Heli Kortesalmi

Developing the Intelligent Accounting Digital Maturity Model for SME Accounting Firms

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Tiivistelmä

Digitaalinen murros ja uudet teknologiat muuttavat taloushallinnon prosesseja ja käytäntöjä, mutta pienet ja keskisuuret yritykset (pk-yritykset) ovat automaation ja tekoälyteknologioiden käyttöönotossa jäljessä verrattuna suurempiin organisaatioihin. Tämä väitöskirja vastaa haasteeseen kehittämällä kokonaisvaltaisen älykkään taloushallinnon digitaalisen kypsyysmallin erityisesti pk-kokoisille tilitoimistoille. Kehitysprosessi noudattaa design science -tutkimuksen kolmea sykliä: relevanssia, tieteellistä huolellisuutta ja kehittämistä.

Väitöskirja koostuu neljästä empiirisestä esseestä. Ensimmäisessä esseessä tutkitaan pk-yritysten syitä automatisoida taloushallinnon prosesseja ja tunnistetaan automaation käyttöönottoon vaikuttavia tekijöitä. Toisessa esseessä sovelletaan teknologian hyväksymismallia (TAM) ja tutkitaan, ovatko ensimmäisessä esseessä aloitetut automaatiokokeilut vakiintuneet käyttöön. Tulokset osoittavat, että vaikka automaatio koettiin hyödylliseksi, sen käyttöönottoa rajoitti koettu vaikeus. Kolmannessa esseessä tarkastellaan tekoälyn käyttöönoton esteitä ja edistäviä tekijöitä taloushallinnon ammattilaisten keskuudessa. Keskeisiksi tekijöiksi nousivat osaaminen, järjestelmien yhteensopivuus, datan laatu ja helppokäyttöisyys. Neljännessä esseessä kehitetään kolmen ensimmäisen esseen osoittaman tarpeen pohjalta älykkään taloushallinnon digitaalinen kypsyysmalli (IADMM).

Väitöskirja tuottaa kolme toisiinsa kytkeytyvää teoreettista kontribuutiota. Ensinnäkin siinä kehitetään kokonaisvaltainen digitaalinen kypsyysmalli älykästä taloushallintoa varten. Malli kattaa taloushallinnon ydintoiminnot myynti- ja ostoreskontrasta palkanlaskentaan, raportointiin ja asiakasviestintään. Toiseksi malli kuvaa, miten taloushallinnon prosessit etenevät perustasolta älykkäisiin tekoälypohjaisiin prosesseihin, ja tarjoaa käsitteellisen viitekehyksen, joka laajentaa aiempaa kirjallisuutta digitaalisen taloushallinnon kehityksestä. Kolmanneksi väitöskirja tarjoaa uusia empiirisiä selityksiä siitä, miten pk-yritykset ottavat käyttöön automaatioteknologioita. Tulokset osoittavat, että onnistunut automaatio edellyttää teknologisen valmiuden lisäksi organisatorista valmiutta, yhteistyöverkostojen tukea sekä huomiota inhimillisiin tekijöihin kuten käytettävyyteen ja osaamisen kehittämiseen. Näin väitöskirja täydentää asiantuntijapalveluyrityksiä (PSF) koskevaa kirjallisuutta. Lisäksi IADMM-mallia voidaan hyödyntää tilitoimistoissa digitaalisten valmiuksien arviointiin ja järjestelmällisen kehittämisen suunnitteluun.

Asiasanat: taloushallinnon automaatio, älykäs taloushallinto, tilitoimistot, kypsyysmalli, pk-yritykset, design science

Abstract

Digital transformation is reshaping accounting processes and practices, yet small and medium-sized enterprises (SMEs) lag behind larger organisations in adopting automation and artificial intelligence technologies. This dissertation addresses this challenge by developing a digital maturity model specifically for SME accounting firms. The development process follows the design science research cycles of relevance, rigour and design.

The dissertation comprises four empirical essays that together form the foundation for this model. The first essay examines small firms' motivations for automating accounting processes and identifies factors influencing automation adoption. The second essay applies the technology acceptance model (TAM) to explore whether the automation experiments initiated in the first essay have transitioned into routine use. The findings show that although automation was perceived as useful, its adoption was constrained by perceived difficulty. The third essay investigates barriers to and enablers of artificial intelligence (AI) adoption among accounting and finance professionals. The professionals identified competence, system compatibility, data quality and ease of use as key factors. The fourth essay develops the Intelligent Accounting Digital Maturity Model (IADMM) in response to the needs identified in the three preceding essays.

The dissertation makes three interrelated theoretical contributions. First, it develops a holistic digital maturity model for intelligent accounting, encompassing core accounting functions from order-to-cash and purchase-to-pay to payroll, reporting and customer communication. Second, the model describes a staged progression of accounting automation from basic digitisation to intelligent, AI-driven processes, providing a conceptual framework that extends previous literature on the evolution of digital accounting. Third, the dissertation offers new empirical explanations of how SMEs adopt automation technologies in organisational settings, demonstrating that successful automation requires organisational readiness, collaborative network support and attention to human factors such as usability and competence development, thereby contributing to the professional service firm (PSF) literature. In addition to its theoretical contributions, the dissertation has practical relevance, as the IADMM can be applied in accounting firms to assess digital capabilities and plan systematic improvements.

Keywords: accounting automation, intelligent accounting, professional service firms, accounting firms, maturity model, SMEs, design science

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Helsinki, 3 August 2026.

Heli Kortesalmi

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Abbreviations

AI	Artificial Intelligence
BI	Business Intelligence
CMMI	Capability Maturity Model Integration
DSR	Design Science Research
EU	European Union
ERP	Enterprise Resource Planning
IADMM	Intelligent Accounting Digital Maturity Model
IoT	Internet of Things
IT	Information Technology
POC	Proof of Concept
PSF	Professional Service Firm
QMMG	Quality Management Maturity Grid
RPA	Robotic Process Automation
SLR	Systematic Literature Review
SME	Small and Medium-Sized Enterprise
TAM	Technology Acceptance Model

Publications

[1] Kortesalmi, H., Aunimo, L., & Kedziora, D. (2023). RPA Experiments in SMEs Through a Collaborative Network. In: Camarinha-Matos, L.M., Boucher, X., Ortiz, A. (eds) C*ollaborative Networks in Digitalization and Society 5.0. PRO-VE 2023. IFIP Advances in Information and Communication Technology*, (pp. 761-773). Springer, Cham. https://doi.org/10.1007/978-3-031-42622-3_54. © 2023 IFIP International Federation for Information Processing. Reprinted with the kind permission of Springer.

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Author's Contribution

Essay I. First author. Project management; defining the research design; collecting and managing research materials; data analysis; methodology and research methods; verification and analysis of findings; visualisation of results; writing the body text of the original essay; and editing the essay at different stages.

Essay II. First author. Project management; defining the research design; collecting and managing research materials; data analysis; methodology and research methods; verification and analysis of findings; visualisation of results; writing the body text of the original essay; and editing the essay at different stages.

Essay III. First author. Project management; defining the research design; collecting and managing research materials; data analysis; methodology and research methods; writing the body text of the original essay; editing the essay at different stages; and acquiring research resources.

Essay IV. Sole author.

1 INTRODUCTION

1.1 Background

This dissertation develops the intelligent accounting digital maturity model (IADMM), a framework designed to support SME accounting firms in advancing their automation capabilities. The model contributes to the accounting and digital maturity model literature by developing a holistic maturity model specific to intelligent accounting. The development process follows design science research cycles of relevance, rigour, and design (Hevner, 2007). Technological advancements have long been recognised as key drivers of change in accounting (Taipaleenmäki & Ikäheimo, 2013), and today, tasks that were once manual, time-consuming, and error-prone, such as invoice processing, bank reconciliations, and financial reporting, are increasingly automated through intelligent technologies (Kruskopf et al., 2020; Cooper et al., 2022). Nevertheless, prior research has largely examined individual technologies and their effects rather than how enabling conditions and accounting processes jointly evolve as firms mature in digital terms. The IADMM addresses this gap through a design science approach that is both theoretically grounded and practically applicable.

Certain technological advancements have had such a profound impact on working life, including accounting, that the literature, particularly in technology-oriented fields, refers to the industrial revolution and its successive phases using version numbers similar to those of software releases (Industry 1.0, Industry 2.0, and so on) (e.g., Xu et al., 2021; Mourtzis et al., 2022). This numbering convention has also been adopted by the European Union (European Commission: Directorate-General for Research and Innovation, 2021). As this dissertation examines the development of automation and artificial intelligence and their impact on accounting work, these industrial revolution 'versions' provide a useful framework for situating the transformation in its historical context. The following paragraphs therefore briefly outline the characteristics of each phase.

Since the First Industrial Revolution (Industry 1.0) in the late eighteenth century, technological innovation has been a driving force behind economic and societal change. Industry 1.0 introduced mechanical power through steam engines, while Industry 2.0, emerging in the late nineteenth and early twentieth centuries, brought electrical energy and mass production. Although these early industrial revolutions had limited direct impact on accounting practices, they laid the groundwork for the technological developments that would later transform the profession. The Third

Industrial Revolution (Industry 3.0), beginning in the late twentieth century, marked the integration of electronics and information technology into production systems, bringing the first significant changes to accounting through computerisation and early automation (Jaatinen et al., 2021; Mourtzis et al., 2022).

The Fourth Industrial Revolution (Industry 4.0), emerging in the 2010s, had an even more profound impact on the field of financial management by leveraging emerging technologies such as cloud computing, artificial intelligence (AI), blockchain, the Internet of Things (IoT), and big data analytics (Moll & Yigitbasioglu, 2019; Kruskopf et al., 2020; Mourtzis et al., 2022; Igou et al., 2023). These technologies enable the creation of smart, interconnected systems that can operate autonomously and adaptively, introducing new opportunities to automate financial processes, improve data accuracy, and enhance decision-making capability (Lehner et al., 2022). While Industry 4.0 continues to reshape financial administration, Industry 5.0, introduced in the early 2020s, shifts the focus from purely technological advancement to human-centric innovation. It emphasises sustainability, resilience, and worker well-being, complementing Industry 4.0 by integrating societal goals into industrial transformation (Xu et al., 2021; Kans & Campos, 2024). Notably, the European Commission has explicitly endorsed Industry 5.0, arguing that industrial transformation should move beyond the technology- and efficiency-driven focus of Industry 4.0 towards a sustainable, human-centric, and resilient European industry (European Commission: Directorate-General for Research and Innovation, 2021).

Within this technological landscape, intelligent automation is a particularly significant development for accounting. The concept of intelligent accounting builds upon traditional automation by incorporating advanced AI capabilities. This includes intelligent automation, which combines robotic process automation (RPA) with AI (Siderska et al., 2023). Accounting is a rule-based and data-intensive domain, and is therefore particularly suited to such a transformation (Kokina & Davenport, 2017; Leitner-Hanetseder et al., 2021). The literature already includes investigations of some implementation in the form of cognitive computing in accounting task automation (Marshall & Lambert, 2018), intelligent process automation in auditing (Zhang, 2019), and smart robots in AI-based accounting (Leitner-Hanetseder et al., 2021). The impact of intelligent accounting extends beyond efficiency gains, to encompass a more transformative shift that affects both accounting processes and the professionals who conduct them (Igou et al., 2023; Jackson & Allen, 2024; Kokina et al., 2025; Mukherjee et al., 2025). These technologies enable systems to learn from data, adapt to new patterns, and autonomously manage tasks that previously required human judgement (Dong, 2024).

Despite their significant potential these technologies have not been widely adopted across organisations of all sizes. According to Eurostat (2025), only 11% of small and 21% of medium-sized enterprises in the EU have implemented AI solutions, compared to 41% of large firms. Large organisations have already begun to automate routine accounting tasks such as invoice processing, reconciliations, and reporting, SMEs are only beginning to follow. For SMEs, understanding and adopting these changes is both an opportunity and a challenge (Eller et al., 2020; Matalamäki & Joensuu-Salo, 2022). Nevertheless, SMEs play a vital role in national economies, in the European Union, they represent over 99% of all businesses and account for approximately two-thirds of total employment (European Commission, n.d.). However, they typically operate with limited financial resources, smaller IT infrastructures, and fewer specialised personnel than their larger counterparts, factors that hinder the adoption of advanced technologies. Moreover, research suggests that SMEs often overestimate their level of digitisation and ICT capabilities (Bley et al., 2016), underscoring the need for systematic tools to assess digital maturity and to guide technological development. This challenge is especially relevant in professional service firms (PSFs), such as accounting firms, which combine the resource constraints typical of SMEs with knowledge-intensive, low-capital and professionalised service delivery operating within regulated environments (von Nordenflycht, 2010).

Digital maturity models offer a structured approach that organisations can adopt to assess their current technological capabilities and identify the next steps for development (De Bruin et al., 2005; Becker et al., 2009). A maturity model, typically presented in a matrix format, describes development through stages or levels, where each level represents greater capability, and the model also shows what is needed to reach the next stage (Becker et al., 2009). Although digital maturity models are well established in the information technology (IT) domain, the accounting literature has devoted comparatively little attention to their development and application. Existing models tend to focus on specific subdomains such as management control systems (Pekkola et al., 2015), electronic invoicing (Cuylen et al., 2016), auditing (Mantelaers & Zoet, 2018; Dobrinić, 2020), or tax consulting (Diller et al., 2020), rather than encompassing all core accounting processes. Some models assess individual professionals' digital competencies (Karcıoğlu & Binici, 2023) rather than organisational capabilities, while others, such as the questionnaire-based index by Hentati and Boulila (2023), measure current levels of digitalisation rather than providing a developmental framework for advancing maturity.

Although interest in accounting automation and intelligent accounting is increasing (Moll & Yigitbasioglu, 2019; Kruskopf et al., 2020), and digital maturity models are widely studied (see De Bruin et al., 2005; Becker et al., 2010; Proença & Borbinha, 2016; Williams et al., 2019; Thordsen et al., 2020; da Silva et al., 2024), no holistic digital maturity model for intelligent accounting has yet been developed. As discussed above, existing maturity models in accounting have focused on isolated subdomains rather than providing a holistic view of how intelligent accounting evolves as an organisation-wide capability. That gap limits our theoretical understanding of how intelligent accounting develops as an organisational capability, particularly in resource-constrained contexts where the dynamics of capability development may differ from those observed in larger organisations.

1.2 The purpose of this dissertation

This dissertation seeks to advance the theoretical understanding of how intelligent accounting develops as an organisational capability. It addresses that aim by developing a holistic digital maturity model for intelligent accounting processes, grounded in theory and practice. The development process is structured around the design science research cycles of relevance, rigour, and design (Hevner, 2007), ensuring both theoretical grounding and practical applicability.

As SMEs typically outsource their financial management to accounting firms, the maturity model is specifically designed for accounting service providers (also referred to as professional service firms, or PSFs). This approach offers an effective means of advancing financial management development across the SME sector. It also responds to calls for more research on professional service firms in the accounting domain (Yigitbasioglu et al., 2023).

This dissertation adopts a mixed-methods research approach, combining qualitative case studies, an exploratory survey, and design science research, thereby explicitly balancing scholarly rigour with practical relevance, making it particularly suited to developing artefacts intended for real-world applications (Iivari, 2007). Within this framework, the first three studies delimit the problem and assess its relevance. The first essay relies on a multiple case study to examine motivations and experiences of small enterprises that implement automation in their accounting processes. The second essay applied the technology acceptance model (TAM) (Davis, 1989) to investigate whether the automation pilots mentioned above were integrated into routine. Its results revealed that although automation was considered useful, it was not perceived to be easy to use. These observations were further examined in the third essay, which conducted an exploratory survey investigating barriers to and enablers of AI adoption among accounting and finance practitioners. In combination, these empirical studies constitute the relevance cycle of design-science research (Hevner, 2007), establishing both the practical need and the relevance criteria that design science requires. The fourth essay develops a digital maturity model to address the identified challenges, providing organisations with a structured pathway to support technological development. The fourth essay represents both the design cycle and the rigour cycle of Hevner's (2007) framework: the maturity model constitutes the design cycle artefact, while the iterative expert validation and systematic literature review ensure scholarly rigour in line with the rigour cycle. The development of the maturity model followed the procedure model proposed by Becker et al. (2009). A theoretical foundation was constructed through a systematic literature review, after which the model was iteratively refined through 15 expert interviews conducted in five rounds to ensure practical applicability. The development process was documented throughout, and finally, the model was validated through application in three accounting firms of different sizes.

This dissertation offers three interrelated theoretical contributions that integrate technological, organisational, and human dimensions of accounting automation. First, it develops a holistic digital maturity model for intelligent accounting that encompasses all core accounting functions, contributing to the accounting information systems literature by providing a theoretically grounded framework for assessing and advancing automation capabilities. Second, the model reveals a staged progression of accounting automation moving from basic digitisation to intelligent, AI-driven processes. In doing so, the model contributes to extending prior literature on the evolution of digital accounting (Jaatinen et al., 2021; Lehner et al., 2022) by offering a conceptual framework illustrating how accounting work transforms across progressive levels of maturity. Third, the dissertation offers new empirical explanations of how SMEs adopt automation technologies in real organisational settings. The three empirical studies demonstrate that successful automation in SMEs is not solely a technological challenge but requires organisational readiness, collaborative network support, and attention to human-centric factors such as usability and competence development. These findings contribute to the PSF literature (Tomo et al., 2020; Cardinali et al., 2023; Rieg & Radeck, 2024) and align with the human-centric perspective emphasised in the emerging Industry 5.0 discourse (Xu et al., 2021). Beyond its theoretical contributions, the maturity model is useful in practical terms, as it can be directly applied in accounting firms to assess current digital capabilities and plan systematic improvements.

The remainder of this dissertation is structured into five main chapters. Chapter 2 presents the overall contribution of the dissertation and outlines the specific contributions of each of the four essays. Chapter 3 provides the theoretical underpinnings for the study. It begins with an overview of maturity models and digital maturity models, followed by a discussion of the phases of accounting development from early computerisation to intelligent accounting. The chapter concludes by examining PSFs and their digitalisation, establishing the organisational context within which the maturity model is applied. Chapter 4 describes the methodological foundations of the dissertation. It begins with the philosophical positioning of the research, followed by a discussion of the mixed methods approach combining qualitative, quantitative, and design science research. The chapter further elaborates on design science as the overarching framework for developing the maturity model, presenting Hevner's (2007) three cycles: the relevance cycle, the rigour cycle, and the design cycle, and their role in structuring the empirical studies. The chapter concludes with a description of the data collection and analysis methods applied across the studies. Chapter 5 summarises the four individual essays. The first three essays address different aspects of automation adoption, implementation barriers, and practitioner perceptions. In contrast the fourth essay presents the development and validation of the Intelligent Accounting Digital Maturity Model as the primary design science artefact. The essays are provided in the appendix. The sixth and final chapter presents the conclusions, including a summary of the dissertation, theoretical and practical implications of the findings, limitations of the research, and directions for future research.

2 CONTRIBUTION

This dissertation makes three interrelated contributions that integrate technological, organisational, and human dimensions of accounting automation in SMEs, examined through the lens of PSFs as the primary organisational context.

2.1 Contribution of the dissertation

The first contribution is the development of the Intelligent Accounting Digital Maturity Model (IADMM), a holistic framework intended to aid small and medium-sized accounting firms. While digital maturity models are well-established in IT research (Williams et al., 2019; da Silva et al., 2024), their application to accounting remains limited. Existing models focus narrowly on single functions such as electronic invoicing (Cuylen et al., 2016), or auditing (Mantelaers & Zoet, 2018), or measure digital maturity levels without providing structured developmental guidance (Hentati & Boulila, 2023). The IADMM addresses this gap by encompassing all core accounting functions within a single integrated framework. The model comprises 11 dimensions and five maturity levels. Four dimensions address foundational capabilities: technology infrastructure, process management, vision and leadership, and data and cybersecurity. The remaining seven dimensions are tailored to accounting practice: the role of the accountant, reporting and customer communication, sales-to-cash, purchase-to-pay, payments, general ledger, and payroll. The model was developed following the design science paradigm (Hevner, 2007; Geerts, 2011), and especially by the procedure model by Becker et al. (2009), ensuring both theoretical rigour and practical relevance through systematic literature review, 15 expert interviews, and validation in three accounting firms.

The second contribution emerges from the development process itself. The maturity model reveals a staged progression of accounting automation, from basic digitisation through rule-based automation to intelligent, AI-driven processes. This staged view offers a conceptual framework describing how accounting work transforms across different levels of automation maturity. Prior research has documented the historical evolution of digital accounting from computerisation of financial accounting (1970–1990) through digitally processed administration (1990 onwards) to robotics and AI in the mid-2010s (Jaatinen et al., 2021; Lehner et al., 2022). While Jaatinen et al. (2021) identify electronic automated financial accounting as the latest phase without elaborating its internal development, and Lehner et al. (2022) distinguish digitally-assisted, semi-autonomous, and fully autonomous accounting, this dissertation provides a more granular view by decomposing that transition into five distinct maturity levels with actionable descriptors for each stage (see Figure 1). This perspective has implications for the transformation of accounting work. The accountant's role evolves from one based on data entry and statutory compliance at lower maturity levels through consultative support to integrate specialised expertise at the highest levels.

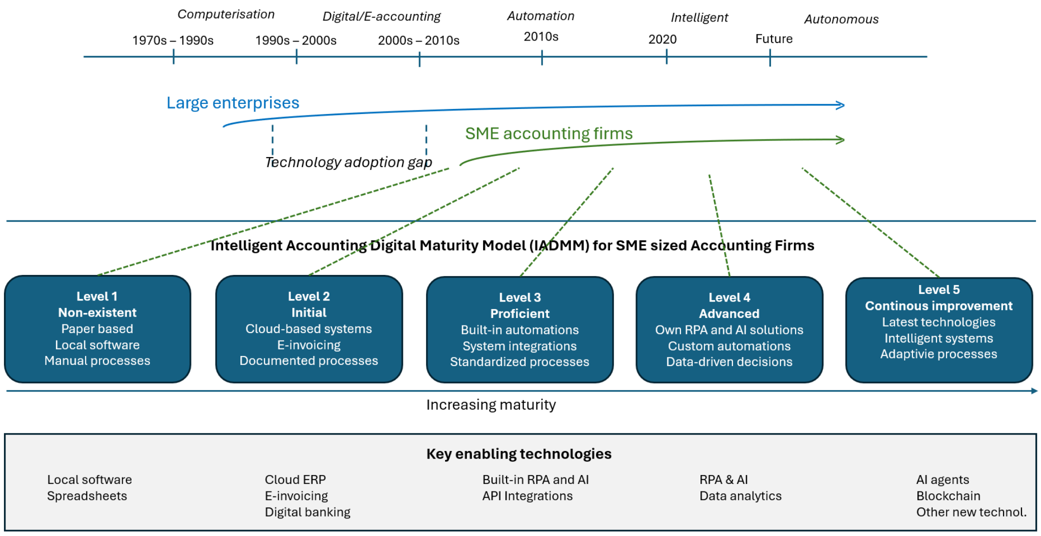

Figure 1. Evolution of accounting technology and digital maturity

Third, the dissertation offers new empirical explanations of how SMEs adopt automation technologies in real organisational settings. This contributes to a growing body of research recognising that technology adoption in smaller firms follows different patterns from those in large organisations (Eller et al., 2020; Matalamäki & Joensuu-Salo, 2022). The essays integrate case studies, interviews and exploratory surveys to show that adoption patterns in small firms are governed less by technological potential and more by human-centric enablers such as job meaningfulness, usability, skills availability and collaborative networks, findings that reflect the emerging Industry 5.0 perspective (Xu et al., 2021). The findings also reveal that SMEs rely on external ecosystems to compensate for missing internal capabilities. These insights contribute to the under-researched literature on small PSFs (Tomo et al., 2020; Cardinali et al., 2023; Rieg & Radeck, 2024).

