firm size. In all models, we run ordinary least squares with robust standard errors. All variables included in interaction terms are mean-centered. Two-tailed (one-tailed) tests are presented for nondirectional (hypothesized directional) expectations. Coefficients and (t-scores) provided. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

At the firm level, we observe in Table 6 a negative and significant association between the level of MAs' digital competence and the presence of an independent DA department across all models. This is consistent with H4, which predicts that the level of MAs' digital competence is negatively associated with the firm having an independent data analytics department. Finally, all models show that, although the association is positive, there is no significant relationship between MAs' digital competence and firm size, providing no support to H5.

Regarding the interactive associations, we first observe in Table 6 that the interactive term between age and position is positive and marginally significant in relation to MAs' digital competence. Figure 1 illustrates the predictive margins of digital competence across different age groups, separately for MAs holding a controller position and those who do not. The graph is based on the regression model presented in Table 6, column (3). The results indicate that while digital competence declines with age, this decline is less pronounced for controllers. The confidence intervals suggest that the difference is not statistically significant at younger ages but increases and becomes statistically significant as age advances. These findings support H6, which predicts that the negative association between MAs' digital competence and age is stronger for those who do not hold a controller position.

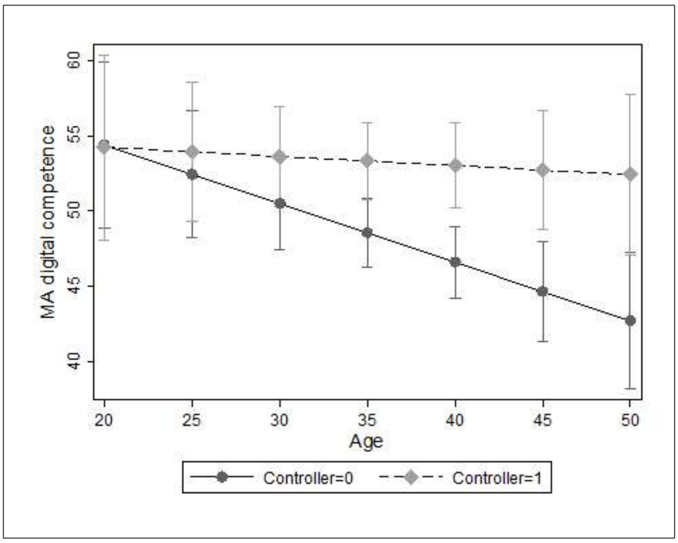

Figure 1. Interaction between age and position

We next observe in Table 6 that the interaction term between age and interest in technology is not statistically significant in relation to MAs' digital competence.

Figure 2 illustrates the predictive margins of digital competence across different age groups, comparing MAs with high versus low levels of interest in technology. This variable was dichotomized: MAs who selected '5' were coded as 1, and all others as 0. The graph is based on the regression model presented in Table 6, column (5).

The results suggest that, among older MAs, digital competence does not vary significantly with interest in technology. In fact, the trend appears reversed: among younger MAs, digital competence is lower when interest in technology is low. However, these interpretations should be made with caution, as the interaction is not statistically significant. Overall, these findings do not support H7, which predicts that the negative association between age and digital competence is stronger for those with lower interest in technology.

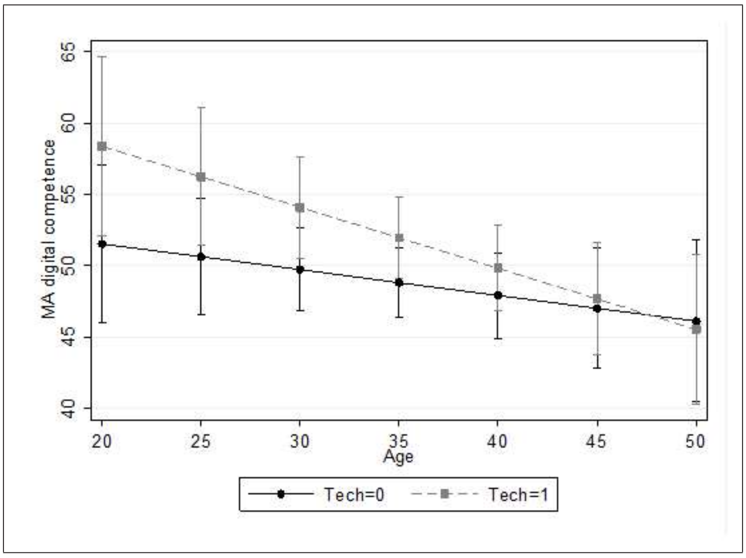

Figure 2. Interaction between age and interest in technology

5 Discussion and Conclusion

This study sought to examine the determinants of MAs' digital competence at both the individual and firm levels, while also proposing and validating a novel measurement instrument grounded in the competencies identified by professional associations such as the IMA and CIMA. Our analysis offers three main insights.