The contribution of this dissertation extends beyond its theoretical contributions to issues of practical relevance. The IADMM serves as a diagnostic and developmental tool that enables accounting firms to assess digital capabilities and plan improvements. By decomposing transformation into incremental steps across defined dimensions, the model enables resource-constrained organisations to pursue development without large-scale investments.

For researchers, the model also provides a foundation for future empirical work. The structured dimensions enable the quantification of digital maturity for statistical testing in cross-sectional and longitudinal studies.

2.2 Contributions of the individual essays

The first essay contributes to the accounting literature by demonstrating that small and micro-sized firms adopt RPA primarily to eliminate repetitive office work and improve internal process quality, rather than to pursue cost savings or external differentiation. In doing so, the essay shows that the motivations behind automation in small firms differ from those typically reported in large-firm settings. The findings also confirm prior research indicating that RPA is most successful in situations where tasks are rule-based, frequent and well documented, and extend this pattern to the small-firm context. Importantly, the essay demonstrates that business process modelling and governance are equally essential in small firms as they are in larger organisations: clear processes and explicit process descriptions are necessary prerequisites for viable automation. Finally, the essay highlights the role of collaborative networks as practical surrogates for internal centres of excellence, enabling test-before-invest experimentation and peer learning that help resource-constrained firms lower the barriers to early adoption.

The second essay contributes to accounting research by applying the TAM (Davis, 1989) to small-firm accounting automation and revealing a clear asymmetry between perceived usefulness and perceived ease-of-use. Although participants recognised productivity and job satisfaction benefits, implementation lagged due to skills gaps, time scarcity and maintenance concerns. By revisiting the firms (that informed the research reported in Essay I) one year after their initial exposure to automation, the second essay demonstrates how perceived usefulness remains stable over time while ease-of-use constraints persist. The essay advances understanding of collaborative ecosystems as catalysts for internal process change, showing that participation in shared training, peer interaction and test-before-invest activities improves awareness, task identification and the readiness to experiment with automation. At the same time, the findings demonstrate that such ecosystems only partially resolve the skills deficit, meaning that perceived ease-of-use does not increase at the same pace.

The third essay contributes to accounting and finance research by showing that professionals in accounting and finance fields approach AI adoption primarily through a human-centric lens, reflecting elements of the Industry 5.0 perspectives emerging in accounting and finance practice. This extends and reinforces the ease-of-use findings of the second essay by demonstrating that, in the AI context, usability becomes an even more salient practical requirement than ethical or transparency-related issues often highlighted in prior literature. The essay additionally demonstrates that organisational context shapes these human-centric needs: micro-sized organisations rely heavily on collaboration and external networks to compensate for limited internal capabilities, while larger organisations prioritise well-integrated and seamless user experiences to support their more complex system environments.

The fourth essay explicates the intelligent accounting digital maturity model (IADMM) introduced above. The model contributes to accounting and maturity model literature as the first holistic, accounting-specific digital maturity model covering both transversal enablers and the full process landscape of SME-sized accounting firms. The IADMM translates the staged evolution of digital accounting into actionable level descriptors, making role change, process governance and the adoption of RPA and AI empirically tractable for future longitudinal and comparative studies. Methodologically, the essay demonstrates the value of design science in accounting by creating a theory-based but practitioner-validated maturity model that firms can use as a roadmap for sequencing investments from cloud-native automations toward bespoke solutions, thereby reducing implementation risk and aligning technology choices with organisational readiness.

3 THEORETICAL UNDERPINNINGS

This chapter presents the theoretical foundation of the dissertation by examining three interconnected themes. It begins with an overview of maturity models, tracing their historical development and defining digital maturity models as a distinct category, then reviews existing maturity models in the accounting domain and identifies the gap addressed by the dissertation. The chapter then discusses the phases of accounting development, from early computerisation through digital and e-accounting to intelligent automation. Finally, it examines PSFs and their digitalisation, establishing the organisational context within which the maturity model is applied.

3.1 Maturity models

Maturity models are structured assessment tools enabling organisations to evaluate their current state of technology or process adoption, identify quality gaps, and define improvement pathways. An organisation that conducts such an evaluation, can also recognise the new capabilities and skills its workforce may need to develop (Becker et al., 2009; Becker et al., 2010). Becker et al. (2009) reported that a maturity model consists of a series of progressive levels that represent the expected or desired development path of a particular class of objects, such as organisations, business processes, information systems, or project management practices.

The theoretical rationale for maturity models rests on the assumption that organisational capabilities develop through predictable, sequential stages. This premise aligns with broader theories of organisational growth and technological change. Organisational life cycle theory posits that firms progress through distinct developmental phases, each characterised by specific challenges, structures, and capabilities (Hanks et al., 1993; Van De Ven & Poole, 1995). Similarly, Rogers' (2003) diffusion of innovations theory demonstrates that technology adoption follows identifiable patterns from initial awareness through implementation to routinisation. Maturity models operationalise these insights by translating abstract developmental trajectories into observable, assessable characteristics. For resource-constrained organisations such as SMEs, this structured approach offers value: it reduces complexity by decomposing transformation into manageable increments and provides clear benchmarks against which to measure progress (Becker et al., 2009).

Maturity models are commonly structured as a grid or matrix (see Table 1), presenting dimensions along the vertical axis and maturity levels along the horizontal axis (Proença & Borbinha, 2016). Dimensions, also referred to as elements (Saari et al., 2019) or categories (Crosby, 1979), capture the specific areas of capability or processes within a domain, while the maturity levels (or stages) describe the extent to which each dimension has been developed (De Bruin et al., 2005). As illustrated in Table 1, this structure forms a matrix in which each cell describes the characteristics of a specific dimension at a given maturity level. Each maturity level should define its requirements explicitly and be clearly distinguishable from the levels that precede and follow it (Nolan, 1973; Fraser et al., 2002). Based on the results of a current-state assessment, organisations can derive and prioritise improvement actions to progress toward higher maturity levels (Becker et al., 2010).

Table 1. Example of a typical maturity model structure.

Dimension/ Level	Level 1	Level 2	Level 3
Dimension 1	Description	Description	Description
Dimension 2	Description	Description	Description
Dimension 3	Description	Description	Description

The origins of maturity models lie in the 1970s. One of the earliest examples is Nolan's (1973) five-stage model for managing computer resources, which was developed to support more efficient investment in computing and system development. Around the same period, Crosby's (1979) Quality Management Maturity Grid (QMMG) emerged as another seminal framework, categorising quality management practices along five maturity stages and six measurement categories. Although created for quality management, the QMMG provided an important conceptual foundation for later models, most notably the Capability Maturity Model (CMM) developed by the Software Engineering Institute in 1993 (Paulk et al., 1993). The CMM is widely regarded as the first influential IT-related maturity model and was later expanded into CMM Integration (CMMI) (Wendler, 2012).

These early contributions established the foundations for the broad landscape of maturity models used today. While software development remains one of the most common application domains, maturity models have since been adopted across a wide range of fields, including project management, business processes, and knowledge management (Wendler, 2012). In particular, IT and technology-oriented models have become central in evaluating areas such as IT infrastructure management, enterprise architecture management, and knowledge management (Rosemann & De Bruin, 2005).

Despite their widespread adoption, maturity models have been scholarly criticised. A fundamental criticism concerns the assumption of linearity: models typically presuppose sequential progression through defined stages, yet empirical evidence suggests development paths can also be non-linear, with organisations skipping stages or regressing (King & Kraemer, 1984; Pöppelbuß & Röglinger, 2011). Critics have also questioned the universalist orientation, arguing that many models fail to account for contextual factors, such as industry characteristics or organisational culture (Mettler & Rohner, 2009). Notwithstanding these limitations, maturity models remain valuable when designed to account for domain-specific requirements and validated through empirical application. For SMEs, maturity models are effective because their step-by-step structure aligns with situations in which resources are limited and large-scale transformation projects are not feasible.

Among the various forms of maturity models, digital maturity models constitute a distinct category. Williams et al. (2019) identify two key characteristics that differentiate them from general maturity models. First, digital maturity models focus on areas inherently linked to technological activity, such as information technology (IT) or business intelligence (BI). Second, their conceptual vocabulary incorporates terms such as *digital*, *Industry 4.0*, *smart*, *data-driven*, or *cloud*. Despite these digital-specific elements, the fundamental purpose remains aligned with traditional maturity models: to evaluate the gap between an organisation's current and desired future capabilities (Williams et al., 2019). Organisations use digital maturity models to assess progress in digitalisation systematically (Kalpaka, 2023) and to generate quantitative maturity indices that represent their stage of digital transformation (Hentati & Boulila, 2023). Consequently, a wide range of digital maturity models has been developed to address industry-specific needs and organisational contexts (see Williams et al., 2019; Thordsen et al., 2020; Kirmizi & Kocaoglu, 2023).

Although digital maturity models are widely established in the IT domain, research focusing specifically on accounting remains limited. One of the most closely related accounting models is Cuylen et al.'s (2016) electronic invoice process maturity model, which comprises four dimensions, technology, processes and organisation, acceptance, and strategy. Its maturity levels range from non-existent paper-based invoicing to continuous improvement. While directly connected to accounting practice and well-structured for its purpose, the model focuses solely on the e-invoicing process, limiting its suitability for evaluating the digitalisation of accounting functions more broadly (Cuylen et al., 2016).

Hentati and Boulila (2023) propose a broader digital maturity framework in the accounting context and develop a digital maturity index specifically designed for accounting service providers in Tunisia. Unlike traditional matrix-based models, this index adopts a life-cycle approach and computes maturity scores from questionnaire data. The instrument assesses technology use across a range of areas, including software, cloud services, big data, AI, blockchain, connectivity, and cybersecurity, with separate items for auditing, reporting, and taxation processes (Hentati & Boulila, 2023).

Beyond these two accounting-related digital maturity models that are most closely aligned with the present study, several additional models have been developed for specific accounting subdomains over the past decade. One of the earlier contributions is Tavallaei et al.'s (2015) business intelligence maturity model, which evaluates structure and rules, organisational culture, and technology. Around the same period, Pekkola et al. (2015) presented a maturity model designed to assess management control systems at the organisational level, offering a structured framework for assessing the development of management accounting practices. Mantelaers and Zoet (2018) subsequently proposed a continuous auditing maturity model designed to support simultaneous auditing as accounting data entered information systems. In management accounting, Lebedev (2019) developed a maturity model grounded in global management accounting principles, adding another perspective on organisational-level capability development.

More recent contributions expand maturity assessment to additional accounting domains. Dobrinić (2020) developed a comprehensive auditing digitalisation model, measuring maturity across digital culture, organisation, IT, strategy, and transformation management. Diller et al. (2020) constructed a digital maturity assessment for tax consulting companies, highlighting the increasing need for strong managerial leadership and digitally oriented employee competencies. Soguel and Luta (2021) developed a model for evaluating the maturity of accounting standard implementation within Swiss cantonal regulatory frameworks, while Ardiansah et al. (2021) developed a computer-based accounting maturity model tailored to SMEs. Xiang (2022) later proposed a structured model for accounting data management, organised around data strategy, application, and life cycle. Finally, Karcioğlu and Binici (2023) shifted the focus from organisational processes to the individual level by developing a model for assessing the digital abilities and skills of accounting professionals.

Research on accounting-related maturity models is a diverse yet relatively specialised body of work. While not a dominant research stream within accounting, the relevant studies have attracted increasing attention, particularly in areas where accounting intersects with information systems. This interdisciplinary connection is also reflected in the methodological foundations of maturity model development. Accordingly, research on maturity models in accounting typically draws on design science methodologies (Hevner, 2007; Becker et al., 2009), and several of the models discussed earlier, including those by Cuylen et al. (2016) and Lebedev (2019), apply design science principles to support both conceptual grounding and practical relevance.

3.2 Accounting development phases and technologies

Technological advancements have long been recognised as key drivers of change in accounting. As early as in the 1990s, scholars including Elliott (1992), Wallman (1997), and Olivier (2000) emphasised the transformative role of technology in the field. Subsequent research has reinforced this view, demonstrating how digital technologies have reshaped both accounting practices and the profession itself (Taipaleenmäki & Ikäheimo, 2013).

The evolution of accounting can be divided into distinct phases based on technological capabilities. The first phase, spanning the 1970s to the 1990s, was characterised by computerisation, which shifted accounting from manual bookkeeping to digital data entry and processing (Knudsen, 2020; Jaatinen et al., 2021). The second phase emerged in the 1990s with the rise of electronic and paperless bookkeeping, often referred to as digital accounting (Jaatinen et al., 2021). This phase involved the digitisation of financial documents through electronic invoicing and other structured, machine-readable data formats, but at the same time brought more responsibilities to accounting departments by giving access to new sources of data (Knudsen, 2020). Throughout the 2000s and early 2010s, the gradual adoption of web-based technologies and digital platforms allowed accounting information systems to consolidate data flows from multiple sources and process financial information in real time (Jaatinen et al., 2021; Pargmann et al., 2023).

The third phase, beginning around 2010, introduced greater levels of automation in accounting processes (Knudsen, 2020; Jaatinen et al., 2021). From the mid-2010s onward, rule-based robotic process automation emerged, enabling software systems to handle tasks such as transaction processing, reconciliation, and reporting (Lehner et al., 2022). Building upon automation, intelligent accounting represents the current frontier of development. This concept integrates RPA with AI capabilities (Siderska et al., 2023), creating systems that replicate human cognitive functions such as problem-solving and strategic thinking (Coombs et al., 2020). Unlike traditional automation, intelligent systems can adapt, learn, and generate strategic insights to support decision-making (Marshall & Lambert, 2018; Leitner-Hanetseder et al., 2021).

Looking ahead, scholars envision a fully autonomous accounting system as the ultimate stage of development. At this level, AI would perform advanced cognitive tasks, apply regulations, generate real-time insights, and interact with auditors through secure infrastructures. Accounting processes would become self-managed and adaptive, with AI systems capable of learning and making strategic decisions autonomously (Lehner et al., 2022; Pargmann et al., 2023). However, this vision remains largely speculative, and is subject to significant technical, ethical, and regulatory uncertainties. Questions regarding accountability, transparency, and the appropriate role of human judgement in financial reporting remain unresolved.

In the current technological landscape, accounting organisations increasingly depend on cloud-based accounting information systems to manage core processes such as sales-to-cash, purchase-to-pay, and payroll. These systems have transitioned from locally installed software to scalable ERP solutions maintained by external service providers, incorporating features such as structured data input, real-time reporting, e-invoicing, digital bank statements, and automated transaction processing (Moll & Yigitbasioglu, 2019; Ma et al., 2021).

Automation in accounting has been largely based on rule-based systems, particularly RPA, which is effective for tasks governed by clear rules and structured digital data (Kokina & Blanchette, 2019; Tiron-Tudor et al., 2024). Robotic process automation aims to automate repetitive tasks, such as invoice processing, bank reconciliation, and report generation. Its accessibility has been enhanced by low-code platforms, which enable employees lacking programming expertise to create simple automation workflows (Bock & Frank, 2021). However, RPA presents challenges arising from its limited adaptability; because it relies on predefined rules and structured inputs, maintaining and updating RPA solutions can become resource-intensive when underlying systems or processes change (Kokina & Blanchette, 2019).

Intelligent accounting combines RPA with artificial intelligence (AI) to overcome the limitations of traditional rule-based automation (Siderska et al., 2023; Coombs et al., 2020; Leitner-Hanetseder et al., 2021). Such AI-enabled tools can automate high-volume tasks and thereby streamline core accounting processes, such as accounts payable, accounts receivable, and payroll, by processing both structured and unstructured financial data, the latter of which traditional RPA could not handle alone (Kokina & Blanchette, 2019; Zhang, 2019). In addition, artificial intelligence can draw on an organisation's historical data and earlier human judgements to perform accounting tasks such as preparing accrual estimates, identifying potential impairment indicators, and carrying out reconciliations (Petkov, 2020).

Artificial intelligence tools also expand data analysis and reporting options. Organisations comfortable with big data and data analytics can process both structured and unstructured data, as well as vast and complex datasets, enabling real-time decision-making and more accurate risk identification (Mukherjee et al., 2025). Artificial intelligence can thus enhance the credibility and accuracy of financial reporting while enabling timely and data-driven analysis across accounting functions (Abdo-Salloum & Chehade, 2026). However, while big data has transformative potential for accounting by enabling data-driven insights, realising these benefits requires adequate resources, expertise, and attention to data quality and reliability (Theodorakopoulos et al., 2024).

Blockchain technology has similarly attracted scholarly attention in accounting research, given its potential to enable secure, transparent, and tamper-proof record-keeping (Abdennadher et al., 2022). In principle, blockchains could transform accounting by enabling real-time verification of transactions, reducing the need for traditional reconciliation processes, and enhancing audit trail integrity (Dai & Vasarhelyi, 2017). Some scholars suggest that distributed ledger technology could eventually support continuous auditing and triple-entry accounting systems, where transactions are cryptographically sealed and shared by relevant parties (Cai, 2021). However, despite considerable academic interest, blockchain adoption in practical accounting remains limited. Most studies on the topic are conceptual or exploratory, and implementation is hindered by technical complexity, scalability concerns, educational issues, and evolving regulatory frameworks (Han et al., 2023; Ariciu et al., 2025).

3.3 Professional service firms (PSF) and digitalisation

Professional service firms (PSFs) are found across industries but are typically concentrated in accounting, law, and management consulting. Such firms are characterised by the three following elements in particular: knowledge intensity (meaning the firm's value creation relies on an intellectually skilled workforce); low capital intensity owing to their operating without significant physical assets or inventory; and a professionalised workforce, regardless of domain (Von Nordenflycht, 2010).

However, digitalisation and automation can challenge these foundational characteristics. Professional service firms have traditionally granted their employees considerable autonomy and informal organisational structures to retain skilled professionals (Løwendahl, 2005), whereas digital automation requires standardised and unified processes. At the same time, employees in PSFs often find routine tasks unfulfilling, creating an inherent tension: professionals resist standardisation yet may welcome automation that eliminates repetitive work. Similarly, the low capital intensity of PSFs means that human expertise typically constitutes the primary organisational asset (Løwendahl et al., 2001), yet increasing reliance on AI and automation gradually shifts value creation away from individual professionals toward technological systems.

Innovation and technology adoption in small PSFs have attracted scholarly attention. Existing studies indicate that the motivation for innovation in PSFs varies depending on firm size. Tomo et al. (2020) reported that micro-sized firms primarily seek efficiency gains, smaller firms prioritise service quality improvement, and medium-sized firms pursue access to new professional niches. The findings showed that the effectiveness of IT implementation depends less on employees' technical expertise and more on organisational trust and a collaborative culture (Tomo et al., 2020). Research on PSFs also reveals that digitalisation involves complex organisational tensions between efficiency gains and professional autonomy, and that firms increasingly depend on external networks of technology providers, clients, and other PSFs to manage these processes (Cardinali et al., 2023). Furthermore, digitalisation is reshaping the business models of small accounting firms, driven by cost-reduction pressures and changing client expectations. However, the decision-making processes behind digital adoption remain insufficiently understood (Rieg & Radeck, 2024).

4 PHILOSOPHICAL FOUNDATIONS AND METHODOLOGICAL APPROACH

This chapter presents the philosophical and methodological foundations of the dissertation. It begins by situating the research within a pragmatist philosophical framework and then discusses the mixed-methods research approach. The chapter then elaborates on design science research as the overarching methodological framework for developing the maturity model, presenting Hevner's (2007) three cycles and their role in structuring the empirical studies. The chapter concludes with a description of the data collection and analysis methods applied in the four essays.

4.1 Research philosophy

This dissertation draws on multiple philosophical perspectives to address the research questions from different angles. The overarching philosophical orientation stems from the nature of the research objective itself: the development of a maturity model for intelligent accounting. Maturity models represent a typical output of design science research (Becker et al., 2009) and design science research is inherently pragmatic (Hevner, 2007; March & Smith, 1995). Pragmatism is a philosophical tradition that emphasises practical consequences and real effects as vital components of both meaning and truth, focusing on the usefulness and applicability of research outcomes rather than abstract theoretical purity (Goldkuhl, 2012). This pragmatic foundation provides a coherent rationale for combining different methodological approaches depending on the nature of each study, as pragmatism permits the research question to guide philosophical and methodological choices rather than requiring adherence to a single paradigm (Creswell, 2014). This philosophical plurality reflects the multifaceted nature of the research phenomenon of this dissertation: the adoption of automation and AI in accounting and its implications.

Nevertheless, pragmatism is not without criticism. Some scholars argue that its focus on what works can oversimplify complex social phenomena and lack philosophical rigour, while others contend that it may open the door to methodological eclecticism without sufficient theoretical justification (Biesta, 2010). The current dissertation addresses such concerns by explicitly grounding each study in its appropriate philosophical foundations and ensuring that methodological choices were driven by research questions rather than convenience. The following sections outline the philosophical underpinnings of each essay.

The philosophical foundation of the first two essays (Essays I and II) rests on interpretivism, an approach grounded in the understanding that social reality is not objectively given but is socially constructed through the meanings that actors attach to their experiences and interactions (Burrell & Morgan, 2011; Chua, 1986). Rather than seeking universal laws or causal explanations, interpretive research aims to understand accounting practices as they unfold in real organizational settings and to capture the meanings that actors attach to technological change (Hopwood, 1983). This perspective recognises that accounting is not merely a technical practice applied to reveal pre-existing aspects of reality, but a social phenomenon that both shapes and is shaped by its organizational context (Hopwood, 1983; Chua, 1986). The nature of the research problem itself drove the choice of an interpretive approach. Understanding how rapidly evolving automation and AI technologies are adopted in accounting practice requires gaining first-hand knowledge of how organisations experience and make sense of these changes. Given that intelligent accounting is an emerging, still ambiguously defined phenomenon, an interpretive lens was necessary to capture the diverse ways in which practitioners understand, adopt, and integrate these technologies into their daily work. Adopting an interpretive approach carries inherent limitations. Researchers may struggle to reconcile their own perspectives with those of study participants (Chua, 1986), and interpretive research aims for analytical rather than statistical generalisation (Lukka & Kasanen, 1995).

Essay III employed a survey method to examine the barriers and enablers of AI adoption among accounting and finance professionals. While surveys are often associated with positivist research, assuming an objective reality that can be measured through systematic methods enabling statistical analysis and generalisable inferences (Creswell, 2014), this study adopted an exploratory approach. The aim was to understand how practitioners perceive adoption-related factors in the current context of AI adoption rather than to test hypotheses or establish causal relationships. This orientation resembles post-positivism, which acknowledges that while objective reality exists, our understanding of it is inherently imperfect and shaped by context (Creswell, 2014). This design reflects the pragmatic orientation of the dissertation: theoretical foundations from existing research were utilised while remaining open to new insights emerging from practitioners' experiences.

The design science study (Essay IV) aligns most directly with the pragmatic foundation of this dissertation. As established at the outset of this chapter, design science research aligns directly with the pragmatic foundation (March & Smith, 1995; Hevner et al., 2004; Hevner, 2007). While it shares interpretivist concerns for context and meaning during the problem identification and evaluation phases, it also incorporates elements of systematic, structured enquiry. This philosophical orientation supports the overall aim of developing a maturity model that is both theoretically grounded and practically applicable.

The validation strategies appropriate for each philosophical approach are discussed in Section 4.4 alongside the specific data collection and analysis methods employed in each study.

4.2 Research approach

This dissertation adopts a mixed-methods approach at the dissertation level rather than within its individual constituent essays. Mixed-methods research integrates qualitative and quantitative approaches within a single research programme to achieve a more comprehensive understanding of the phenomenon (Tashakkori & Creswell, 2007; Modell, 2010; Grafton et al., 2011). Pragmatism provides the philosophical foundation that permits this integration, while mixed methods serve as the methodological strategy for its implementation. Instead of treating methodological traditions as incompatible, this approach draws on their complementarity to address different facets of the research problem (Teddlie & Tashakkori, 2003).

This dissertation adopts a sequential exploratory mixed methods design (Tashakkori & Creswell, 2007; Creswell et al., 2003), beginning with qualitative research, followed by a quantitative phase, and culminating in design science research. This structure aligns with the design science approach, where problem identification and understanding precede artefact development (Hevner, 2007).

The first two essays employ qualitative case-based research to explore emerging practices and meanings associated with automation deployment in SMEs' accounting processes. The third essay employs a quantitative, survey-based approach to extend this understanding by examining how accounting and finance professionals perceive the barriers and enablers to AI adoption. In addition to this sequential exploratory structure, the development and evaluation of the IADMM is then undertaken through design science research (DSR), consistent with the pragmatic orientation of this dissertation (Figure 2).

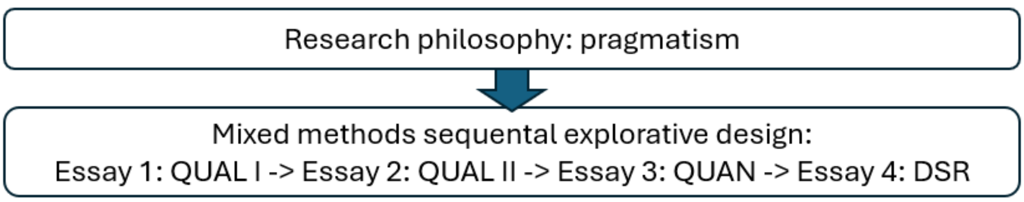

Figure 2. The philosophical and research approach

Applying mixed methods at the dissertation level rather than within individual essays was a deliberate strategy to ensure methodological coherence, maintain depth within each study, and avoid some weaknesses typically associated with mixed-methods research, such as inadequate integration between components or superficial application of multiple methods (Modell, 2010; Grafton et al., 2011). The sequential structure enabled each study to build on the preceding ones, allowing complementary rather than cross-validatory insights (Modell, 2005).

4.3 Design science in developing a maturity model

Building on the pragmatic philosophical foundation and the sequential mixed-methods logic described in the previous sections, this dissertation employs design science research (DSR) as the methodological framework for developing the Intelligent Accounting Digital Maturity Model. Design science research is a natural culmination of the research sequence, transforming insights from the earlier interpretive and survey-based studies into a purposeful artefact that addresses the identified practical need.

Design science research is a problem-solving paradigm focused on creating innovative artefacts that address real-world challenges (Hevner, 2007; Peffers et al., 2007). In contrast to behavioural science, which seeks to understand and explain phenomena, DSR aims to produce prescriptive solutions and artefacts that are both theoretically grounded and practically applicable (March & Smith, 1995). The central assumption is that knowledge about a problem domain can be advanced through building and evaluating purposeful artefacts (Hevner et al., 2004). To support methodological rigour, Hevner (2007) further articulates this through three interconnected cycles: the Relevance Cycle, linking research to its practical environment; the Rigor Cycle, connecting it to the existing knowledge base; and the Design Cycle, which iteratively builds and evaluates the artefact (Figure 3).

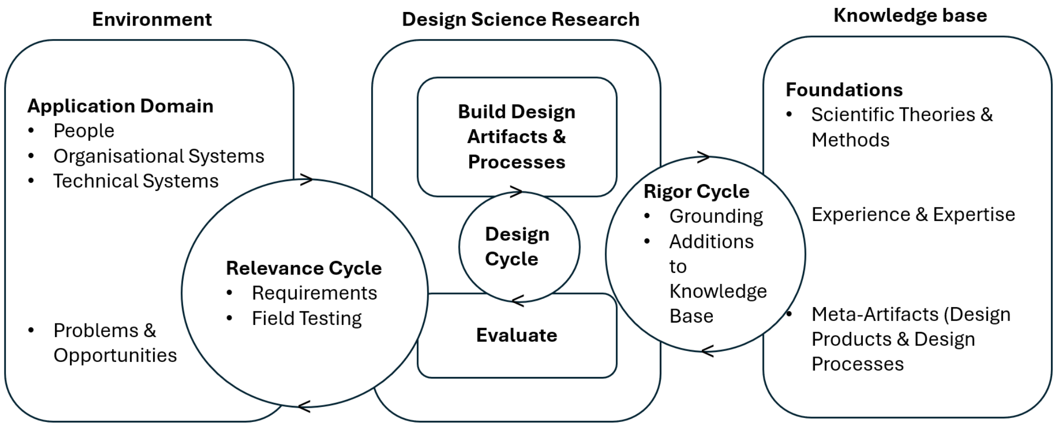

Figure 3. Design Science Research Cycles (adapted from Hevner, 2007)

Maturity models represent a specific class of design science artefacts, providing structured frameworks for assessing organisational capabilities and guiding improvement across predefined dimensions (Becker et al., 2009). Despite their popularity, they have been criticised for lacking academic rigour, particularly when developers do not articulate their motivations, methodological procedures, or evaluation strategies (Becker et al., 2009; Thordsen et al., 2020). Becker et al. (2009) developed a comprehensive procedure model for maturity model development to address these concerns and reduce the risk of maturity models becoming consultancy tools rather than scientifically grounded instruments. The resulting model, informed by Hevner et al.'s (2004) design science guidelines and the DSR research cycles (Hevner, 2007), identifies eight methodological requirements and organises them into a five-phase development process (Figure 4). Within accounting research, Becker's procedure model has been applied in the development of the Electronic Invoice Processing Maturity Model (Cuylen et al., 2016).

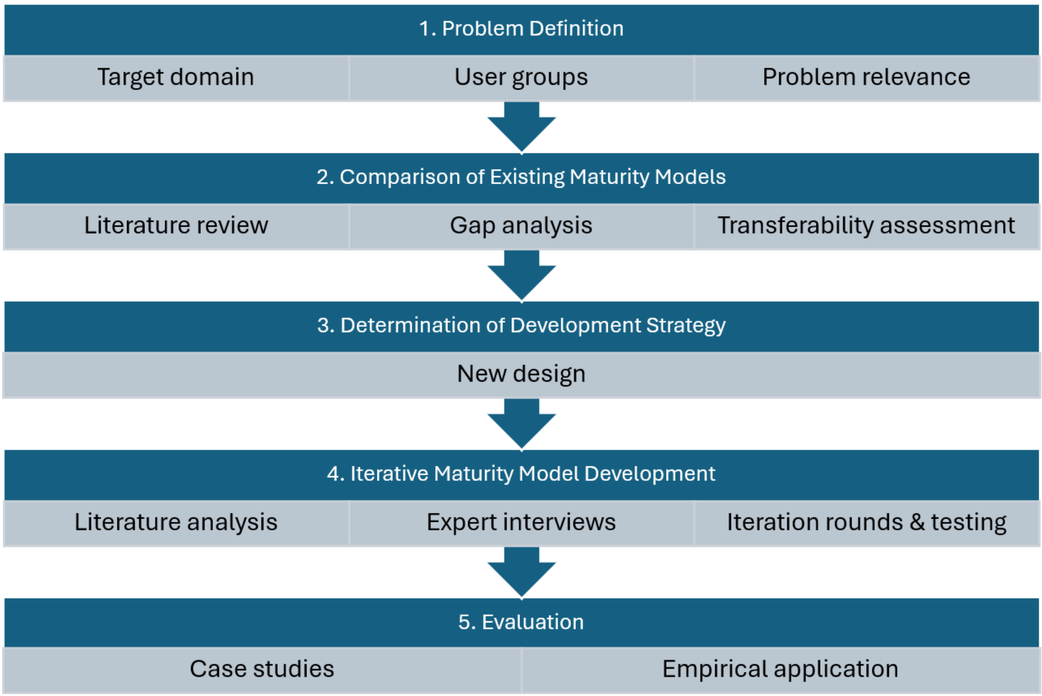

Figure 4. The procedure model (adapted from Becker et al., 2009)

Although Essay IV specifically follows the Becker et al. (2009) procedure model during the maturity model development, this dissertation follows the DSR approach throughout the research programme. The Relevance Cycle is addressed in the first two essays, which investigate automation adoption in SMEs and identify the need for accessible and user-friendly tools to support SMEs in their automation efforts. Hevner et al. (2004) recommended employing theoretical frameworks to demonstrate practical significance. Accordingly, Essay II applies Davis's (1989) TAM to examine perceived usefulness and ease-of-use in the context of accounting automation. The essays' findings indicate that automation was considered useful but not easy to use, providing more practical motivation for developing a maturity model to guide SMEs in technology adoption. Essay III deepens this understanding by identifying barriers and enablers of AI adoption among accounting professionals, offering empirical input for the model's dimensions.

The Rigour Cycle is addressed through the systematic literature review in Essay IV and through the theoretical grounding applied across all essays. As no suitable existing model was identified for adaptation, the chosen development strategy was to design a new model. In addition to grounding the development of IADMM in literature, its knowledge base was strengthened with 15 expert interviews which provided additional depth and practitioner validation.

The Design Cycle is exemplified in Essay IV by developing and evaluating the IADMM in five iteration rounds following Becker et al.'s (2009) procedure model as detailed in Essay IV. Methodological rigour was ensured through the application of established research methods, interpretive case studies, an exploratory survey, and systematic maturity model development procedures, rather than ad-hoc choices.

4.4 Data collection and analysis methods

This dissertation employs multiple data collection and analysis methods in its four essays, combining qualitative case studies with a quantitative survey, systematic literature review, and expert interviews. The choice of method in each essay was guided by the research questions and the nature of the phenomenon investigated.

Essays I and II adopted a qualitative multiple case study approach to investigate automation adoption in SMEs. Case study methodology was chosen because the research sought to understand how and why SMEs adopt accounting automation, which are questions that require in-depth exploration within real-world contexts (Yin, 2018). The studies involved 12 firms participating in a collaborative RPA implementation project funded by the European Union. Data were collected through semi-structured interviews, supplemented by observations and project documentation. Essay II employed a longitudinal design, conducting follow-up data collection with the same firms one year after initial implementation to examine how perceptions of usefulness and ease-of-use evolved. The multiple case design enabled cross-case comparison (Eisenhardt, 1989; Yin, 2018) while the longitudinal element captured the dynamic nature of technology adoption (Pettigrew, 1990).

The primary data collection method in Essays I, II, and IV was semi-structured interviews; however, the purposes of the interviews differed. Each interview study featured purposeful sampling to select participants who could provide rich, relevant information about the relevant phenomena (Shaheen et al., 2018). In the case studies (Essays I and II), the interviews explored the experience with automation adoption, implementation challenges, and perceived benefits of 12 SME representatives. In Essay IV, 15 expert interviews were conducted as part of the maturity model development process, following Becker et al.'s (2009) iterative procedure model. These expert interviews served to validate and refine the maturity model dimensions and criteria based on practitioner knowledge.

All interviews followed structured interview guides to ensure consistency while allowing flexibility to explore emergent themes (Kvale, 2007). Interviews were recorded with participants' consent, transcribed verbatim, and analysed systematically using NVivo software to identify patterns and themes (Miles &

Huberman, 1994; Lumivero, 2024). The interview data underpinning Essay I were analysed thematically to elicit automation adoption experiences and motivations. In Essay II, the interview data were analysed through the lens of the TAM (Davis, 1989) to trace perceived usefulness and perceived ease of automation. In Essay IV, the expert interview data were analysed thematically to evaluate and refine the dimensions and criteria of the maturity model. Ethical considerations were addressed throughout: research permits were obtained, participants provided informed consent, and all data were anonymised to protect participant identities (National Board on Research Integrity TENK, 2023).

Essay III employed a quantitative survey methodology to examine barriers and enablers of AI adoption among accounting and finance professionals. A survey approach was selected to capture perceptions across a broader population than case studies would permit, enabling systematic documentation of how professionals view AI adoption challenges. The survey used a ranking-based response format in which respondents selected the five most significant barriers and enablers from predefined lists and ordered them by importance. This forced-choice design was preferred over traditional Likert-style scales because it requires respondents to make explicit trade-offs between competing factors, producing more differentiated and prioritised data (Groves, 2009; Hauck, 2024). Data from 103 responses were analysed by calculating both the frequency with which each option appeared in respondents' top-five selections and the distribution of assigned ranks (five points for the most important choice, four points for the second, and so forth). This dual analysis allowed identification of factors that were frequently selected and also consistently rated as highly significant. The survey was distributed online through institutional networks, professional associations, and social media, using snowball sampling to reach a diverse group of respondents throughout the Finnish accounting sector (Saunders, 2017).

Essay IV also employed a systematic literature review (SLR) as part of the design science process that created the IADMM. The review adhered to established guidelines for SLRs (Kitchenham, 2004) and applied a predefined protocol including search strategy, inclusion and exclusion criteria, and systematic screening procedures. A more detailed description of the SLR protocol, including databases, search strings, inclusion and exclusion criteria, and the final number of studies selected, is provided in Essay IV. The review served two purposes within the design science framework: first, to establish the theoretical foundation for the maturity model dimensions and criteria; second, to fulfil the comparison phase of Becker et al.'s (2009) procedure model by analysing existing maturity models in related domains. The systematic approach ensured comprehensive coverage of relevant literature and transparency in the selection process.

The development of the maturity model drew on both the SLR and the expert interviews. The first version of the model was constructed based on the systematic literature review. The model was then iteratively refined through five iteration rounds using the 15 expert interviews. The experts, drawn from the accounting firm sector with practical experience in automation, provided feedback that helped validate the model dimensions and incorporate practitioner perspectives. Additions and modifications to the model were systematically documented between iteration rounds to ensure transparency. In addition to the iterative refinement, the model was evaluated in three accounting firms of different sizes to assess its functional applicability and practical usefulness, as recommended for design science artefacts (Hevner et al., 2004; Becker et al., 2009). The detailed description of the development and evaluation process is provided in Essay IV.

Research quality was safeguarded through method-specific strategies appropriate to each methodological approach. In the qualitative case studies, validity was enhanced through triangulation of data sources, combining interviews, observations, and documentary evidence, and by following Lukka and Modell's (2010) suggestions for interpretive research, which emphasises integrating authenticity with credibility. In the survey research, the instrument was piloted before distribution (Groves, 2009), and the ranking methodology reduced response biases common in Likert-scale surveys. For the design science study, validity was established through the iterative development process, expert evaluation, and systematic documentation of methodological choices, ensuring both theoretical grounding and practical applicability (Hevner et al., 2004). The maturity model was also validated, as recommended by Becker et al. (2009). All procedures complied with the guidelines of the Finnish National Board on Research Integrity (National Board on Research Integrity TENK, 2023).

5 SUMMARY OF THE ESSAYS

This section summarises the four essays examining automation and new technologies applied in accounting processes. The first three essays investigate the opportunities to automate accounting processes in SME sized firms, identify the need for a dedicated maturity model, and examine the barriers to and enablers of AI adoption among accounting and finance professionals. The fourth essay presents the central outcome of the dissertation: the intelligent accounting digital maturity model.

5.1 Essay I: RPA Experiments in SMEs Through a Collaborative Network

The first essay, titled "RPA Experiments in SMEs Through a Collaborative Network," was conducted in collaboration with Dr Lili Aunimo and Dr Damian Kedziora and published in 2023. I was the lead author, contributing the initial concept, drafting most of the theoretical framework and results, and collecting and analysing the empirical data from the case companies.

The essay examines how small and micro-sized enterprises initiate RPA adoption and how business process modelling and governance practices support those early trials. The study addresses a gap in prior RPA research, which has predominantly focused on large organisations, and contributes empirical insight into first-stage automation in small-firm settings.

The theoretical framing of the essay builds on three interconnected strands of literature. First, prior work on RPA characterises automation as most effective for rule-based, repetitive and digital tasks, particularly in accounting, payroll and audit processes. The literature also demonstrates that organisations typically begin with task-level automations before attempting broader, end-to-end workflows, and that early-stage adoption is shaped by simplicity, regularity and exception-minimisation in task selection. Second, the essay draws on Business Process Management (BPM) and process governance frameworks, which emphasise documentation, standardisation and analysis as prerequisites for automation. The literature on BPM highlights that well-governed processes enable more reliable RPA identification, reduce operational risk and provide clarity on bottlenecks, roles and task dependencies. Although BPM practices are often associated with large organisations, prior studies suggest that they can be transferred and adapted to SME contexts, where process understanding is frequently limited and workflows are informal. Third, the study builds on literature on collaborative networks which conceptualise inter-organisational collaboration as a mechanism for capability building, peer learning and resource sharing in digital transformation. Collaborative networks are understood as structures that support SMEs lacking internal centres of excellence by offering training, exemplars and test-before-investment experimentation opportunities. This framing positions networks as critical external enablers that lower the entry barriers to early RPA adoption for resource-constrained micro and small firms.

The essay is based on a qualitative multiple-case study of 12 Finnish SMEs participating in an EU-funded project. Data were collected through workshops, consulting sessions and process documentation, from which RPA proofs of concept were developed for nine companies which were mature enough for them. The rest of the companies received process improvement recommendations and digitalisation suggestions for their processes. The analysis focuses on how the SMEs identified candidate tasks, how process documentation shaped feasibility assessments and how collaborative networks facilitate knowledge transfer and experimentation.

The findings show that SMEs are primarily motivated by a desire to remove repetitive office work and improve employee satisfaction, with cost reduction and productivity considerations playing a secondary role. Process modelling proved essential for clarifying tasks and identifying simple, rule-based activities suitable for automation. In several cases, process improvement or digitalisation was recommended before RPA, highlighting that automation should not be applied to poorly governed processes. The collaborative network, comprising training, peer examples and free proof-of-concept development, played a crucial enabling role, functioning as an external substitute for centres of excellence typically found in large firms. Overall, the essay establishes the empirical foundation for the dissertation's broader examination of automation adoption in SME-sized firms, highlighting the baseline conditions that the subsequent studies build upon.

5.2 Essay II: Collaborative Ecosystems for Increasing Automation in Accounting Processes in Small Firms

The second essay, “Collaborative Ecosystems for Increasing Automation in Accounting Processes in Small Firms”, was written together with Dr Lili Aunimo and Dr Eija-Leena Kärkinen in 2024. I served as the lead author, contributing the initial concept, drafting most of the theoretical framework and results, and collecting and analysing the empirical data from the participating companies.

The essay examines how small firms perceive accounting automation one year after participating in a collaborative ecosystem. Building on the information derived from the companies studied in Essay I, the essay investigates how collaborative ecosystem participation influences technology awareness, experimentation, and subsequent adoption decisions, and how SMEs assess the usefulness and ease-of-use of RPA-based solutions.

The theoretical framing of the second essay builds on two elements. First, the concept of collaborative ecosystems provides the contextual foundation for understanding early-stage automation in small firms. Collaborative ecosystems are treated as structures that supply shared training, peer learning, expert support and test-before-invest experimentation, thereby compensating for the limited internal capacity characteristic of micro- and small enterprises. They also create social learning settings in which firms observe, imitate and adapt practices introduced by peers and external specialists. Second, the essay uses the TAM as an analytical frame to guide the interpretation how entrepreneurs evaluate RPA-based automation initiatives. The TAM is applied specifically to two perception constructs, perceived usefulness and perceived ease-of-use, and is used to interpret how firms assess the benefits of the proof-of-concepts (e.g., productivity, job satisfaction, customer service). The model applies the perceived ease-of-use construct to illuminate how the selected entrepreneurs evaluate the skills requirements, maintenance demands, and feasibility of automation solutions. The TAM is not used as a predictive model but as an interpretive lens to understand how perceptions shape adoption decisions one year after initial ecosystem exposure.

The study applies a qualitative, interpretive approach. During 2021–2023, the firms were involved in an EU-funded project which was a collaborative network. The programme included training, workshops and consulting, including the development of RPA proofs of concept. When the project concluded a year later, 12 semi-structured interviews were conducted with entrepreneurs to capture perceived benefits, ease-of-use assessments and the practical relevance of the proofs of concept.

The findings indicated that most firms considered that collaborative ecosystem participation was beneficial. The perceived benefits included improving awareness of office automation options, helping identify suitable tasks, and providing hands-on experimentation through a test before invest approach. Workshops offered peer learning opportunities that were described as especially valuable for micro-firms with few internal colleagues. With respect to the TAM, perceived usefulness was uniformly high. Firms associated automation with improved productivity, job satisfaction and, in several cases, enhanced customer service. However, adoption outcomes differed: only three firms integrated the original POCs into production, although most developed simpler alternative automation options. The reasons for non-deployment related to contextual factors such as changing needs, low task frequency, time constraints or perceived cost-benefit mismatches rather than doubts around usefulness.

Perceived ease-of-use remained at a low level for most firms' respondents. While participants gained the ability to recognise automation opportunities, skills to aid implementation, maintenance and risk handling did not increase sufficiently. Two firms reported greater ease-of-use when the proofs of concept were simple or where ongoing support was available. These patterns reflect broader observations that resource and skill scarcity often constrain SME digitalisation and that benefits materialise more fully when ecosystem support is sustained. Overall, the essay provides insight into early-stage accounting automation in small firms by linking collaborative ecosystem programme participation, TAM perceptions and adoption outcomes. It shows that collaborative ecosystems can meaningfully enhance awareness and readiness for experimentation, but that persistent skills gaps limit ease-of-use and therefore inhibit full implementation. The essay thus complements Essay I by revealing how SMEs experience automation over time and clarifies why perceived usefulness does not automatically translate into adoption in the absence of capability development in parallel.

5.3 Essay III: Transition to Organisation 5.0 - Barriers and Enablers of AI Adoption in Accounting and Finance

The third essay, titled "Transition to Organisation 5.0 - Barriers and Enablers of AI Adoption in Accounting and Finance," was written with Dr Lili Aunimo, Dr Mariitta Rauhala and Dr Stephan Schlögl. I served as the lead author, Dr Aunimo contributed the initial concept and analysed the data. I wrote part of the theoretical framework, research design, created the survey questionnaire and was responsible for collecting the data. I also did the corrections and additional data analysis to the paper according to the anonymous reviewers' feedback.