First, consistent with prior studies (e.g., Lee et al., 2010; Laakkonen et al., 2024), our results confirm that individual characteristics, particularly age, occupational position, and interest in technology, are more strongly associated with MAs' digital competence than firm-level factors. Consistent with H1, digital competence declines with age, supporting prior evidence that older professionals may face cognitive and motivational barriers to acquiring new technological skills (Lee et al., 2010; Hauk et al., 2018). In line with H2, MAs holding a controller position exhibit higher levels of digital competence, reflecting the greater technological demands and data-oriented responsibilities of this role. Similarly, we find support for H3, as MAs with greater interest in technology demonstrate higher competence levels, echoing the role of intrinsic motivation in skill development (Hidi & Renninger, 2006).

Second, our firm-level findings reveal a more nuanced picture. Contrary to expectations in H5 and prior studies (e.g., Li et al., 2018; Fähndrich & Pedell, 2025), firm size is not significantly related to MAs' digital competence. This suggests that organizational scale alone may not translate into effective skill development for finance professionals, perhaps due to uneven distribution of training opportunities or the persistence of role-specific boundaries, that is, MAs may still be "boxed in" by their defined job roles and not given opportunities to develop skills outside them, even in larger firms. More strikingly, in line with H4, we find that the presence of an independent data analytics (DA) department is negatively associated with MAs' digital competence. This result supports the notion that centralizing analytics functions may reduce opportunities for MAs to engage in hands-on data analysis, inadvertently limiting their exposure to digital tools and methods.

Third, our moderation analyses provide partial support for the role of occupational position in shaping the age–competence relationship. As predicted by H6, the negative association between age and digital competence is significantly stronger for MAs who are not controllers, highlighting the role of career progression in sustaining motivation for skill development. However, we do not find support for H7, as interest in technology does not significantly moderate the age–competence relationship.

Our findings contribute to the literature on management accounting in the digital era in three ways. First, they underscore that individual-level factors may outweigh firm-level characteristics in explaining digital competence, suggesting that personal motivation and career role are pivotal for adapting to technological change. Second, they challenge the assumption that structural investments, such as creating a dedicated DA department, inherently foster broader digital capabilities across the finance function. Instead, such initiatives may centralize expertise and reduce skill diffusion. Third, by developing and validating a scale to measure digital competence in MAs, this study provides a methodological tool for future research examining technological adaptation in accounting roles.

For practitioners, our results suggest that organizations should focus on nurturing digital competence through targeted professional development, especially for older MAs and those not in controller roles. Rather than fully outsourcing analytics to independent departments, firms may benefit from hybrid approaches that maintain MA engagement in analytical processes. This could enhance not only individual skill sets but also the strategic integration of digital insights into management accounting practices.

Like any study, ours has limitations that, at the same time, open opportunities for future research. This study's cross-sectional design limits causal inference, and the sample is restricted to professionals in Brazil, which may limit generalizability. Future research could adopt longitudinal designs to capture competence development over time, explore cross-country comparisons, and investigate how specific training interventions influence digital competence. Additionally, further work could examine how organizational culture and leadership (e.g., CFO—Chief Financial Officer) commitment to digital transformation interact with individual factors to shape competence outcomes.

Overall, our study highlights that MAs' digital competence is shaped more by who they are and the roles they hold than by the size or resources of their firms. We provide a validated instrument to measure this competence and evidence that certain structural arrangements, such as independent analytics departments, may unintentionally hinder skill development. These findings point to a potential trade-off for organizations: while centralizing analytics may yield efficiency gains, it may also slow the digital upskilling of finance professionals, an important consideration for firms seeking to future-proof their management accounting function.

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