The essay examines how accounting and finance professionals perceive the barriers to and enablers of artificial intelligence (AI) adoption and assesses whether these perceptions signal prgress toward the human-centric principles associated with Organisation 5.0. Addressing a research gap noted in earlier debates, the essay provides empirical evidence on which challenges practitioners themselves consider decisive, contrasting with the academic emphasis on ethics, transparency and accountability, and connects these insights to the operationalisation of human-centric digital transformation in accounting and finance.

The theoretical framing integrates three strands: Organisation 5.0, Collaborative Networks 5.0 and research on the use of AI in accounting and finance. Organisation 5.0 is conceptualised as emphasising human-centricity, resilience and sustainability in digital transformation, with collaboration and co-creation as its central mechanisms. The work on Collaborative Networks 5.0 complements these insights by describing how inter-organisational structures support shared learning and capability development around emerging technologies. In addition, prior literature on AI implementation in accounting and finance and in adjacent domains has identified a range of practical challenges related to skills, data, usability, privacy and system integration. This body of work is used to determine whether the barriers observed in practice align with, diverge from or extend the general challenges documented in earlier research.

The study is underpinned by an exploratory online survey of 103 accounting and finance professionals in Finland. Respondents ranked the five most important barriers to and facilitators of AI adoption. The barrier items were derived from empirical research on AI implementation challenges, skills, data quality, privacy and governance, while the facilitator items reflected Organisation 5.0 themes such as continuous training, learning-oriented culture, usability and collaboration. Analyses were conducted by organisational size, employer type and employee age to identify patterns relevant to capability-building and ecosystem design.

The findings reveal a distinct hierarchy in practitioners' concerns. The most important barrier is a lack of expertise, followed by compatibility problems with existing tools and systems, data availability and quality issues, concerns about privacy and cybersecurity, and inadequate change management. The least important barriers included ethical issues, algorithmic bias, and transparency, despite being frequently cited in the literature. Viewed through the TAM lens, perceived usefulness does not constrain adoption; rather, ease-of-use, interpreted as skills readiness, integration feasibility and usability, is the dominant limitation.

Facilitators mirror these patterns. Continuous, high-quality training and skill development, together with an innovative and learning-oriented organisational culture, are the two most powerful enablers across respondent groups. Usability and seamless user experience emerge as the third most important facilitator, aligning closely with the human ethos of the Organisation 5.0 concept. Differences across subgroups add nuance: micro-sized organisations rate collaboration and networks with other organisations more highly as an AI adoption facilitator than do large organisations, which instead emphasise usability and system integration. Similarly, younger professionals prioritise experimentation and testing more than their older counterparts, who place greater emphasis on skills development and user experience.

Overall, the essay provides insights into how practitioners understand AI adoption and that accounting and finance organisations are beginning to move toward initiating the principles of Organisation 5.0. The findings highlight that human-centric factors: training, organisational culture, usability and collaborative support, represent the most actionable levers to foster AI readiness, while ease-of-use constraints remain the decisive bottleneck in practice. The essay complements the earlier essays by extending the dissertation's analysis beyond RPA to encompass broader AI adoption and by showing how professional perceptions shape the trajectory of human-AI collaboration in contemporary accounting and finance.

5.4 Essay IV: Intelligent Accounting Digital Maturity Model for Small and Medium-Sized Accounting Firms

The author is solely responsible for the fourth and final essay An Intelligent Accounting Digital Maturity Model for Small and Medium-Sized Accounting Firms. It was published in the Journal of Accounting & Organizational Change in autumn 2025.

The essay presents the intelligent accounting digital maturity model (IADMM), a holistic maturity framework designed specifically for small and medium-sized accounting firms. The essay addresses two gaps in existing literature. First, accounting-specific maturity models are scarce, most cover only single processes or offer high-level diagnostic indexes without deeper structure. Second, resource-constrained firms lack a practical tool for sequencing capability-building as intelligent accounting evolves toward AI-enabled operations.

The theoretical foundation of the essay builds on two strands. First, the literature on intelligent accounting and the technological evolution of digital accounting describes how financial administration has progressed from digitised documents to integrated data flows, rule-based automations and, ultimately, AI-enabled intelligent accounting capable of learning and continuous improvement. This development positions cloud-based systems, RPA, and AI as complementary layers that small accounting firms combine to advance toward more automated and data-driven operations. Second, the study draws on maturity-model theory, which conceptualises maturity as a staged, multidimensional assessment framework used to evaluate organisational capabilities and guide development. Prior digital maturity models typically employ five levels across process, technology, leadership and data-related dimensions. However, existing accounting-specific maturity models are narrow in scope, often focusing on a single process such as e-invoicing or offering diagnostic indices rather than structured maturity levels. The situation highlights the need for a holistic, accounting-specific model that captures the full process landscape of SME accounting firms.

The essay adopts a design science approach that aligns with Becker et al.'s (2009) procedure model. Development proceeded iteratively through an SLR, 15 semi-structured expert interviews, and five rounds of model refinement. Key additions during the iterations included a dedicated payroll dimension due to its automation potential, refined descriptors to improve clarity, and restructuring of categories such as leadership, reporting and accountants' roles. The model was subsequently evaluated with three accounting firms of different sizes, demonstrating that the dimensions and levels distinguish maturity states in practice and support reflection on development needs.

The resulting IADMM comprises 11 dimensions: technology, processes, vision and leadership, data and cybersecurity, role of the accountant, reporting and customer communication, sales to cash, purchase to pay, payments, general ledger and payroll. Each of those is articulated across five levels ranging from non-existent to continuous improvement. The levels describe how firms advance from manual or paper-based practices to cloud systems with built-in automation, and further to bespoke RPA/AI solutions, integrated workflows, citizen development and continuous scanning for technological opportunities. Although the model consists of five levels, maturity level three can be the most efficient for a small accounting firm. The evaluation indicates that the model is sufficiently sensitive to classify a range of firms. Sole-entrepreneur practices operate mainly at the lowest levels but employ isolated higher-level practices for certain clients; micro-sized cloud-native firms primarily align with level three; and small firms with in-house robotics expertise can achieve levels four and occasionally level five. Feedback highlighted the model's usefulness for identifying process-governance gaps preceding automation, while also noting that simplified wording or a questionnaire might have enhanced self-assessment for non-experts.

Overall, the essay provides the first holistic digital maturity model tailored to SME accounting firms. It translates the staged evolution of intelligent accounting into observable level descriptors that make role transformation, process governance, and the adoption of RPA and AI empirically examinable in future longitudinal or comparative research. Methodologically, the Essay IV demonstrates the value of design science in accounting by producing a theory-grounded yet practitioner-validated artefact. The model serves as a practical roadmap for enabling firms to sequence technological investments, strengthen documentation and process standards, and progress from cloud native automations to bespoke intelligent solutions in alignment with organisational readiness.

6 CONCLUSIONS

This dissertation addresses a significant gap in the accounting information systems literature by developing a maturity model for intelligent accounting in SME-sized accounting firms. The primary aim is to enhance the understanding of intelligent accounting as an organisational capability and to offer a practical model to support its development. Drawing on three empirical studies, the research shows that the adoption of automation and AI in smaller professional service firms is influenced less by concerns over their usefulness and more by factors such as skills, usability, and organisational context. The resulting intelligent accounting digital maturity model (IADMM) consists of 11 dimensions structured across five maturity levels and encompassing both the enabling conditions and the core areas of the accounting process. The first three empirical studies of the dissertation reflect the relevance cycle of design science research (Hevner, 2007), establishing the practical need and empirical foundations for the development of the model. The fourth essay built on those insights to shape the IADMM in accordance with rigour and design cycles, grounded on an SLR, refined through 15 expert interviews, and evaluated in three accounting firms. While the number of evaluation cases is limited, design science methodology prioritises demonstrating functional applicability over statistical generalisability (Hevner et al., 2004).

In combination, the essays present a consistent narrative on how smaller organisations approach technological development. The case studies presented in Essay I illustrate that firms typically introduce automation to remove routine work tasks and improve daily operations, and that progress depends as much on process clarity and basic governance as on any technology. Essay II applied the technology acceptance model (Davis, 1989) to examine whether the automation pilots first reported in Essay I had been adopted into regular use. The findings revealed that while automation was perceived as useful, it was not perceived as easy to use, which limited sustained adoption. Collaborative networks, such as EU-funded projects designed for SMEs, provided valuable external support by offering examples, training opportunities, and avenues to trial new tools prior to commitment. However, the studies also show that these networks focused primarily on experimentation rather than on building the capabilities necessary to sustain implementation. Progressing beyond the pilot stage would require such initiatives to emphasise post-pilot training, longer support periods, and ensuring that the solutions introduced match the firm's current maturity level.

The survey study in Essay III extends this perspective to AI adoption. Practitioners identified skills, system compatibility, data quality, and ease-of-use as their primary concerns, while issues that feature frequently in academic debate, such as ethics or algorithmic transparency, were perceived as less pressing owing to the current level of technological maturity. Although the survey did not directly measure perceived usefulness, the prominence of ease-of-use among practitioners' concerns reinforces the pattern observed in the case studies and aligns with TAM research suggesting that ease-of-use is often the most critical barrier during early stages of adoption (Davis, 1989; Venkatesh, 2000). The IADMM reflects these observations by translating them into maturity levels that allow firms to identify gaps and plan development in a structured way. These findings offer empirical insights into the adoption of automation in SME accounting firms as a specific instance of small PSFs, among which resource constraints, organisational culture, and external network support uniquely influence the process of digitalisation (Tomo et al., 2020; Cardinali et al., 2023).

The IADMM contributes to the aims of this dissertation in several key respects. First, it unites previously disparate aspects of accounting digitalisation into a single framework, enabling assessments covering the whole firm rather than isolated processes. Second, it elucidates the evolution of accounting practices from digitised routines to more analytical and advisory roles, as technological integration progresses. Finally, the IADMM is underpinned by and was evaluated using a design science approach (Hevner et al., 2004; Becker et al., 2009). That approach helped ensure that the model is both theoretically sound and practical to apply. The SLR conducted in Essay IV found no existing models addressing both infrastructure and the full accounting process landscape for SME-sized accounting firms. The IADMM therefore fills a gap left open in earlier work. It offers a more detailed account of how roles, processes, and data practices change as firms mature, and shifts attention from the technologies themselves to the conditions that support their effective use. This human-focused view, emphasising skills, learning, and organisational culture, aligns with broader discussions on Industry 5.0 concerning how digital transformation should be implemented in professional settings (European Commission: Directorate-General for Research and Innovation, 2021).

The model provides a practical tool to assess the current status and planning development in accounting firms. It breaks down technological change into steps that can be carried out gradually and highlights the importance of process standardisation, documentation, and secure data practices as a foundation for subsequent investment. Nevertheless, the IADMM is currently an Excel-based matrix and transforming it into a more accessible self-assessment tool would enhance its practicality.

This dissertation has several limitations that should be acknowledged. First, all four empirical studies were conducted in Finland, a country that ranks among Europe's most advanced in terms of digitalisation and AI adoption. While this context provides a relevant and information-rich setting, the findings may not be directly transferable to countries with less developed digital infrastructure, different regulatory environments, or a greater variance of cultural attitudes to automation. This geographic limitation applies particularly to the IADMM, whose maturity levels reflect Finnish accounting practices such as widespread e-invoicing and a supportive regulatory framework. The international applicability of the model should therefore be assessed with caution. Second, the empirical studies relied on relatively small samples. The qualitative case studies in Essays I and II focused on 12 small firms, which limits statistical generalisation and suggests that those studies should be considered exploratory rather than conclusive. Similarly, the survey in Essay III was conducted in a single country with a sample consisting predominantly of experienced professionals, potentially underrepresenting younger practitioners. Third, the first two empirical studies focused primarily on RPA technology; however, AI and other emerging automation technologies are increasingly relevant to accounting processes. Nevertheless, Essays III and IV extended the scope to include AI-driven solutions more broadly, and the IADMM encompasses intelligent, AI-driven accounting processes as its highest levels of maturity. Future research should nonetheless continue to investigate emerging automation technologies as they develop. Fourth, the sequential mixed-methods design means that later studies build on the framing established in earlier ones, and the survey findings rely on self-reported perceptions rather than observational or longitudinal data, which limits the robustness of causal conclusions. Finally, as with any maturity model, the staged structure necessarily simplifies actual development paths, which may in practice be non-linear. For many small accounting firms, reaching the middle levels of the model may be both realistic and sufficient, and progression to the highest levels should not be treated as a universal objective.

Intelligent accounting is developing rapidly, and recent advancements, such as AI-based agentic systems capable of autonomous planning and action, suggest that new capabilities will continue to emerge. Accordingly, the IADMM should be viewed as a framework that must be regularly updated. It also offers a foundation for future work in both practice and research. Future research could test the model in other national contexts and conduct larger-scale assessments to establish baseline maturity levels across the accounting sector. Firms could also adopt the model to review their situation over time.

Overall, the current dissertation conceptualises accounting automation as a gradual process rather than as a singular technological shift. That process must necessarily involve learning, organisational adjustment, and the development of new forms of collaboration. By integrating enabling conditions with the accounting service chain, the IADMM offers SME-sized practices a structured means to approach digitalisation and a basis for future refinement as technologies and professional expectations continue to evolve.

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RPA Experiments in SMEs Through a Collaborative Network

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Abstract. Robotic Process Automation (RPA) technology has been widely applied in many types of organizations. It is embraced in the hope of increased productivity, quality, and employee satisfaction. Intelligent Automation, being its further enhancement will strongly impact Society 5.0, as it drives productivity through digital technologies, contributing to a more human-friendly working environment. Our research describes the implementation of RPA in financial processes at several SMEs in Finland, as well as the construction of a collaborative network for building and sharing expertise on RPA. With our multiple case study, we explored the main drivers of RPA implementation at SMEs. The research was conducted among 12 SMEs and numerous other organizations participating in a collaborative network for RPA. We conclude that the desire to automate routine work to increase satisfaction at work is the main driver behind RPA implementation in SMEs.

Keywords: Intelligent automation · collaborative networks · business process modelling · technology adoption · financial processes · RPA · Society 5.0 · SMEs

1 Introduction

The application and importance of Robotic Process Automation (RPA) is increasing in many types of organizations. It is triggered by such drivers as increased productivity, quality and job satisfaction as routine tasks are automated [1]. RPA may be applied to any field and tasks where repetitive processes exist in knowledge work. Intelligent automation through RPA is one factor that may contribute to the Society 5.0 as it drives productivity through digital technologies. At the same time, it may contribute to a more human-friendly working life as employees are freed from routine tasks and may concentrate on tasks requiring human competences. An RPA implementation typically begins by carefully modelling existing business processes [2]. Some parts of the modelling process or of the RPA process itself may employ artificial intelligence (AI). Examples of these are the automatic generation of rules based on business data and the task of automatic information extraction from invoices, respectively.

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As the previous research on RPA adoption in SMEs is scarce, more research is needed to determine the reasons behind this. Hsiung and Wang [3] who explored the adoption of RPA in Taiwan SMEs suggested to scale the research to other continents and countries. The study of RPA adoption in SMEs by Turcu and Turcu [4], suggested to further study other departments and processes than HR. Also, Brzeziński [5] recommended to address the aspect of process management and governance in RPA implementations for the SMEs sector. According to Matthews and Greenspan, the Future of Work (FoW) will be driven by automation and collaborative robotics that require further exploration [6]. Addressing these recommendations, our research describes both the implementation of RPA in financial processes in several small and mediumsized enterprises (SMEs) in Finland and the construction of a collaborative network for building and sharing expertise on RPA. Hence, we formulated the following research questions:

RQ1: What drives SMEs in the implementation of RPA?
RQ2: What is the role of business process modelling in RPA implementations for SMEs?
RQ3: What is the role of a collaborative network in the business process transformation with RPA in SMEs?

The narrative of our paper is organized as follows: Sect. 2 describes related work and Sect. 3 describes the empirical setting and the company cases. The results are presented in Sect. 4. Section 5 analyses the significance of the results, both theoretically and in practical terms. Section 6 concludes the paper.

2 Related Work

RPA technology can be used to perform repetitive tasks, such as invoice or transaction processing, reporting, updating databases, data validation and filling in documents [7]. As many accounting, financial, and payroll tasks are repetitive, rule based and already in digital format, RPA is often started by automating company's accounting related tasks [8]. While it may trigger some doubts, or even fear among accountants' or other office workers, it may on the other hand increase job satisfaction and work-life balance when automating the mundane and boring tasks [9].

RPA automations can be implemented at task level, where software robots perform only one routine task such as bank reconciliation, extracting information from invoices, updating of master data information or transfer of information from one system to another. In such an arrangement, humans are only responsible for handling the exceptions [7]. In other words, the manual work of "extracting data from one system, performing data processing and moving the adjusted data to another system" [10] is automated. However, RPA can also support companies with the automation of an entire process, sometimes with some help of AI solutions [10]. In such cases, no manual intervention is needed, e.g. in a purchase invoice process that includes receiving, validating and paying the invoice. However, many researchers note that it is typical for organizations to start with task automations, while entire processes are typically automated only in large companies [11].

The importance of business process governance is growing, also due to the increased automation of processes [12]. This also applies for accounting processes as the well-governed processes are easier to automate with RPA. Even though Business Process

Management (BPM) is mostly used at large organizations, also SMEs can benefit from it [13]. BPM is a structured method of understanding, documenting, modelling, analysing, simulating, executing, and continuously changing end-to-end business processes and all relevant resources in relation to an organisation's ability to add value to the business. Aguirre and Rodriguez [1] present a case study where business processes have been automated through RPA. Through careful BPM, also SMEs can take well-informed decisions on the prioritization of automation pipelines in an organization. BPM provides information on which task automation would provide most added value to the business. This is very relevant also for SMEs, as their resources tend to be scarcer than those of large enterprises. IT governance helps to align decisions on RPA with the strategic objectives of a company [14].

RPA drivers and benefits can be categorized into four main groups: 1) Cost reduction, 2) Productivity enhancement, 3) Customer service improvement, and 4) Impact on employees. Each of the categories contains several detailed benefits, such as time savings or removal of non-value processes that are benefits linked to cost reduction, flexibility with capacity and working hours, as well as more detailed data capture and management. These solutions can enhance productivity, bring faster processes and quality improvements, improve customer service, and in the same time help employees by removing repetitive mundane tasks, increasing their job satisfaction and morale [11].

Collaborative networks, such as the European Digital Innovation Hubs (EDIHs) aim at enhancing and facilitating digital transformation in Europe. There are several AI and industrial automation related EDIHs, but no EDIH is specifically targeted at the automation of knowledge work. However, there are some networks that are developing standards relevant both for business process modelling and financial sector. An example of such is the Object Management Group Standards Development Organization, an international non-profit organization that gathers together organizations from the industry, government and academia. The way of working of individual experts is often very dependent of collaborative networks, by which we mean networks that consist of autonomous and heterogeneous entities that collaborate to achieve common or compatible goals through interaction that is made possible through computer networks [15] Financial experts may collaborate thorough various digital platforms and communication channels with other experts inside and outside of their organization and exchange ideas, knowledge and experiences.

3 Research Design

The research was conducted under an EU funded project 'Center of Intelligent Process Automation for SMEs (CIPAS)', run at Haaga-Helia University of Applied Sciences during 2021–2023. The project focused on providing training and consulting about digital accounting and automating accounting processes for SMEs in the capital region of Finland. As part of the project, the participants got an opportunity to implement their first RPA trials, and then decide whether they wish to implement it into their production environment.

Project participants were invited with an open invitation to join the project by email or by participating at different events organized by Haaga-Helia. Altogether 99 companies and their 115 employees took part at the project. The first step was to participate in online webinars conducted by the project. The webinars consisted of one-hour sessions which contained information about what is RPA, how it can be implemented, how to improve processes and analyse business cases for RPA projects. Organizations could choose which seminars were the most interesting to them and participate in them freely.

After the webinars, the participants were welcome to take part at RPA and Process Development Workshops, which were one-day contact sessions, where the participants learned how to use the no-code/low-code RPA tools, such as UiPath StudioX or MS Power Automate. Alternatively, they had a chance to learn how to model their processes and recognize the tasks which could be automated, or just learn advanced Excel usage. These workshops contained hands-on training, where the participants learned how to use the software and build their own automations, as citizen developers. Over 50 companies participated in these workshops.

The workshops allowed participants to discuss and consider their own automation needs, and companies that had enough interest were selected to receive individual consulting. Additionally, the company's technological maturity level had to be sufficiently high in order to proceed into the consulting phase. Altogether, 12 participants were selected to receive company level consulting, where the automation needs were analysed and a RPA Proof Of Concept (PoC) was offered. The findings collected from those 12 case companies are presented in this paper. Case companies are listed in Table 1.

Table 1. The case companies, their sizes, industries and the automations done.

Company	Size	Industry	Turnover kEUR	Automation
Company 1	sole entrepreneur	accounting services	100	task digitalization
Company 2	small	accounting services	7,500	process development
Company 3	micro	accounting services	700	POC
Company 4	micro	other services	50	POC
Company 5	micro	trade	500	process development
Company 6	micro	accounting services	250	POC
Company 7	micro	accounting services	250	POC
Company 8	micro	other services	2,600	POC
Company 9	micro	accounting services	150	POC
Company 10	sole entrepreneur	other services	50	POC
Company 11	micro	trade	500	POC
Company 12	sole entrepreneur	accounting services	200	POC

The size of case companies varies both in number of employees and turnover. All companies are registered in southern Finland, in the Uusimaa area. Most of the companies were micro sized companies which employ 2–10 employees. Only one company employs 50–100 persons. Three participants were single entrepreneurs but had a registered limited liability company. Turnovers are rounded to 50 kEUR and varied from 50 kEUR to 7,6 million. What comes to the industry, 7 of the 12 companies provide accounting services, as our project was run in collaboration with the national accounting service providers union. The remaining 5 companies came from various businesses, 3 providing different kind of services either to private people or businesses, 2 being trade organizations and 1 of the participants had both own production and trade.

When joining the automation consulting stage, a one-hour online meeting was arranged where the potential automation task was described, so that the development and consulting could begin. In these meetings, the following topics were discussed: 1) Which task/process the company wanted to develop, 2) Defining the current state of the task/process, recognizing the challenges and bottlenecks, 3) Reasons behind the wish to develop and automate the task or process, 4) Possibilities for alternative automation solutions. It is good to notice that all cases were task automations instead of process automations. After the online meeting, the project consultant documented the process into a flowchart and the process was reviewed by the company representative in the next meeting. In this meeting the development and automation ideas were discussed, including analysing the possibility for an RPA PoC.

Automations or other developments done for case companies are presented in Table 2. Nine of the case companies had an RPA PoC was done, whereas for three of the participants other development ways were decided instead of RPA. Companies which did not advance to automation PoC had some challenges related to technological maturity level. Company 1 was a small accounting service provider, and its processes were mainly paper based, while the entrepreneur didn't have sufficient IT skills and awareness. For this company, we were able to digitalize part of the paper process, but it was suggested that further automation could be done after the entrepreneur got used to the new cloud-based tools. Company 2 had all digital accounting solutions in use, but the challenge was with process harmonization. Many employees were doing the same task in the company in different ways. In this case, task standardization was suggested and thus the company did not wish to proceed to RPA PoC yet. Company 5 had a very manual purchase process, which was not that suitable for business purposes and rather hindered company's growth. Suggestion was to first improve the process, and only after that consider any automation trials. Additionally, the IT-skills in the company were not on such a level that the company employees could maintain an RPA automated task.

For the companies that were chosen for a RPA PoC, the process was documented in detail, and an external service consultant prepared the POC either with Microsoft Power Automate, or UiPath StudioX. These two software platforms were seen as the most suitable for SMEs. Once the POC was ready, one final session was organized to present the results and give feedback. It was then up to the company to decide if they want to buy a production version of the solution from the service provider.

Table 2. The RPA automation POCs or other development done to case companies.

Company	Description of the automated/developed task
Company 1	Digitalizing a paper-based fund application process
Company 2	Suggestions for process harmonization in accounting document handling and uploading to accounting information system
Company 3	RPA POC for giving auditor a sample of documents to be audited manually
Company 4	RPA POC for Excel-based CRM automation with MS Teams-invitations and documentation prepared for the meeting
Company 5	Suggestions for process development in manual purchase invoice handling
Company 6	RPA POC which collects selected information from tax authorities' system, for example information requests and tax filing status
Company 7	RPA POC which based on information stored in excel does profit distribution related tax filing to tax authorities' system
Company 8	RPA POC which makes calendar reservations based on a project plan documented in a company's Excel template
Company 9	RPA POC which processes company's sales report in excel and does the needed tax filing into tax authorities' system
Company 10	RPA POC which issues customer invoices based on employees' calendar events
Company 11	RPA POC which automates excel based CRM's service booking and suggests service times for customers
Company 12	RPA POC which creates a needed set of folders for accounting customers' monthly document filing

4 Results

4.1 Regarding RPA Implementation Drivers for SMEs

The automation drivers for case companies are presented in Table 3. For most of them, the key reason was to get rid of repetitive tedious tasks and thus either improve employee satisfaction, or in the case of self-employed people, improve their own work. When discussing the objectives of automation, it was found to be the main driver for all companies, excluding 2, 3, and 6. Automating routine work and getting more satisfied employees can easily be understood when reviewing the automated tasks: company 1 had a manual, paper-based process to be developed, companies 4, 7, 8, 9 and 11 all used time in modifying MS Excel templates regularly, company 5 processed large number of pdf-based purchase documents manually. Company 10 wanted to automate the creation of hundreds of data folders for its customers, and company 12 automated its invoicing based on calendar notes. All these tasks might be time-consuming, but the processing is routine and does not need any human decision making, they were part of some other processes and were seen tasks which could easily be given to a 'digital helper'.

What comes to other companies' automation drivers, company 2 was a bigger accounting service provider and they had recognized a need for RPA as part of the

Table 3. Classifying the drivers for automation and tasks which were automated.

Company	Employee satisfaction	Internal quality assurance	Cost reduction	Increase productivity
Company 1	x			
Company 2			x	x
Company 3		x		
Company 4	x			
Company 5	x		x	
Company 6		x		
Company 7	x			
Company 8	x			
Company 9	x			
Company 10	x			
Company 11	x			
Company 12	x			

competitive environment. However, they had not used RPA yet. For them, cost reduction, increasing productivity, but also removing non-value tasks was brought up as the motivator. They had recognized tasks which were done by several accountants to several customers and saw the potential for automation on those. Also, company 5 mentioned cost savings as one of the motivations, they had negotiated with their accounting service provider that they would do more accounting work themselves and this way would pay less for the services. Nonetheless, eventually when the process got analysed deeper, the employee did spend quite much time on processing the invoices manually, and as did the accountant in the external service provider and the accounting fees were quite high. The manager of the company commented that they would not mind paying so much for accounting services, as long as they did not need to spend so much time processing the documents themselves.

Company 3 provided auditing and quality assurance services, and their driver for automation was to increase quality for the audit work they performed to minimize auditing risks. With an RPA PoC, the auditors could have a more systematic approach for auditing accounting documents. Obviously, larger auditing firms already have such automations, but for a smaller auditing company it might be too costly, and this had to be done manually. It is noticeable that audit services are such that are performed for a customer, but a quality improvement in audit does not affect the customer as much as it minimizes the auditor's risk of giving the wrong statement of the company. Thus, the quality improvement is internal. Similar internal quality improvement was sought by company 6, where the automation collected information on the company's customers' tax filing status. The company was responsible for over 100 customers' tax filing and in case being late, the tax authorities would impose sanctions which would fall for company 6 to be paid if it had been their mistake. To avoid this, the management of the company wanted a checklist of the tax filing status for each of the customers. So, for these two companies the main driver was internal quality assurance.

4.2 Regarding the Role of Process Modelling at SME RPA Development

For each of the consulted companies at least two meetings were held to define the process or task companies wanted to automate. Before documenting the process, the regularity and time-consumption of the process was assessed. Only simple, regular and time-consuming processes or tasks were accepted for further development. Companies typically had a longer process in mind, but as it was their first RPA trial, the project budget was limited, and only one task or a small process was accepted for the PoC. None of the companies had process documentation in place and processes were documented by the project consultants with MS Visio or PowerPoint. This documentation or process modelling was essential for an external person to understand the process in question and often in the second meeting some corrections were made to the process documentation.

Once the process documentation was in place, the process was analysed to recognize bottlenecks or other challenges in the process. Solutions for the bottlenecks were searched from such perspectives as: 1) was the process part needed at all, 2) could existing software provide the solution. For example, for Company 1 where a grant application process was under analysis, some data collection phases were moved into latter phase of the process, as it was not necessary to collect such information from everyone who had send the application. This way the process was simplified. For company 1 several development points were recognized – also ones which could have been automated with RPA, but as the company was not technologically mature, it was decided to digitalize the most time-consuming and paper-based task. The maintenance of the possible software robots would have been challenging for the company. Company 5 also had several automation options, but their purchase process was not optimal for business purposes and thus the project team did not recommend automating such a process, but rather gave suggestions on how to digitalize their accounting and use their existing sales and purchase system more efficiently.

In all cases, the new process was documented as well and given to the case company. Some of the companies' employees were not the ones who made the final decision on the process development and RPA. They asked for the project documentation so they could communicate about the coming development and get approval for it. Thus, the project documentation was used in several manners in the project and had important role.

4.3 Regarding the Role of Collaborative Network at SME Digital Transformation with RPA

In the beginning of the project, a service design method was applied to find out the RPA needs of the companies. Three points were diagnosed: first, respondents were interested of the benefits of RPA, secondly, they wanted to know what peer companies had done with RPA, and thirdly the participants preferred RPA trainings and services which would be provided independently of time or place. Also, many participants did not know what RPA was, so raising awareness was needed.

Benefits and experiences of RPA were shared during various events. In the beginning, it was difficult to find participants in the project, but eventually the project started to attract more participants. However, it was learnt that SMEs are extremely busy and were not keen on participating in RPA events arranged by the project. Most probably the companies didn't even know what RPA was and thus such events were easily ignored. Consequently, the project team realized that information should be shared in networks where the entrepreneurs already are. For this reason, the project team started to participate at other industry events: run by organizations such as Finnish Association of Accounting service providers, Real Estate Management Federation and The Federation of Finnish Entrepreneurs. In addition, originally the project team was planning to create a platform where SMEs could discuss their RPA needs and challenges as the RPA POCs are universal, while the companies would prefer to learn about RPA examples of their own industry. Again, these associations and federations would maybe be the correct place for this kind of discussion, whereas different projects could just bring in new knowledge.

The training courses and services were provided both remotely, but also in contact sessions. Even though the original wish was to have time and place independent training courses, the project specialists felt it was easier to give software training in a contact session, rather than remotely. However, lots of webinar recordings were offered. In the future, also the software training should be provided virtually and maybe short video recordings to be done on how to build small automations.

What was learnt during the project but not recognized in the service design analysis was the usefulness of test-before-invest concept. Testing before investing is a service concept provided e.g. by European Innovation Digital Hubs which allows SMEs experimenting new technologies before actually investing in them [16, 17]. Project was EU-funded and provided the services free of charge, for a small company this is certainly a needed approach. In our project the POCs or POCs were provided for the companies but if the company wanted to implement them in real-life, they needed to get a production version from the consulting company who had created the POC. Without this possibility most of the case companies might not have tested RPA automations or started to develop their work with automation.

Project shared information about RPA possibilities success, only Company 2 had previous experience with office work automation and RPA. This company was bigger than the others and had done some automation trials before, however they had not implemented any solution yet. All the other companies either had participated in some of the Center of Intelligent Automation for SMEs project's training courses, just an Excel training or watched some webinars on what RPA is. In these training courses the project specialists discussed with companies, and the participants understood the possibilities of automation. Additionally, the training and workshops served as an experience sharing event. Some of the project participants did not proceed to the PoC-phase, but participated in a citizen development workshop with UiPath StudioX or MS Power Automate. Usually, these participants had already made their first trials with automation and shared their experience openly with others. Sharing information on what other similar companies had done either by the project team or by the participants was essential in raising the interest of starting the automation also in the case companies. Knowing the benefits and experiences of automation achieved by others was important when deciding to apply RPA in companies' own processes.

5 Discussion

When analysing the drivers of RPA implementation in the Nordic companies, we can use the four category classification: 1) Cost reduction, 2) Productivity enhancement, 3) Customer service enhancement and 4) Impact on employees [11] In our study, focusing on the RPA adoption in SMEs, category 4) Impact on employees was the most important driver. We also found out that the improvement of internal processes quality was an important driver for RPA implementation for some SMEs, which is a novel contribution to the available literature.

We agree with Chong [13] and Jurczuk [12] that business process governance: especially process understanding, documentation and analysis is essential for its successful automation, also when SMEs and micro-sized companies want to automate their processes no matter how small the automated task would be. Proper BPM enables smooth RPA implementation, and in our study the companies were able to use proof-of-concepts that were the result of proper process analysis.

In addition to the findings concerning the added value that the SMEs saw in implementing RPA, we observed that the tasks that were chosen by the SME for the RPA proof-of-concept were the simplest ones with the smallest number of exceptions. Also, repetitive tasks were chosen, but it was the second most important criteria. This is in line with the findings from Sharma et al. [18].

Our study encompassed the very first stage of RPA implementation, i.e. the "test before invest" stage. Additionally, our study does not discuss the actual decisions on taking RPA into use in the SME, as the 12 cases were dealing with companies that implemented the PoC. An RPA implementation would be the next step in the process. A future study could address SMEs that have actually implemented RPA.

The second part of the study contained the establishment of a collaborative network for RPA knowledge creation and sharing among SMEs. The network consisted of over 100 SMEs interested in RPA, companies offering RPA services and non-profit organizations, such as a university and associations for financial experts, entrepreneurs and other professionals. Large organizations typically create organization-wide Centers of Excellence (CoEs), focused on aligning organizational resources, establishing standards and tools, providing training and education to establish RPA readiness. Sharma et al. [18] found that CoEs are positively related to the intention to adopt RPA. Our study focused on micro-enterprises of less than 10 people. These firms cannot have organization specific CoEs because of the small organization size. Thus, the Center for Intelligent Automation was created to take over at least some of the tasks that large organizations typically handle through CoEs. Collaborative networks, of which the Center for Intelligent Automation is an example, play an important role in digitalization [19].

6 Conclusions

RPA is often implemented in larger companies, but smaller organizations such as SMEs or even micro-sized companies may equally benefit from it. Once learned about the automation possibilities, even small companies are willing to get rid of the repetitive routine tasks and thus improve their employee satisfaction. SMEs may also see in RPA a possibility to improve their internal quality or to enable substantial cost savings. However, currently many SMEs and micro-sized companies are still implementing their first RPA trials and automation is not yet in the companies' strategy. Additionally, efficiency related benefits of RPA are not yet widely seen by SMEs. Well planned RPA in a small company can benefit the organization in many ways. Consequently, SMEs should learn how to use these tools.

Surprisingly, our case companies did not see RPA as a competitive factor yet. Even there were companies from same industries, they were willing to share their RPA ideas with others. However, the project did only one RPA PoC for each company, and it was required them to be as multipliable and scalable RPA PoCs as possible. Probably a larger set of RPA automations would not be shared with competitors.

To avoid faulty investments and automations of wrong tasks, even smaller organizations should find the time to go through their processes and thus identify the ones which should be developed. SMEs' resources are scarce, and thus should be used wisely, however too much time spent on planning might make them lose the competitive advantage of RPA. Nevertheless, before a SME automatizes its accounting processes, the process should be as digital as possible as this might already bring the benefits looked for.

Small organizations with limited number of employees, R&D funds and knowledge are not usually the front-runners in new technologies and innovations. They tend to wait until evidence of the benefits of the new technologies is demonstrated and preferably by their peers. Co-operation with national federations, universities and non-profit organizations provides good opportunities for learning and implementing new technologies, such as RPA and AI. Fortunately, at least in Europe, projects supporting SMEs have been funded quite well and with help of collaborative networks SMEs will remain competitive. It is crucial, that the SMEs understand the importance of improving and questioning the current ways of working.

Considering our limitations, our case explored organizations from only one country, so it would be interesting to extend this research beyond Finland and study also other locations. Moreover, it is recommended to study more examples and cases of RPA technology implementations from the perspective of its synergy with process management and process improvement. In the upcoming months, due to the rapid growth in the popularity and importance of AI solutions (such as ChatPGT), it is also recommended to explore how RPA products could be transformed to provide better and more approachable offerings of automation services not only to large organizations, but also to medium and small enterprises (SMEs) that would like to deploy this technology and collaborate with software robots and assistance, as part of hybrid workforce.

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Collaborative Ecosystems for Increasing Automation in Accounting Processes in Small Firms

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Abstract. Automation of accounting processes promises various benefits for firms, such as enhanced productivity, improved customer service and job satisfaction. Despite the enhancements, small firms are often reluctant to undertake accounting process automation projects. This research studies how collaborative ecosystems support small firms in adopting accounting automations. The study draws on the Technology Acceptance Model (TAM) and studies the perceived usefulness and ease of use of automation technology in the context of small firms. In this qualitative research, 12 firms joined a collaborative ecosystem to develop automated accounting processes. A year later, 12 semi-structured interviews were conducted to examine the technology uptake by the firms. Our findings indicate that a collaborative ecosystem provides support in the first steps of technology uptake, especially by adding to the perceived usefulness of the automations. However, it did not increase automation-related skills enough to increase the perceived ease of use of the technologies.

Keywords: Intelligent automation · collaborative ecosystems · collaborative networks · accounting processes · accounting process automation · technology adoption model · small firms · skills · RPA · society 5.0

1 Introduction

Over the years, accounting work and processes have undergone significant changes due to automation and digitalization. New technologies such as cloud, artificial intelligence (AI), robotic process automation (RPA), big data, and blockchain may lower the burden of accounting-related routines and free up management and employee time [1, 2]. Out of these technologies, AI and RPA are the ones which are used for automating business processes, first, by adopting RPA and then possibly, second, by enhancing it with AI algorithms [3]. However, even though AI solutions in accounting exist, they are not commonly used yet [4]. Siderska et al. [5] present potential technologies and common barriers for adopting AI within RPA systems. Due to the relatively low adoption rate of

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machine-learning technologies in RPA, the more traditional rule-based RPA has attracted the attention of accounting researchers during the past years. For instance, prior studies have examined task suitability, implementation, and impact on performance in large firms [6] and Big 4 accounting firms [7], RPA-related technology acceptance in a big oil firm [8] and the impacts of RPA on individual and organisational behaviour in a big service firm [9]. Moreover, RPA has been said to bring cost savings, improve customer service and its quality, increase productivity, and raise job satisfaction because RPA allows for routine tasks to be automated [10, 11]. However, most of the prior research on RPA focuses on large firms, but RPA may be even more important in the context of small firms. In addition, prior research shows that technology adoption, including digital transformation, is often a challenge to SMEs while large firms are forerunners in this area [12]. Small firms may have limited resources such as the skills, time or finances needed for development [13]. Nevertheless, small and medium enterprises (SMEs) play a vital role in most economies, constituting 50% of employment and 90% of firms [14]. Therefore, it is important to examine solutions that could support the small firms in digital transformation such as adopting automations.

We define collaborative ecosystems (CE) as innovation ecosystems that include a collaborative network. An innovation ecosystem is a loosely interconnected network of companies and other entities that co-evolve capabilities around a shared set of technologies, knowledge or skills, as well as work cooperatively and competitively to develop new products and services [15]. A collaborative network is an organisation of a variety of entities (e.g., organisations and people) that are largely autonomous, geographically distributed and heterogeneous in terms of operating environment, culture, social capital and goals; nevertheless, these entities collaborate to better achieve common or compatible goals [16] and are considered as core enablers of the digital transformation of Industry 4.0 [17]. In the European Union (EU), the EU-funded European Digital Innovation Hubs (EDIHs) form innovation ecosystems (i.e. CEs), which aim at enhancing and facilitating digital transformation of SMEs in Europe [18]. Whereas the EDIHs are large, multi-year projects, similar CEs can be created from a dynamic virtual ecosystem where organisations aim to increase and share their knowledge for a short period of time [16] such as an EU-funded project [19] Participating in CEs can benefit firms in several ways [18, 20], however, less is known about how CEs can benefit firms in improving and digitalizing their internal processes, such as accounting processes, or provide support in increasing the skills these technologies require.

To address the gap in previous studies, this paper explores whether a CE can support small firms in automating their accounting processes with RPA and in developing the necessary human skills for this emerging technology. As RPA is a new technology for small firms, this study applies the technology acceptance model (TAM) [21]. TAM is the most widely used framework for predicting information technology adoption [22]. This paper adopts a qualitative methodology, analysing the experiences of 12 small firms which participated in a CE in the form of an EU-funded project called the Center of Intelligent Automation for SMEs (CIPAS) during years 2021–2023. The CE provided the firms with training, workshops and an RPA technology-based proof of concept (POC) for accounting process automation. One year later, 12 interviews were conducted with the firm representatives about their experiences and understanding of the current state of accounting process automations. Hence, the following research questions were formulated: RQ1: How can a collaborative ecosystem support small firms in accounting automation? RQ2: How is the usefulness and ease of use of accounting automation perceived in small firms?

This study makes three main contributions. Firstly, the study contributes to previous collaborative ecosystems literature by filling the gap concerning the role of CE in supporting small firms in developing their internal processes, specifically focusing on accounting-related automations. Secondly, the study shows the importance of new skills when implementing new technologies in small firms. Thirdly, this study adds to the accounting literature by showing how accounting process automations are perceived among small firms. There has been a call for more empirical studies on the adoption of new internet-related technologies in the field of accounting, especially among small firms [1]. This research responds to this call.

The organisation of our paper is as follows: Sect. 2 describes prior studies focused on collaborative ecosystems, the technology acceptance model (TAM), benefits of automation and RPA in accounting processes and skills required for automating accounting processes. Section 3 describes the empirical setting and the interviewed firms. The results are presented in Sect. 4. Section 5 analyses the significance of the results, both in theoretical and practical terms. Section 6 concludes the paper.

2 Prior Studies

Considering that today's collaborative networks are emerging technologies-based ecosystems which can be formed to solve difficult societal problems by using co-creation and focusing on human-centred goals [23] Firms participating in such networks may pilot, test and experiment with digital innovations to support their digital transformation processes [18]. In addition, collaboration may provide a possibility of sharing (R&D) costs, increasing innovative capacity and decreasing dependence on a third party, such as a consulting firm, through the creation of privileged links to firms that possess knowledge and skills. Active participation in collaborative ecosystem seem to yield greater benefits [20]. While not many studies have been done on the role of collaborative ecosystems in accounting, some studies exist on their role in the broader context of knowledge work [24], the importance of collaborative networks between universities and businesses in digital transformation [25] and the creation of collaborative networks for testing blockchain technologies [26]. As Davenport [27] stated, knowledge workers' process automation is not as straightforward as in other types of work. Experts' ways of working are often very dependent on collaborative ecosystems. Knowledge workers typically collaborate through various digital platforms and communication channels with other experts inside and outside of their organisation to exchange ideas, knowledge and experiences. With the advent of recent technological advancements, some of those human collaborators have been replaced by or augmented with AI [28].

The Technology Acceptance Model (TAM) is the most commonly used framework for predicting information technology uptake in organizations [22]. TAM is based on two factors determining the acceptance or rejection of information technology solutions. The first factor, perceived usefulness, refers to the degree to which an employee believes the technology is beneficial and enhances job performance. The second factor, ease of use, refers to the degree to which an employee believes that the system is easy to use and requires little or no mental effort [21]. In the context of accounting, TAM has been successfully applied to explaining the adoption of integrated accounting and budgeting software [29], the usage of digital accounting systems in SMEs [30], and the adoption of new technologies among accounting professionals [31], among others.

Robotic Process Automation (RPA) is a technology that allows software programs to mimic human actions as they interact with computer applications to perform necessary tasks. Configuring RPA is thought to be easy, as the new low-code/no-code solutions allow users just to drag, drop and connect functions with the corresponding code generated automatically. Additionally, the implementation of RPA requires little knowledge [32], and it is relatively easy to implement as it does not require customized software or deep systems integration [33]. Such an easy technology to use is the best way to start the process of automation development in firms, particularly in small firms. Once this technology is well in use, more advanced technologies can be implemented.

TAM model has been enhanced with other explanatory factors depending on the domain of the research [34]. In an accounting and RPA context, the perceived usefulness could mean cost reduction, productivity enhancement, revenue growth, improved customer service, and the attraction of new clients, as well as improved opportunities for meeting customer expectations, aligning firm behaviour with that of competitors, and fostering higher job satisfaction [11, 31]. On the other hand, barriers for acceptance could be the cost of the hardware or its implementation, upgrades and the licensing of automation tools, management or staff support, or even lost billable hours. Automation might not work for all processes, and thus the benefits of using such could remain low [31].

Perceived ease of use in RPA-based accounting automations can be viewed from the point of view of skills. New technologies require new skills be acquired by employees [35], which indicates that missing skills might prevent the adoption of technologies. For this reason, in this study, the perceived ease of use is combined with the skills required. Using new technologies requires evaluation, implementation, maintenance, and risk evaluation [1, 28]. Also, when letting new technologies such as AI or RPA take care of the routine work, employees might need to do more challenging work, which can also require that they learn new skills [36]. In addition, interdisciplinary skills, IT skills and the skills and abilities to use digital tools easily are seen as important [37]. Automation may also lead to deskilling, as automated solutions can result in individuals losing the ability to perform the tasks in question [1]. In summary, in this study, the TAM model's perceived usefulness and ease of use are thus combined with the literature on RPA and accounting automation (Table 1).

Table 1. TAM theory combined with benefit and skill factors from RPA and accounting automation literature.

TAM factor	Factor related to accounting automation	Supporting literature
Perceived usefulness	Cost reduction; Productivity enhancement; Improved customer service; Higher job satisfaction	[11, 31]
	Revenue growth; Attracting new customers; Meeting customer expectations; Aligning with competitors	[31]
Perceived ease of use	Skills and ability to use digital tools easily	[37]
	Recognition of new automated processes; Control over the system: Implementation, Maintenance and Risk evaluation skills; New skills when transitioning from routine tasks to those requiring more expertise; Deskilling	[1]
	IT skills which support ease of learning	[28, 31]
	Collaborative ecosystem support, skills, and knowledge	[17]

3 Research Design and Method

This research applies a qualitative methodological [38] approach to interview data. It focuses on understanding businesses' views and perspectives by adopting an interpretative approach [39]. The research subjects were selected by purposeful sampling [40] from firms participating in an EU-funded CIPAS project during 2021–2023. The project delivered automation-related training and workshops to over 50 small- and medium-sized enterprises (SMEs). Among these firms, 17 SMEs received additional consulting from project specialists and potentially an automation proof of concept (POC) via a 'test before invest' approach. These firms were also able to collaborate with each other in the workshops. Out of the 17 firms, 12 small firms were selected for this research due to their size and activity in the CE. This sample size is considered a sufficient number of research subjects for a qualitative study [41]. A year later, these 12 firms were contacted for interviews and all agreed. The characteristics of firms participating in this research are presented in Table 2. To simplify reporting of the results part, the firms are coded as Firm 1 to Firm 12 (F1 to F12).

An interview guide[1] was created to conduct semi-structured interviews with the 11 entrepreneurs and one employee of the 12 firms. Interview questions were formulated based on the theoretical framework [42] presented in Table 1. First, the experiences with the CE were discussed, followed by an examination of the perceived usefulness and the skills gained. Interviews were done by phone during May 2024. The interviews were conducted by the first author in Finnish, with a translated interview guide. The length

[1] Interview guide can be accessed via: https://shorturl.at/Vaa3P.

Table 2. Characteristics of firms that participated in the research.

Firm	Size	Industry	Turnover kEUR	Automation
Firm 1	sole entrepreneur	accounting services	100	Task digitalization
Firm 2	micro	accounting services	700	POC
Firm 3	micro	other services	50	POC
Firm 4	micro	accounting services	250	POC
Firm 5	micro	trade	500	Process development
Firm 6	micro	other services	2,600	POC
Firm 7	micro	accounting services	150	POC
Firm 8	micro	trade	500	POC
Firm 9	micro	accounting services	250	POC
Firm 10	micro	accounting services	200	POC
Firm 11	sole entrepreneur	real estate management	40	POC
Firm 12	sole entrepreneur	other services	50	POC

of the interviews varied within 11–35 min, with the average length being 20 min. If the firm had deployed the POC or created more automations, the interview lasted longer as there were then more questions to answer in comparison to those for firms who had not deployed any automations. Notes from the interviews were entered into an Excel spreadsheet, after which they were analysed with NVivo [43] which is a qualitative data analysis software. In NVivo, the interview data were coded into eight codes: Collaborative ecosystem, Expectations, Use or not, Ease of Use, Usefulness, Benefits, Constraints, and Skills.

4 Results

4.1 Collaborative Ecosystems Supporting Small Firms in Automation

During the interviews, interviewees were asked whether joining the CE was beneficial for the implementation of accounting automations. If the CE was seen as beneficial, then the interviewees were asked to specify the types of benefits they had gained by joining the CE. Half of the interviewees were unaware of office automations before joining the CE, leading to an increase in general knowledge of the subject. Nine of the interviewees reported that participating in the CE was beneficial, whereas for three (F2, F6, F7) it was not. F2 and F7 participated least in CE activities due to time constraints, and F6 had technical challenges in using the automation tools with their operating system (Mac).

When it comes to the trainings, all participants acquired the skills to identify tasks or processes suitable for automation and learned that automations could be done by themselves with no-code/low-code automation tools (MS Power Automate or UiPath). Interviewees especially praised the one-day workshops as that setting allowed entrepreneurs to not only learn how to use automation tools but also to collaborate with other entrepreneurs and share experiences. In small firms, the lack of colleagues to collaborate with in the firm makes networking with other firms important. F6 expressed willingness to share automation experiences with the CE, whereas F2 wished more opportunities for collaboration had been provided.

Initially, an RPA-based automation POC was made for 10 firms (Table 2). The remaining two firms received consulting support for process digitalization and advice on how to develop their existing processes, as the processes were not mature enough to be automated. Nine of the automation POCs were made using MS Power Automate [44] and one with the open-source automation technology Robocorp [45]. As the project provided POC based on the 'test before invest' idea, it was thought that deploying the POC into a production environment required the firms to use an external consultant. However, the consultant cost was lower because the cost of the automation coding had already been completed.

Only three firms (F1, F3, F10) had deployed the POCs developed in the project. F3 had paid consultants to deploy the automation, whereas F1 and F10 had deployed them on their own. Nine firms had created more automations, meaning that even though not all firms deployed the POC developed in the project, they still developed alternative solutions, either independently or with external assistance. Five firms (F3, F4, F6, F9, F10) had been able to develop the automations themselves whereas four firms (F1, F8, F11, F12) had found someone within their networks to assist with the automations. F7 found the POC interesting, but they had expected the project to deploy it for them.

In summary, a CE can support small firms in increasing technology-related knowledge and skills even in firm internal process development. In this study, the acquired skills were knowledge of automation possibilities, skills to recognize potential automations and, in some cases, even the skills to develop automations. Solutions to engage entrepreneurs and address their lack of time should be identified, as active participation in the CE appeared to enhance the perceived benefits of participation. Consulting and the 'test before invest' concepts were seen as important, as they increased practical knowledge of new technologies. Getting all these services free of charge was a huge benefit for the small firms with limited resources. Interviewees also valued the collaborative aspect of the ecosystem: small firms want to learn and share knowledge with each other. Even though some of the firms were from the same industry, they did not consider their accounting processes as a competitive factor.

4.2 The Perceived Usefulness and Ease of Use of the POC Automation

The firms were asked whether they found the automation POCs useful, and all of them acknowledged their usefulness (Table 3). When asking why they were useful, the responses varied. For F1, a paper-based process had been digitalized but no real automation or RPA-based POC had been created due to the firms lacking the IT skills of the entrepreneurs. One respondent, a soon-to-retire entrepreneur, perceived the new process as a way to improve productivity and job satisfaction by reducing working hours. Due to the respondent's plans to retire, the firm had not looked for new customers to fill in the working hours saved through participation. The billings remained the same, so even the automation saved time, and it did not reduce the revenues. In F3, an external consulting firm had been recruited to deploy the automation in F3's production environment. For F3, the original goal was to automate mundane, time-consuming tasks and to use the extra time for customer service and acquisition. The automation did exactly what was expected: it saved time. So far, the entrepreneur had used the time for creating new automations. In the end, the entrepreneur saw that once the planned automations were in place, the revenues would increase because of new customers. F3 was a sole entrepreneur, service firm, but its size did not prevent the firm from enjoying the benefits of automation. F10 had also put the automation in use and developed new automations. Automations had improved the quality of customer service but also reduced the prevalence of boring, routine work.

Table 3. Perceived usefulness of the automation POCs according to the firms under study. The factor of perceived usefulness is presented by [11, 46]

Factors of perceived usefulness	Firms
Automation was seen useful	All firms
Productivity enhancement	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
Higher job satisfaction	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12
Higher customer satisfaction	3, 6, 9, 10, 11
Revenue growth	4, 12
Developing firm	4, 12
Rejection: Lack of time	7, 8, 11
Rejection: Fear of automation costs	2, 7, 9

There were several reasons why some firms did not adopt the POC-related automations. For F4, the POC aimed to use the tax authorities' user interface (UI) more efficiently. As the CIPAS project had a representative from the national tax office in its steering group, the information about this need was forwarded to their development department, and in the end, the improvement was done directly to the UI by tax authorities, making the automation unnecessary. Although minor manual work remained, F4 had not seen the need to automate it yet but did report considering the idea of making the change. However, they had created other, simpler automations themselves. F6 believed that the automation from the POC would have enhanced their productivity, job satisfaction, and customer satisfaction. Unfortunately, since the automation was related to a type of project they currently did not have, it was not deployed. F9's automated task was done only once a year, and they felt that the deployment would have taken more time than the manual work. Additionally, the entrepreneur was intimidated by the costs of automation. On the other hand, even the POC had not been deployed; it had inspired F9 to create other automations to eliminate routine work. F12 had not deployed the POC either, as they had put a new accounting system in use, but they had created other automations which saved a day of work per month. This automation allowed the firm to take new customers, and thus revenues had increased as a result. The developed automation was an innovation which could even be sold as a service if developed further. F5 was the other firm that did not receive an RPA, POC in the project. Instead, they were given recommendations for how to improve their processes before considering automation. F5 had done some improvements, which provided savings in both accounting costs and time spent, but the firm had been sold during summer 2023. Finally, F2, F7, F8 and F11 had not put the automations in use even if they considered the automations to be useful. F2 believed automation would be useful to enhance productivity, improve job satisfaction and align the firm with the technology utilized by its competitors. Despite this, F2 feared the costs of automation. F7's employees were frustrated with the manual process, but due to a lack of time, they had not found out the deployment cost, which would then need to be passed on to the customer. Also, F8 and F11 did not have time for deployment, though they believed automation would enhance productivity and improve customer service and employee satisfaction.

Additionally, the ease of use was discussed in the interviews. As presented in the theoretical section, ease of use is related to the skills the user has, and thus those skills were assessed. According to the interview results, only F1 and F10 perceived the automations as easy to use (Table 4). F1 was given a very simple automation, but its maintenance relied on external expertise. F10 used the POC and had created some of its own automations. The firm was able to develop the automations with the help of a project consultant who had been able to create more automations.

Table 4. Perceived ease of use of the automation as seen by the firms. The assessment is based on the skills of the user as presented in [1, 17, 37].

Factor	Firms
Automation was seen easy to use	1, 10
Recognizing new processes to automate	1, 2, 3, 4, 5, 6, 7, 8, 9, 10
Developing own automations	3, 4, 6, 9, 10, 12
Maintaining automations and preparing for risks	3, 4, 6, 9, 10, 12

F3, the firm that deployed the POC, faced numerous challenges before the automation was fully operational in the production environment, despite having received assistance from an external consultant. Perhaps due to the struggles, the firm's skills in automation had increased, and it was able to develop new automations. For F3, practically all automation-related skills were increased during the project: evaluation of new automations, creation of own automations, maintenance of automations, and preparation for possible risks. As the automation was addressing very simple tasks, no deskilling was recognized.

Five firms (F4, F5, F6, F9, F12) did not take the POCs into use; they started to make their own automations or developments with the skills they either previously had or that they had acquired from the project, or with some help from their own network. They saw the project gave them the first prompt to question existing processes. The rest of the firms (F2, F7, F8, F11) did recognize the need for automation and tasks which could be automated, but they were not able to do it on their own.

5 Discussion

In general, collaborative ecosystems (CE) are important in increasing small firm's knowledge on new technologies. The findings of the paper show that the CE inspired small firms and provided the first initiatives on automations. The skill of recognizing automation possibilities increased, and the possibility to test new technologies in practice without investment was seen as beneficial. This is in line with the European Union's objectives to provide digital innovation hubs to support SME digitalization [18]. By providing proof of concepts (POC) the CE shared costs and decreased the need for third party consulting before implementing the POC, which is in line with previous studies on benefits of collaborative networks [20].

According to our study, the main challenge is increasing the technology-related skills of employees when the entrepreneurs are very busy and have no time to participate in CE activities. The finding that small firms typically lack the resources and skills for adopting automations is in line with the research of [12] on the challenges that small firms face when implementing digitalization opportunities. The lack of resources is typically demonstrated by the lack of time or lack of possibility to resort to the support of external consultants. In these cases, SMEs typically can receive support from publicly funded initiatives undertaken by both academic and non-academic institutions [12]. The collaborative ecosystem in which the firms of this study participated is an example of such an ecosystem. In addition, perceived benefits of collaborations are greater when firms participate more actively [20], which was also seen in this study.

Collaborative ecosystems can also have an impact on the national level. One of the firm's automation POCs was built in the national tax authorities' user interface (UI), and the automation would serve all of the over 6000 accounting firms in Finland. Even the POC was created in the project, the project had a representative of the tax authority in the steering group, and at the end the development, it was made into the tax UI. Based on this experience, we suggest considering the inclusion of public authorities in the ecosystems. Mueller and Hopf [47] present a somewhat similar initiative in Germany, targeting the digital transformation of SMEs. The collaborative ecosystem consisted of five partners from both academic and other organizations. The EDIHs (European Digital Innovation Hubs) also represent a somewhat similar competence centre for SMEs, and they also typically consist of a consortium of both academic and non-academic partners [48]. However, public authorities seem to be missing from the consortia quite often.

The Technology Acceptance Model (TAM) was used to explain the adoption of the new technologies. This paper has demonstrated that all firms considered the automations useful, especially for enhancing productivity and increasing job satisfaction when routine, time-consuming tasks are automated. However, the automations were so specific and rarely done that the firms did not see any real cost-savings. This is partly in line with the findings in Kedziora et al. [11] who studied larger firms. For two firms, the automation was seen as a possibility for generating bigger revenues, and this result was also recognized in Jackson et al. [46]. The automations were not seen as easy to use. Every firm felt they had increased their knowledge about the benefits that automations would give them, but only a few had increased their skills in implementing, maintaining and thus controlling the automations. Learning takes time, which the small firms do not have. We agree with Moll and Yigitbasioglu [1] that new digital technologies, automation, and

IT should be among the skills which are learnt in universities' accounting programs, so future accountants are able to automate their work. The lack of relevant skills has been identified as a barrier in the adoption of RPA in organizations, see e.g. Flechsig et al. [49] and Siderska [50]. However, there is a lack of studies concentrating on SMEs and small firms.

This paper adds to the existing accounting literature by showing that small firms can adopt new technologies in their accounting processes even though they do have challenges. However, the automations in small firms can be much simpler than among big firms and thus complicated development processes are not needed, as was documented in Zhang [6] focused on two big firms. In addition to process improvement, the interviewed firms expected the automations to give more job satisfaction. This is in line with the studies conducted in big firms, where despite the fear of losing jobs, automations eventually improved workers' work-life balance [7].

6 Conclusions

This paper examined how a collaborative ecosystem supported small firms in adopting accounting automation technologies (especially RPA) to lessen manual work in accounting processes. More precisely, the Technology Acceptance Model (TAM) was applied to study the perceived usefulness and ease of use of automation technology in the context of small firms. In total, 12 firms participating in the automation-related CIPAS project during 2021–2023 were selected for the study. The project provided training, consulting, and RPA automation proof of concepts (POC) or automation consulting for the firms. One year after the project had ended, semi-structured interviews were conducted with the firms' representatives. The results show that collaborative ecosystems are important for small firms when implementing new technologies. By joining the CE, the firms were able to increase their knowledge of new technologies and get inspired to automate their processes. Also, in the CE, the small firms were able to learn from each other's experiences. However, only a few of the firms had deployed the POCs, but those that did were using them regularly. These firms had even advanced their automations further. Regarding the non-implemented POCs, some were no longer relevant to the firms, but they had automated other tasks instead. Nevertheless, some firms remained dependent on third parties for automation, implementation, and maintenance, so their automation skills had not increased enough.

This study makes three primary contributions. Firstly, it addresses a gap in the existing literature by highlighting the role of collaborative ecosystems in supporting accounting-related automations in small firms. Secondly, it enriches the accounting literature by illustrating how small firms can benefit from accounting process automations. Thirdly, it shows the importance of acquiring new skills when implementing new technologies in small firms.

More research should be conducted on how skills such as evaluating, implementing, and maintaining new technologies in the field could be increased in small firms in order for them to stay competitive and effective. In general, collaborative ecosystems are important in increasing small firms' knowledge of new technologies, but they require active participation and time. Another track for future research is that of a wider investigation of the collaborative ecosystem. The current work focuses on only one stakeholder:

the small firms for which the POCs were created. Other stakeholders that had potentially great benefits from the innovation ecosystem were the firms performing IT-consulting and the academic partner. More research on the forms and digital platforms of collaboration among the different stakeholders of the network would shed light on what type of collaborative networks and practices are beneficial when adopting automation in the domain of accounting services.

This paper has some limitations by virtue of being a qualitative research project focused on 12 very small firms. In a qualitative study, understanding the terms of a certain context is important, and therefore it may not be generalized to the larger population but rather considered as a pilot study. In addition, a limitation is that the research was conducted in Finland, which is advanced in digitalisation. Hence, the results could be relevant for similar developed countries but probably not for less developed ones. This study also focused on RPA solutions, whereas other technologies such as AI are also very relevant for accounting processes (or will be in the future). However, the CIPAS project concentrated on RPA solutions and thus gave the setting for this research. More studies on AI in automating small companies accounting processes should be conducted.

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Transition to Organisation 5.0 - Barriers and Enablers of AI Adoption in Accounting and Finance

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Abstract. This research explores the extent to which accounting and finance organisations are transitioning to Organisations 5.0, and what they perceive as barriers and facilitators in this transition process. Our study builds on existing literature regarding the challenges and facilitators of AI implementation, expanding on these concepts through a survey in the professional accounting and finance domain. Our findings indicate that the primary challenges to AI adoption are a lack of expertise and incompatibility with existing tools, programs, and systems. According to accounting and finance organisations, the two most impactful ways to address these challenges are to provide their personnel with good-quality training and opportunities for updating skills and to create an organisational culture that fosters learning and innovation. Surprisingly, the third most important facilitator is usability and a seamless user experience, which aligns with the focus on human-centredness put forward by the Organisation 5.0 concept.

Keywords: Organisation 5.0 · Transition · Human-AI Collaboration · Accounting · Finance · AI

1 Introduction

In this study, we investigate the barriers and enablers of artificial intelligence (AI) adoption in accounting and finance organisations. Specifically, we examine whether the enablers are aligned with the human-centric principles of Organisation 5.0. We aim to understand the extent to which what extent these organisations are applying a more human-focused, sustainable, and collaborative model of AI deployment. Artificial intelligence and other technologies can improve the performance and security of financial systems, yet they pose challenges such as high costs, compatibility issues, and data privacy concerns [1]. These technologies may also enhance accounting and finance processes by improving efficiency, security, and work flexibility. However, AI adoption in accounting and finance is lagging behind other business functions, such as marketing and sales [2] even though the business models of financial services are completely digitisable [3].

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Previous accounting research suggests that new technology adoption should prioritise a human-centric approach rather than focusing solely on cost savings and efficiency [4]. This aligns with the core principles of Industry 5.0 and, by extension, the concept of Organisation 5.0—an approach in which workers are seen as investments rather than mere cost factors [5]. Organisation 5.0 refers to entities operating under the Industry 5.0 paradigm, where human well-being, sustainability, and regenerative economic value creation are central. This stands in contrast to the technology- and efficiency-driven focus of Industry and Organisation 4.0 [6]. In other words, an Organisation 5.0 leverages human skills in combination with the technological potential of robots and intelligent systems, guided by three key pillars: (1) green orientation, (2) resilient ways of working, and (3) human-centricity [7]. This fifth industrial revolution also emphasises the importance of collaborative networks, through which organisations can foster synergies, drive innovation, and better address complex global challenges [8]. Although Industry 5.0 often centres around manufacturing, the same concepts may be applied to knowledge work, such as that found in accounting and finance. Thus, in this paper, we examine the extent to which accounting and finance organisations are currently transforming toward Organisation 5.0.

Building on this human-centric foundation, recent developments further underscore the need for human-centered AI (HCAI) systems, where human abilities and well-being are augmented. While the developments of the last decade predominantly focused on task automation and the consequent replacement of human roles, HCAI rather emphasises technology transparency, explainability, and ethical AI practices, asking for increased human control and involvement. Examples in healthcare [9, 10] education [11], and manufacturing [12] already pave the way and highlight the potential of this shift. The ongoing trend towards the use of GenAI solutions and the consequent rise of so-called AI agents, however, demands appropriate human-AI collaboration paradigms in other fields as well. Thus, also in accounting and finance we see technological advancements reshaping the field and thereby impacting its workforce; particularly in middle-class jobs and female-dominated sectors [13]. The transformation of work dynamics in accounting and finance, driven by automation and AI, thus raises critical questions about the balance between technological efficiency and human well-being. Investigating the collaborative potential between AI and human workers, however, may identify strategies to enhance productivity while ensuring that technological adoption remains inclusive and equitable.

This study responds to the call for further research on the integration of technology in accounting and finance [14], offering fresh insights from the emerging shift from Industry/Organisation 4.0 to Organisation 5.0 [15]. By introducing the Organisation 5.0 perspective into the accounting discourse, the study highlights the significance of a human-centric approach to digital transformation—particularly in the implementation of artificial intelligence (AI). This way our work contributes to the growing conversation about the barriers and facilitators influencing AI adoption in accounting and finance. To address this gap, we propose the following two research questions:

1. *What are the main barriers finance and accounting organisations face in the deployment of AI and other emerging technologies?*
2. *To what extent do Organisation 5.0 elements support finance and accounting organisations in preparing for these challenges?*

To address these research questions and contribute to the ongoing discussion around transitions towards Organisations 5.0 in the accounting and finance sector, we analyse survey data collected from 103 professionals working in organisations of varying sizes and types across Finland. The data were gathered in Spring 2025. By examining how these professionals engage with AI technologies, we aim to shed light on whether and how accounting and finance organisations are progressing toward becoming human-centric, collaborative Organisation 5.0 entities.

The remainder of this paper is structured as follows. Section 2 discusses related work. Section 3 outlines the research methodology, including data collection. Section 4 presents the empirical findings, while Sect. 5 discusses these results in relation to existing theoretical frameworks. Finally, Sect. 6 concludes the paper by summarising the key insights and suggesting directions for future research.

2 Related Work

Since the First Industrial Revolution (Industry 1.0) in the late 18th century, humankind has leveraged technology for advancement, evolving from mechanical power to electrical energy in the Second Industrial Revolution (Industry 2.0), and to the integration of automation into productions through electronics and IT in the Third Industrial Revolution (Industry 3.0) [16]. Emerging technologies such as cloud computing and AI then laid the foundation for the Fourth Industrial Revolution (Industry 4.0) which also had a significant impact on the accounting profession [17]. Industry 5.0 now aims to achieve societal goals beyond economic growth by making production sustainable and prioritising workers' wellbeing. As such, it complements Industry 4.0 by driving the transition to a human-centric, resilient, and sustainable European industry through research and innovation [6].

Organisations that operate in alignment with the core pillars of Industry 5.0, i.e. green orientation, resilience, and human-centricity, can be characterised as Organisations 5.0 [7]. These organisations do not function in isolation; rather, they derive value and address complex challenges through collaborative networks. These next-generation networks (Collaborative Networks 5.0) are grounded in emerging technologies but distinguish themselves by placing human needs and values at the forefront of their design. They emphasise co-creation, inclusivity, and ethical considerations, ensuring that collaborative processes are not only technologically advanced but also socially responsible and accessible to all stakeholders [18].

Accounting and finance organisations should place particular emphasis on Organisation 5.0 features and operate within collaborative networks, for previous research shows that ethical questions and trust have been key challenges accounting and finance organisations face when implementing AI technologies. According to Lehner et al. [19], e.g., the biggest challenges in implementing AI in accounting and auditing organisations are objectivity, data privacy, transparency, accountability, and reliability. Kruse et al. [3] highlight almost the same challenges for the financial services sector, including a lack of transparency, which complicates the understanding and monitoring of operations, and data privacy issues, as AI systems process large amounts of personal data, which can lead to data breaches and privacy violations. Kellogg et al. [20] confirm this finding.

Regarding accountability, the division of the responsibility between AI system developers and users remains unclear, which undermine ethical decision-making and lead to the shifting of accountability [3]. Furthermore, AI system algorithms can contain biases and errors created by humans, which affect the objectivity of decision-making [20]. Additionally, AI systems' decision-making processes and algorithms are often opaque, making it difficult to understand and monitor their operations. Finally, the reliability of AI systems and people's trust in them are considered critical factors affecting their acceptance and use [21].

Finance organisations are no different. On top of the ethical matters, missing skills may also cause issues around AI implementation. The implementation of AI in financial organisations thus presents several challenges related to the management of technology, data, processes, and people. Implementing AI, e.g., requires a deep understanding of both the technological and business perspectives. For example, AI can be used to design and optimise complex market analyses and mechanisms, but this requires a deep understanding of market operations and AI algorithms. In forecasting, reliability largely depends on the quality and availability of data, and AI models can be sensitive to changes and anomalies in the data [22, 23]. Rahman et al. [24] add that in banking services, data privacy and security risks, as well as employees' insufficient skills in data analysis, hinder the implementation of AI. Kruse et al. [3] further highlight digital skills, data privacy, and security risks and point out issues with the availability and quality of training data, outdated IT infrastructures, and hierarchical organisational structures. Finally, according to Aldoseri et al. [22], implementing AI requires high-level technical expertise, so the lack of trained professionals can slow down its implementation and prevent effective utilisation.

Despite these challenges, the finance and accounting field can build on lessons learned from other domains. Examples from Industry 5.0, show how human-centred AI approaches, focusing on transparency and explainability, can foster people's trust in and reliance on AI technology [25, 26]. Moreover, Mazarakis et al. [27] underline the importance of an interdisciplinary approach to implementing HCAI at work. Only then can AI technology be successfully and sustainably embedded into existing, often well-established working routines. To this end we also need to better understand the different roles AI can play in the collaboration spectrum. Leng et al. [28], e.g., suggest to clearly distinguish between collaborative intelligence, where humans and AI join forces to perform tasks; self-learning intelligence, where the AI autonomously learns from data and finds optimal solutions to existing as well as new problem spaces; and crowd intelligence where multiple human-machine groups collaboratively or competitively carry out tasks and therefore shape a rather complex interrelationships of an AI augmented work environment. These concepts must be considered so as to shift from a purely technology-driven to a more value-oriented way of collaboration. Taking the example of human-centred smart manufacturing, Martini et al. [29], e.g., show how different phases of the manufacturing process (i.e., design, production, maintenance) may require different levels and types of intelligence integration, while Rožanec et al. [30] illustrate how such a flexible integration of AI into existing work processes could be achieved. The finance and accounting sector may also benefit from such integration as shown by Massaro et al. [31] who demonstrate the opportunities AI may hold for forecasting and business planning activities.

Organisations can furthermore proactively prepare for these challenges and thereby ensure a smooth transition towards Organisations 5.0 by leveraging a range of facilitators across functional, organisational, and strategic levels. At the functional level, organisations can build the necessary competencies by offering both internal and external training while fostering a culture of innovation and continuous learning [15]. Emphasis should also be placed on ensuring a seamless user experience with technology by aligning tools with actual work tasks, increasing the usability of tools and selecting solutions that integrate naturally into the industry and workflows [15, 32]. At the organisational level, fostering collaboration, at least between internal departments, and ideally extending to external networks, can significantly enhance knowledge sharing and collective problem-solving [15]. Organisations can also encourage employees to test new technologies and participate in or create forums and communities to share knowledge and experiences [33]. At the strategic level, organisations can support transformation by piloting emerging technologies, establishing robust digital governance structures, and cultivating a willingness to invest in digital initiatives [15]. Among these facilitators, the organisational-level elements are particularly aligned with the principles and practices of Collaborative Networks 5.0 and Organisation 5.0, which emphasise interconnectedness, co-creation, and human-centric innovation.

3 Methodology

3.1 Research Design

To address the research questions outlined in Sect. 1, we developed a survey as an initial exploratory instrument. Its purpose was to generate preliminary insights into the topic and serve as a foundation for future research, potentially guiding subsequent studies toward (1) a more comprehensive understanding of the biggest challenges accounting and finance companies face in AI implementation and (2) methods to facilitate AI adoption by accounting and finance companies [15]. Our survey included two main questions: The first addressed key challenges in AI adoption and the second asked how organisations can prepare for these challenges. Additionally, the survey featured eight background questions on demographics and professional context, including age, location, education, company type, job position, and experience. The survey was tested with 12 accounting and finance professionals.

The final survey consisted of the background questions and two survey questions.[1] In the survey, respondents were asked to choose five most relevant barriers or facilitators and rank them in order of importance. The ranking approach has been selected because studies show that respondents tend to be too comfortable with likert-scale surveys [34] and may sometimes answer them somewhat fast without deep thinking and overly using the middle scores [35]. The ranking task forces them to pay attention and to consider the options in more depth. The AI challenge question listed 13 options of AI implementation challenges. These 13 options were based mainly on qualitative research results of Kokina

[1] Survey and its sources can be accessed via: https://tinyurl.com/57fabdxa.

et al. [36] and Kedziora et al. [37] as well as some general statistical results from Statistics Finland [38]. The options are presented in Table 1. The final drivers-related question contained 12 options. These facilitation question options were based on qualitative results of Kans and Campos [15] and Jackson and Allen [33] and can be found in Table 2.

Table 1. The barriers to AI adoption in accounting and finance organisations, ordered according to their perceived importance, illustrated by the total score. Counts for 0, 1, 2, 3 4, and 5 points show how many times they were selected. Zero means that the challenge was not selected at all.

Barrier	Counts of the points						Total score
	0	1	2	3	4	5	
The company lacks the necessary expertise	19	11	10	12	21	30	301
Compatibility issues with existing tools, programs, or systems	37	10	9	21	16	10	205
Problems with the availability or quality of the required data	43	12	10	12	15	11	183
Concerns about data privacy or security, as well as cybersecurity	50	8	10	15	10	10	163
Lack of change management	53	8	11	10	11	10	154
Costs seem too high	66	9	7	9	4	8	106
Skills deterioration due to automation and fear of dependency on AI vendors/software	65	11	8	7	4	8	104
Uncertainty about legal issues, such as copyrights or AI legislation	75	4	10	4	6	4	80
AI may work in testing but might not function in a real environment	77	5	9	4	3	5	72
Low transparency in the reasoning chain	81	9	3	3	4	3	55
Concerns about biases, e.g., in algorithmic decision-making such as loan approvals	82	6	7	2	6	0	50
The company does not benefit from AI	90	5	5	0	1	2	29
Ethical reasons	96	3	2	2	0	0	13

Table 2. The facilitators for AI adoption in accounting and financial organisations, ordered according to their perceived importance, illustrated by the total score. The counts for 0, 1, 2, 3 4, and 5 points show how many times they were selected. Zero means that the facilitator was not selected at all.

Facilitator	Counts of the points						Total score
	0	1	2	3	4	5	
Providing continuous and high-quality training, and developing skills	23	12	10	4	30	24	284
Creating an innovative and learning-oriented organizational culture	32	10	6	8	10	37	271
Investing in the usability of information systems and seamless user experience	48	8	14	14	11	8	162
Close collaboration between IT and financial management units	53	8	15	15	5	7	138
Familiarizing with work tasks and acquiring seamlessly fitting digital tools	51	14	12	12	6	8	138
Testing new technologies	55	19	9	6	6	8	119
Participating in projects and sharing knowledge and skills within them	70	5	4	13	9	2	98
Updating technology and tools, including investment strategy	65	9	11	5	13	0	98
Through organizations, such as Financial Management Association	76	6	8	8	4	1	67
Engaging in various networks	77	7	7	7	3	2	64
Through online platforms, such as software vendor community	95	0	1	6	0	1	25
Contributing to open content creation or open source	101	0	1	0	1	0	6

3.2 Data Collection

The survey was conducted online using the Webropol platform between March 26 and April 30, 2025. It was available in Finnish. The target respondents were accounting and finance professionals across various roles, organisations, and organisational sizes. To collect data, a multi-channel distribution strategy was employed leveraging the networks of one of Finland's largest business-oriented higher education institutions (HEIs). The survey was distributed through the HEI's corporate and alumni networks, national and smaller accounting firms, social media groups, and the authors' LinkedIn profiles to ensure broad and diverse participation. A snowball sampling technique was employed, whereby recipients were encouraged to forward the survey to other professionals within their accounting and finance networks, and the organisations shared the survey link on their intranet and webpages [39].

Altogether 104 responses were received, out of which one respondent did not provide informed consent and was thus removed from the data leaving us with a total of n = 103 valid survey responses. In terms of gender, 71% identified as female, 28% as male, and 1% preferred not to disclose their gender. The age distribution was as follows: 1% were under 25 years old, 18% were between 25–34, 36% between 35–44, 29% between 45–54, 14% between 55–64, and 2% were over 64. Regarding educational background, 20% had completed secondary school, 52% held a bachelor's degree, and 28% had a master's degree or higher. Work experience varied, with 3% having less than 1 year, 4% having with 1–3 years, 13% having with 4–6 years, 13% with 7–10 years, and a majority of 66% having more than 10 years of experience. Among the 103 participants, 44% were employed by accounting service firms, 27% worked in the accounting departments of other firms, 15% were employed by financial institutions, 5% by public organisations, and 9% reported working in other types of organisations. Regarding the size of their workplace, 27% were employed by micro-sized companies (organisations with fewer than 10 employees), 17% each in organisations with 10–49 and 50–99 employees, and the majority (55%) worked in organisations with more than 100 employees. The size categories for the firms were taken from the Statistics Finland classification [40].

4 Results

We present below the main barriers hindering the adoption of AI and the most viable ways of overcoming them in accounting and financial organisations as perceived by the respondents. Table 1 and Fig. 1 outline the main barriers and Table 2, and Fig. 2 present the main ways to overcome them.

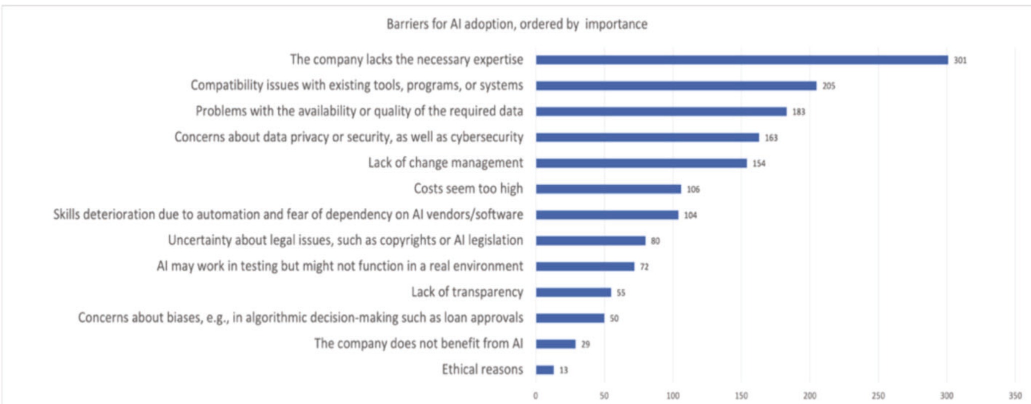

Fig. 1. The most important challenges that the finance and accounting domain is facing regarding AI adoption, ordered by importance. The x-axis is the score of the barrier's relevance to the organisation.

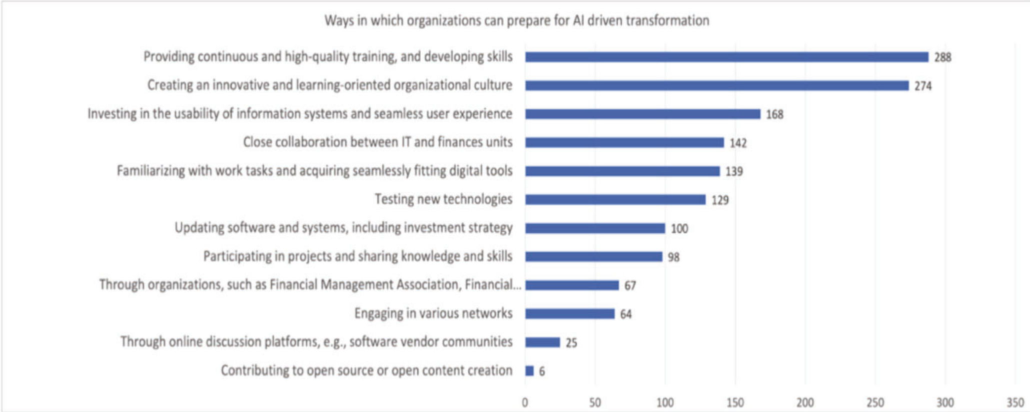

Fig. 2. Ways in which organisations can best prepare for the AI-driven change in accounting and finance, ordered by their importance.

Figure 1 illustrates the most important challenges that organisations face when adopting AI in accounting and finance. The challenges are ordered according to their perceived importance score. The score is calculated as the sum of the scores given by all respondents using the following schema: 5 (very important), 4 (important), 3 (quite important), 2 (relatively important), 1 (somewhat important), 0 (not important). Each informant could assign the scores of 5, 4, 3, 2 and 1 only once. The figure shows that lack of expertise is by far the most important challenge, with a score of 301. The second most important barrier is found in issues related to incompatibility with existing tools programs or systems (score of 205). The next three important barriers are problems with the availability and quality of data (score of 183); concerns about data privacy, security, and cybersecurity (score of 163); and lastly the lack of change management (score of 154).

Table 1 presents the same information as Fig. 1, along with and additional details on the frequency of the responses in the answers. Regarding the most important barrier, *The company lacks the necessary expertise*, we observe that 30 out of 103 respondents ranked it as the most important barrier to AI adoption in their organisation. Along the same lines, we observe that 19 out of the respondents did not consider it as one of the five most important barriers. It is interesting to note that 96 respondents did not consider *ethical reasons* as one of the five most important barriers to AI adoption. Along the same lines, the other reasons that were not considered as important barriers, such as *AI not bringing benefits*, *AI being biased* and *lacking transparency*, exhibit high values for the occurrences of zeros: 90, 82, and 81, respectively.

In addition, we analysed the barriers to AI adoption by company size, company type, and respondent age, as these variables had clearly defined groups within our dataset. Across all company sizes—micro enterprises, companies with 10–99 employees, and those with over 100 employees—as well as most company types, respondents identified the lack of necessary expertise as the most significant barrier. The only exception was financial institutions, where this was considered the second most important issue. For financial institutions, the primary barrier was the availability and quality of data. This concern was also prominent among respondents from large companies, who ranked it as the second major obstacle. In contrast, micro enterprises, companies with 10–99 employees, accounting firms, and accounting departments viewed compatibility issues with existing tools as the second most significant barrier. The third barrier varied depending on the company size and type: micro enterprises were concerned about skill deterioration, companies with 10–99 employees pointed to a lack of change management, and large companies again highlighted compatibility issues. When looking at employee types, accounting firms and financial institutions both considered a lack of change management as the third barrier, while accounting departments identified data availability and quality. Due to limited responses, public organisations and other employer types were excluded from this part of the analysis.

Interestingly, when examining the barriers by age group, we observed some notable differences. Respondents under the age of 35 were primarily concerned about data availability, followed by a lack of expertise. In contrast, all older age groups identified the lack of expertise as the most significant barrier, with compatibility issues with existing tools coming in second. The third most cited barrier varied across age groups: the youngest respondents pointed to compatibility issues, and those aged 34–44 and over 54 highlighted a lack of change management, while respondents aged 45–54 were particularly concerned about data availability.

Figure 2 illustrates the most important facilitators for adopting AI named by the organisations in accounting and finances. The figure shows that *providing continuous and high-quality training and skills development* and *creating an innovative and learning oriented organisational culture* are by far the most important facilitators, scoring 288 and 274, respectively. The third most important facilitator is *Investing in the usability of information systems and a seamless user experience* (score of 168).

Table 2 presents the same information as Fig. 2 along with additional details on the frequency of the responses in the answers. Regarding the most important facilitator, *Providing continuous and high-quality training, and developing skills*, we observe that 24 of the 103 respondents ranked it as the most important facilitator of AI adoption in their organization. Interestingly, the second most important facilitator, *Creating an innovative and learning-oriented organisational culture*, was ranked even more often, namely 37 times, as the most important facilitator. Overall, the difference in the total scores of the most important facilitators is small (13 points).

When analysing the facilitators of AI adoption by organisation size, a clear consensus emerged across all respondents: continuous training and an innovative, learning-oriented organisational culture were consistently identified as the most important enablers. However, the third most valued facilitator varied depending on the organisation's size. Micro-sized organisations emphasised the importance of collaboration and networks, highlighting close cooperation with IT departments, participation in projects, knowledge sharing, and engagement in professional networks as key strategies to overcome adoption barriers. In contrast, larger organisations placed greater emphasis on enhancing the user experience, prioritising the usability and seamless integration of AI tools. A similar pattern was observed when examining responses by employer type. While continuous training and an innovative organisational culture remained the top two facilitators across all employer categories, the third facilitator differed. Respondents from accounting firms stressed the need for employees to familiarise themselves with work tasks and ensure that digital tools fit seamlessly into daily operations. Accounting departments within larger organisations focused on fostering close collaboration between IT and accounting units, whereas financial institutions prioritised investments in usability and a seamless user experience. Age-based analysis revealed comparable trends. Regardless of age, respondents consistently identified continuous training and organizational culture as the top two facilitators. However, younger respondents (under 35) favoured experimenting with new technologies as a means of supporting AI adoption, while older respondents placed more importance on improving the usability of information systems and ensuring a seamless user experience.

5 Discussion

Our research confirms the results of previous studies, stating that the most important barrier to the adoption of AI in organisations is the *lack of expertise*. Missing competencies were among the barriers Jackson and Allen [33] identified in their research on accounting firms. Also, the finance sector recognises the importance of skills due to the complex analysis and mechanisms involved in finance decisions [3, 24]. However, in our study the financial organisations prioritised the quality of data over employees' skills. While our research focused specifically on accounting and finance organisations, similar results have been obtained from other fields. Siderska et al. [41], e.g., studied the challenges related to transitioning from mere automation to intelligent automation. The shortage of skills and competences was identified as one of the main human-related barriers. In addition, our results confirm Jackson and Allen's [33] qualitative finding that the high cost of AI technology is not considered primary barrier to AI adoption, even though costs are often considered a barrier to implementing new technologies (see, e.g. [38].).

One of our study's most striking findings and contributions is the relatively low importance assigned to ethical concerns, algorithmic bias, and transparency as barriers to AI adoption. Contrary to the conclusions drawn in earlier academic literature—such as Lehner et al. [19], Kruse [3], and Berubé et al. [42]—our respondents did not perceive these issues as a significant barrier. In fact, only 7 out of 103 participants selected ethical concerns as a barrier, making it the least cited factor in our survey. This divergence may be explained by three factors: first, many organisations may still be in early stages of AI adoption, where practical challenges such as skills and investments on suitable solutions dominate; second, there may be limited awareness or prioritization of ethical issues among practitioners in comparison to researchers; and third, contextual factors such as industry type or regional norms may influence the perceived relevance of ethical concerns. For instance, if AI is used to automate simple routine work tasks, there may not be any ethical issues to be consider.

According to the accounting and finance organisations, the two most impactful ways by far to address the barriers of AI adoption are to provide their personnel with good-quality training and opportunities for updating skills and to create of an organisational culture that fosters learning and innovation. The first finding is very much in line with the greatest barrier to AI adoption, *lack of expertise,* and is a natural consequence of it. This aligns with Jackson and Allen's [4] survey and interview data from Australian and

South-East Asian accounting firms, where formal training was also seen as one of the most important facilitators for AI implementation. This finding also aligns closely with previous findings in other domains. Aunimo et al. [43] studied the factors impacting the adoption of AI among knowledge workers, which is a broader scope than accounting and financial professionals, also including professionals such as journalists, teachers and software engineers. According to their study, organisations adopting AI typically cultivate informal learning among their employees. This aligns with our findings related to the main facilitators of AI adoption in our study, namely fostering education and a learning culture in organisations and facilitating close collaboration between the financial management and IT units. In addition, especially the micro-sized organisations considered networking and project participation as a facilitator, which indicates the importance of collaborative networks in AI implementation [18].

The second (Creating an innovative and learning-oriented organisational culture) and third (Investing in the usability of information systems and a seamless user experience) most important solutions for overcoming the barriers cannot be directly derived from the most important barriers according to the survey respondents. However, the finding that user interfaces and user experience play crucial role in facilitating AI adoption is significant. The fact that user interface design plays an important role in individuals' technology adoption is not novel in information systems literature (see, e.g., Knutson [44] or discussion around Davis's TAM [45]); however, our finding is new to the accounting and finance literature, where user experience has not received a role as a facilitator of successful technology adoption. It is also important to consider the age of employees when interpreting these findings. According to our survey results, younger employees (under 35) are more willing to experiment with new solutions and place greater importance on testing new systems and technologies than on ensuring a smooth user experience. This suggests that different age groups may prioritise different aspects of system usability and innovation, which should be taken into account when designing and implementing new technologies in organisations.

Undoubtedly, the recognised AI implementation facilitators align closely with the concept of Organisations 5.0 [7, 46], which has also been recognised in the maintenance sector during the transition from Industry 4.0 to Industry 5.0—shifting from automation to human-machine collaboration [15]. A key feature of Organisations 5.0 is the empowerment of employees, typically through education [46], which directly supports the first solution for overcoming barriers to AI adoption. Ivanov's [47] Industry 5.0 framework further emphasises resilience, sustainability, and human-centricity. These principles demand high levels of expertise and collaboration across organisational levels, reinforcing the importance of a learning-oriented culture. Moreover, the human-centric nature of Organisations 5.0 assumes that technologies like AI must be usable and accessible. This includes intuitive and user-friendly interfaces, corresponding to the third solution for overcoming AI adoption barriers [48]. Organisations 5.0 do not operate in isolation. They create value and tackle complex challenges through collaboration and emerging technologies while placing human needs and values at the core of their design. Co-creation, inclusivity, and ethical considerations are central, ensuring that technological advancements are socially responsible and accessible to all stakeholders.

Our findings—highlighting employee empowerment through education, fostering a culture of learning and innovation, and investing in seamless user experiences—are strongly aligned with the principles of Organisations 5.0 and reflect broader developments beyond the financial and accounting sectors.

Our research contributes to the existing literature in several important ways. First, there is a limited understanding of how accounting and finance organisations are navigating the transition toward adopting AI solutions, and whether these organisations can be characterised as Organisation 5.0 entities. Addressing this gap, our exploratory study is among the first to examine both the barriers and enablers of AI adoption in this context. It offers novel insights into the challenges these organisations face and reveals that their approaches to AI integration are increasingly human-centred, aligning with the principles of Organisation 5.0. Second, our findings highlight the significance of the user experience in successful technology adoption—an aspect that has received limited attention in the accounting and finance literature. While the importance of user interface design is well established in information systems research, its role as a facilitator of AI adoption in financial and accounting contexts is a new contribution. Third, we find that ethical concerns are not perceived as major barriers to AI adoption, contrary to what might be expected. This observation warrants further investigation, as it may reflect a gap between ethical discourse and practical implementation. Finally, our results suggest that younger employees approach AI adoption differently: they are more open to experimentation and place greater value on testing new technologies than on ensuring a seamless user experience. This generational difference should be acknowledged in both in future research and organisational practice. Overall, our study offers both theoretical and practical contributions by deepening the understanding of AI adoption dynamics in accounting and finance and by providing actionable insights for organisations aiming to foster innovation and human-centric digital transformation.

Like all research, this study has limitations. First, the survey was conducted solely in Finland, which may limit the generalisability of the findings. However, Finland ranks among the top five European countries in AI adoption [2] and has a highly digitalised regulatory environment, including widespread e-invoicing [49]. These conditions suggest that Finnish professionals are well-versed in AI and automation, making the findings potentially transferable to similarly advanced countries. Second, the relatively small sample size may affect statistical robustness. Future studies should aim for larger, more diverse samples. Third, responses to the second questionnaire may have been influenced by the first, as participants might have aligned facilitators with previously identified barriers [50]. Lastly, the sample consisted mainly of experienced professionals, with only one respondent under 25, possibly underrepresenting younger perspectives. Further research across different countries is recommended to explore how the accounting and finance sectors are adapting to AI and Organisation 5.0.

6 Conclusion

This study set out to examine the barriers and facilitators of AI adoption in accounting and finance organisations, and to explore whether these organisations are transitioning toward the principles of Organisation 5.0. Drawing on survey data from professionals in the field, the research identified a lack of expertise and incompability with existing systems as key challenges, while concerns like ethics, transparency, and costs were considered less significant (RQ1). The most effective facilitators were found to be high-quality training, opportunities for continuous skill development, and fostering a culture of learning and innovation. Additionally, the importance of usability and a seamless user experience suggests that human-centredness is becoming a practical priority, in line with the Organisation 5.0 concept (RQ2). These findings indicate that elements of Organisation 5.0 are beginning to take shape in accounting and finance organisations.

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Intelligent accounting digital maturity model for small and medium-sized accounting firms

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Abstract

Purpose – This paper aims to present a digital maturity model for intelligent automation, specifically designed for small and medium-sized accounting firms. Intelligent automation facilitates the execution of complex accounting tasks, leading to notable improvements in operational efficiency, client satisfaction and employee engagement. Despite these benefits, smaller firms often face challenges in adopting automation due to constrained resources and limited expertise. The proposed maturity model supports firms in evaluating their current level of digital advancement and provides a structured pathway for progressing towards more sophisticated automation capabilities.

Design/methodology/approach – The model was developed following a design science-based procedure model. The development began with a systematic literature review. Subsequently, the model was refined on the basis of feedback from 15 expert interviews conducted in Finland. Finally, it was evaluated in three accounting firms.

Findings – The final digital maturity model encompasses 11 dimensions. Four of the dimensions are typical for digital maturity models: technology, processes, vision and leadership and data and cybersecurity. The remaining dimensions are tailored to accounting firms: role of the accountant, sales to cash, purchase to pay, payments, general ledger, reporting and customer communication and payroll. Each dimension is scaled across five levels: non-existent, initial, proficient, advanced and continuous improvement.

Originality/value – The developed digital maturity model advances the limited academic literature on digital maturity models in accounting, demonstrates the application of intelligent automation within accounting firms and serves as a practical tool to support these firms in their automation efforts.

Keywords SME, IPA, Accounting, Artificial intelligence, Design science, AI, DMA, Digital maturity model, Intelligent accounting, Intelligent process automation, Automated accounting

Paper type Research paper

1. Introduction

This interdisciplinary article presents a practical intelligent accounting digital maturity model (IADMM) for small and medium (SME)-sized accounting firms to enhance their use of intelligent accounting and adopt new technologies. Intelligent accounting, or artificial intelligence (AI)-based digital accounting is a subset of digital accounting and refers to the automation of accounting tasks and decision-making through AI technologies such as machine learning (ML) and cognitive computing (Marshall and Lambert, 2018; Leitner-Hanetseder *et al.*, 2021). By using the newest AI technologies, intelligent accounting can

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autonomously handle complex accounting problems and decision-making processes (Dong, 2024). Even though all accounting automation provides cost savings, reduces errors and improves accounting quality (Kokina and Blanchette, 2019), intelligent accounting will cause major changes in accounting work, as increasingly sophisticated processes and judgments will be carried out using AI-based technologies rather than by humans (Leitner-Hanetseder *et al.*, 2021).

Despite growing interest, intelligent accounting has yet to become mainstream largely due to the limited adoption of AI technologies. Small and medium-sized enterprises (SMEs) in particular lag behind; while 41% of large enterprises in the EU have implemented AI solutions, only 11% of small enterprises and 21% of medium-sized enterprises have done so (Eurostat, 2025). This gap is largely due to limited financial resources and insufficient knowledge about AI among smaller companies. To remain competitive, SMEs must embrace emerging technologies. Successful adoption of new technologies begins with a clear understanding of an organization's current digital capabilities, which maturity models help assess by providing a structured framework for evaluating technology usage and identifying improvement needs (Proença and Borbinha, 2016). Although researchers and consultants have developed a wide range of maturity models – particularly digital maturity models for technology adoption – only a few specifically focus on the accounting function (Williams *et al.*, 2019; da Silva *et al.*, 2024).

This study addresses two key gaps: the limited focus on digital maturity models within accounting literature and the low levels of intelligent accounting adoption in SMEs. To bridge these gaps, this study introduces IADMM. Many SMEs outsource their accounting processes to external firms, which is why the model is specifically designed for SME-sized accounting firms. Through these firms, more efficient and intelligent accounting practices can be effectively introduced into SMEs. To support this objective, the following research question has been formulated:

RQ1. What foundational structure should an intelligent accounting digital maturity model for small and medium-sized accounting firms have?

This research uses design science methods such as those used by Eulerich *et al.* (2022) and Geerts (2011). Specifically, it uses the procedure model of Becker *et al.* (2009) for developing the IADMM. Development started with a systematic literature review, followed by 15 interviews. Eventually, the model was tested in three small accounting firms.

This paper makes three significant contributions to the existing literature. Firstly, it enhances the maturity model and accounting literature by introducing a contemporary IADMM, addressing the need to further explore the digitalization and maturity of accounting firms (Hentati and Boulila, 2023). Secondly, the developed model facilitates insights into how accounting processes in SME-sized accounting firms are conducted across five levels, ranging from manual to intelligent accounting. This work addresses the need for more empirical studies on technologies applied in accounting (Moll and Yigitbasioglu, 2019; Tiron-Tudor *et al.*, 2024) and contributes to the literature on accounting and organizational change by illustrating how these firms are transforming through the adoption of intelligent technologies. These changes affect not only the execution of accounting tasks but also organizational structures, roles and decision-making processes. By modelling these developments, the paper provides a framework for understanding how accounting organizations evolve in response to technological innovation. Thirdly, this research contributes to the development of innovative frameworks for emerging technologies by using design science-based development methods (Eulerich *et al.*, 2022). Finally, this paper has significant practical relevance. The maturity model, developed with input from accounting professionals, serves as a practical tool for SME-sized accounting firms to enhance their accounting processes.

This paper is structured as follows. Section 2 reviews the literature, explaining the concept of intelligent accounting and discussing maturity models. Section 3 outlines the research methodology, explains how the model was developed, and presents the developed maturity model. Section 4 provides the conclusions of the paper.

2. Literature review

2.1 Intelligent accounting

Accounting encompasses bookkeeping, reporting, preparing financial statements and auditing, as well as sub-processes like invoicing and tax reporting (Jaatinen *et al.*, 2021). The development of accounting has evolved significantly from the computerization of financial accounting in 1970–1990 to digitally processed financial administration i.e. digital accounting from 1990 onwards, with robotics and automation being introduced in the mid-2010s (Jaatinen *et al.*, 2021; Lehner *et al.*, 2022).

Digital accounting is a widely used term among accounting practitioners, and in research it serves as a summarizing concept for the digitalization and automation of accounting processes enabled by emerging technologies (Lehner *et al.*, 2019). Alternatively, digital accounting may simply involve storing documents in digital format without automation or AI. Therefore, distinguishing between different phases of digitalization in accounting is important, as each innovation builds upon the previous one and has a distinct impact on accountants' work (Knudsen, 2020).

Digital accounting encompasses several levels. It begins with the digitization of accounting documents through the adoption of e-invoicing and other machine-readable formats. The next phase involves achieving real-time accounting by integrating data flows from various sources into accounting information systems. Eventually, accounting tasks can be automated (Knudsen, 2020; Jaatinen *et al.*, 2021; Lehner *et al.*, 2022), and this ongoing development in digital accounting may ultimately lead to fully autonomous accounting systems (Lehner *et al.*, 2019). AI and other emerging technologies build on rule-based automation and transform it into intelligent automation, which is characterized by its adaptability and capacity for continuous improvement (Coombs *et al.*, 2020). Thus, the culmination of digital accounting development is intelligent accounting – a concept rooted in intelligent automation – where accounting systems not only automate tasks but also learn, adapt and generate strategic financial insights. Intelligent (or AI-based) accounting involves the use of AI technologies such as ML and cognitive computing to automate both routine tasks and decision-making processes (Marshall and Lambert, 2018; Leitner-Hanetseder *et al.*, 2021).

Accounting and auditing firms use accounting information systems to manage processes such as sales to cash, purchase to pay and payroll. These systems have evolved from basic, locally installed setups to advanced, cloud-based Enterprise Resource Planning (ERP) solutions (Tiron-Tudor *et al.*, 2024). These cloud-based systems are maintained by service providers, offering cost-effective, scalable access for both customers and accounting firms (Ma *et al.*, 2021). The systems can receive accounting documents in a structured format and offer real-time data, e-invoicing capabilities, digital bank statements and automated transaction processing (Moll and Yigitbasioglu, 2019). Future predictions envision fully autonomous accounting systems that optimize operations and support business objectives through advanced technologies (Lehner *et al.*, 2022). However, we are not there yet, and currently, these cloud-based systems contain only some automation possibilities. Thus, companies might seek to develop their own automations.

Emerging technologies continue to expand the possibilities for automation in accounting. Among these, rule-based robotic process automation (RPA) has so far proven particularly effective, especially in tasks that are governed by clear rules and involve digital data (Kokina and Blanchette, 2019; Tiron-Tudor *et al.*, 2024). Citizen developers – employees without programming expertise – can easily begin automating simple, repetitive tasks using low-code RPA platforms, making RPA an accessible entry point for enhancing accounting automation (Bock and Frank, 2021; Tiron-Tudor *et al.*, 2024). RPA can also be integrated with AI, which encompasses a range of technologies and applications relevant to accounting. These include ML for transaction processing and fraud detection, intelligent optical character recognition for data extraction and predictive analytics for interactive dashboards (Petkov, 2020; Leitner-Hanetseder *et al.*, 2021).

AI and its sub-technologies, along with data analytics and blockchain, are increasingly recognized as central to the future of accounting. Their combined impact is expected to reshape accounting practices, enhance decision-making and improve the reliability and efficiency of financial processes (Igou *et al.*, 2023; Baiod and Hussain, 2024). Blockchain in particular is anticipated to transform auditing and validation services by enabling secure, transparent and immutable record-keeping (Abdennadher *et al.*, 2022). However, despite their potential, these technologies are not yet widely adopted, especially among SMEs (Bakarich and O'Brien, 2021). When adopting new technologies in accounting, it is crucial to proceed with caution and consider multiple perspectives. This involves upskilling the company's workforce, dedicating budgets for the technology, ensuring management and staff support for the adoption and securing adequate IT resources (Jackson and Allen, 2024).

2.2 Digital maturity models

Evaluating 'maturity' involves assessing how well an organization performs in a specific discipline (Rosemann and De Bruin, 2005). Maturity models help organizations systematically evaluate their current status and identify areas for improvement (Proença and Borbinha, 2016). Digital maturity models specifically measure the maturity of information technology areas, incorporating terms such as "digital", "Industry 4.0", "smart", "data-driven" or "cloud" (Williams *et al.*, 2019; Becker *et al.*, 2009). These models are also used for digital maturity assessments (Kalpaka, 2023), and they can provide maturity indexes (Hentati and Boulila, 2023). Maturity models have become widely used in IT and other technology fields to measure the maturity of IT infrastructure management, enterprise architecture management and knowledge management (Rosemann and De Bruin, 2005). Subsequently, various digital maturity models have been developed (da Silva *et al.*, 2024; Williams *et al.*, 2019).

Maturity models are typically displayed in a grid or matrix layout, with the relevant technological dimensions listed vertically and the maturity scale, usually comprising five levels, arranged horizontally. Dimensions, also referred to as attributes, categories or elements, represent distinct areas of expertise, processes or design within a specific field, such as intelligent accounting, and they must be detailed enough to support the domain's requirements (Proença and Borbinha, 2016). Meanwhile, stages or levels, indicate the maturity of a dimension or domain, with varying numbers of levels depending on the model. Each level should clearly state its requirements and be easily distinguishable from other levels (De Bruin *et al.*, 2005).

Although there are hundreds of digital maturity models in the IT domain, the literature on maturity models within the accounting domain is relatively sparse. The existing literature includes Hentati and Boulila (2023), who developed a digital maturity index tailored for accounting service providers to assess the digitalization levels of accounting firms. This index diverges from traditional maturity models by using a questionnaire format, facilitating ease of analysis and the dimensions encompass technological practices in auditing, reporting and taxation (Hentati and Boulila, 2023). The electronic invoice process maturity model (EIPMM), proposed by Cuylen *et al.* (2016), included four dimensions: strategy, acceptance, processes and organization and technology. This model is particularly practical, focusing on e-invoicing. Similarly, Mantelaers and Zoet (2018) developed a continuous auditing maturity model structured around four dimensions (systems, data, organization and people) and five maturity levels (initial, *ad hoc*, defined, managed and optimized). In addition, Soguel and Luta (2021) constructed a two-level model to assess the extent to which accounting standards have been implemented in the regulations of Swiss cantons. Pekkola *et al.* (2015) developed a maturity model for management control systems and reflective practices, encompassing dimensions such as cultural, planning, cybernetic, reward and compensation and administrative controls.

3. Research methods

3.1 Research design

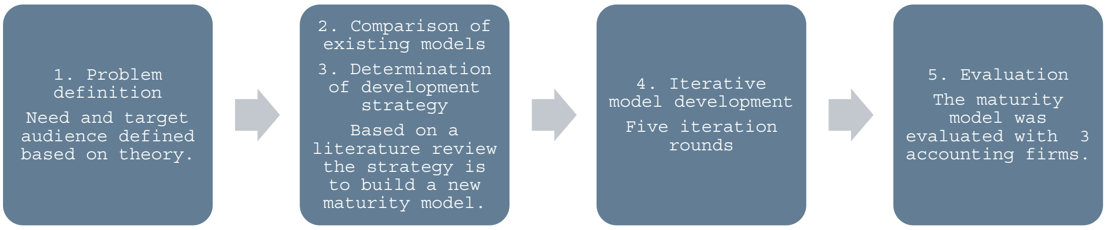
This study adopts a design science approach to develop a maturity model that offers practical solutions for end users. This methodology has been successfully applied in prior research, including studies by Eulerich *et al.* (2022), Geerts (2011) and Cuylen *et al.* (2016). To ensure a systematic, analytical and critical development process, the procedure model proposed by Becker *et al.* (2009) was selected. This model outlines five sequential phases for maturity model development: problem definition, comparison of existing models, determination of development strategy, iterative model development and evaluation. These phases are illustrated in Figure 1 and are discussed in detail in the following subsections.

3.2 Step 1: Problem definition

The first phase involves defining the problem, domain and target group, while assessing the relevance and demand for the model (Becker *et al.*, 2009). The need for a digital maturity model in the context of intelligent accounting is driven by the increasing impact of automation technologies on accounting processes, as discussed in Chapter 2.1. Although smaller firms currently use less AI and other advanced technologies, these innovations are expected to significantly influence operations within the next five years (Bakarich and O'Brien, 2021). To remain competitive, SMEs must increase their adoption of AI and automation. Since small firms typically outsource their accounting functions, the primary target group for the proposed maturity model is SME-sized accounting firms.

3.3 Steps 2 and 3: Comparison of existing models and determination of the development strategy

The second and third phases involve comparing existing maturity models to identify their limitations and to define a suitable development strategy. This process includes determining whether to create a new model or enhance an existing one (Becker *et al.*, 2009). To support this decision, a systematic literature review was conducted. The initial search focused on high-quality accounting journals, including *The Accounting Review*, *Accounting, Organizations and Society*, *Contemporary Accounting Research*, *Journal of Accounting and Economics*, *Journal of Accounting Research*, *Review of Accounting Studies* and *Management Accounting Research*. These journals were searched using keywords such as "maturity model", "digital", "automated", "RPA", "robotic", "AI", "information systems" and "fintech". No restrictions were placed on publication years. A total of 1,444 article titles were reviewed, but none addressed maturity models.



Iteration round	Iteration 1	Iteration 2	Iteration 3	Iteration 4	Iteration 5
Design level	Initial model	Whole model	Whole model	Whole model	Whole model
Approach/ data	Literature review 11/2023-2/2024	6 expert interviews in 4/2024	Logical reorganisation in 5/2024	9 expert interviews in 8-11/2024	Logical reorganisation in 12/2024
Designed Sections	Dimensions and stages	Dimensions and stages	Stages and descriptions	Dimensions and descriptions	Dimensions and stages
Testing	Qualitative expert interviews	Internal review and theoretical validation	Qualitative expert interviews	Internal review and theoretical validation	Done in phase 5. Evaluation with 3 accounting firms
Model structure	Dimensions: 8 Stages: 0 through 4	Dimensions: 9 Stages: 1 through 5	Dimensions: 9 Stages: 1 through 5	Dimensions: 13 Stages: 1 through 5	Dimensions: 11 Stages: 1 through 5
Key Changes		- Payroll dimension added - Descriptions edited - Reorganising stages - Stages renumbered	- Descriptions edited and reorganized	- Dimensions Reporting, Accountants role, Payments and Customer service added - Descriptions edited	- Dimensions People and Skills, and Customer service removed - Dimension Strategy and Management changed to Vision and Leadership - Descriptions edited

Figure 1. Development process of the IADMM across five iteration rounds
Source: Created by the author, drawing on Becker *et al.* (2009) for conceptual foundation and Cuylen *et al.* (2016) for layout inspiration

To broaden the scope of the review, a second search was conducted across eight databases: EBSCOhost, ScienceDirect, Emerald, IEEE Xplore, ProQuest, Sage Journals and Google Scholar. This search used the terms "accounting" AND "maturity model", resulting in 1,183 articles being screened. From this search, 12 articles containing accounting-related maturity models were identified and are presented in Table 1.

Each of these articles was carefully reviewed to assess their relevance for the development of the IADMM. Among them, two models were found to be most closely related to the intended scope: the EIPMM by Cuylen *et al.* (2016), and the digital maturity index for accounting by Hentati and Boulila (2023). However, the EIPMM focuses exclusively on invoice processing and does not address other essential accounting processes. Meanwhile, the digital maturity index is designed to measure the digital maturity rate of accounting firms, rather than to describe digitalization levels in a structured maturity model

Table 1. Accounting-related maturity model studies found in database search

Nr	Database	Journal	Author and date	Title
1	EBSCOHost	*Measuring Business Excellence*	Pekkola *et al.* (2015)	A maturity model for evaluating an organization's reflective practices
2	EBSCOHost	*International Journal of Management, Accounting and Economics*	Tavallaei *et al.* (2015)	Assessing the evaluation models of business intelligence maturity and presenting an optimized model
3	EBSCOHost	*International Journal of Public Sector Management*	Soguel and Luta (2021)	On the road towards IPSAS with a maturity model: a Swiss case study
4	Emerald	*Mediterranean Conference on Information Systems*	Mantelaers and Zoet (2018)	Continuous auditing: a practical maturity model
5	Emerald	*European Journal of Economics and Business Studies*	Lebedev (2019)	Management accounting maturity levels continuum model: a conceptual framework
6	Emerald	*Access to Science, Business, Innovation in Digital Economy*	Karcıoğlu and Binici (2023)	Developing a maturity model to identify digital skills and abilities of accounting professionals: evidence from Turkey
7	Emerald	*Quality – Access to Success*	Ardiansah *et al.* (2021)	Investigating the maturity level of computer-based accounting systems in small and medium-sized enterprises: empirical evidence in Indonesia
8	Google Scholar	*Electronic Markets*	Cuylen *et al.* (2016)	Development of a maturity model for electronic invoice processes
9	Google Scholar	*Computational Intelligence and Neuroscience*	Xiang (2022)	Evaluation of enterprise accounting data management based on maturity model
10	Google Scholar	*Journal of Accounting and Organizational Change*	Hentati and Boulila (2023)	Digital maturity index for accounting firms
11	Google Scholar	*Proceedings of the Central European Conference on Information and Intelligent Systems*	Dobrinić (2020)	Digital maturity of auditing companies in the republic of Croatia
12	IEEE Xplore	*International Conference on Information Retrieval and Knowledge Management*	Zahrullaili and Noordin (2018)	Towards developing a comprehensive business intelligence maturity model for Malaysian public sector: application of mixed methodology

Source(s): Author's own work

format. Given the absence of maturity models that specifically address intelligent accounting in the existing literature, it was concluded that a new model should be developed to fill this gap.

3.4 Step 4: Five iteration rounds of model development

The iterative process of maturity model development involves selecting the design level, determining the approach, designing the model sections and conducting testing, all supported by thorough documentation. This structured process leads to the formulation of the proposed maturity model through multiple refinement rounds, as outlined by Becker *et al.* (2009). In this study, five iteration rounds were conducted, as illustrated in Figure 1.

The primary objective of the first iteration round was to construct the initial version of the IADMM. To establish the foundational structure of the model, relevant dimensions and maturity levels were identified through a comprehensive review of existing literature. This included two review articles that collectively analysed 65 maturity models (da Silva *et al.*, 2024; Williams *et al.*, 2019), as well as the maturity model studies retrieved from the database search presented in Table 1. On the basis of this analysis, five core dimensions – technology, strategy and management, processes, people and accounting data and cybersecurity – were adopted from the most applicable sources, as shown in Table 2. In addition, three dimensions representing key accounting processes – sales to cash, purchase to pay and general ledger and reporting – were incorporated, drawing inspiration from the classification of management control systems proposed by Pekkola *et al.* (2015) in their maturity model framework.

Following the establishment of the model's structure, the maturity levels were defined as 0 (non-existent), 1 (initial), 2 (encouraged), 3 (enabled) and 4 (continuous improvement), following the framework used by Cuylen *et al.* (2016). Once the structural foundation was in place, detailed descriptions for each level within the model's dimensions were developed on the basis of relevant literature, including Hentati and Boulila (2023), Cuylen *et al.* (2016), Karcıoğlu and Binici (2023), Xiang (2022), (Dimitriu and Matei, 2015; Siderska *et al.*, 2023; Kalpaka, 2023; Jaatinen *et al.*, 2021).

The second iteration round focused on refining the IADMM through expert input from the accounting field. In April 2024, six semi-structured interviews were conducted with

Table 2. Dimensions and their sources of the initial model

Dimension	Source
Processes	Williams *et al.* (2019); Cuylen *et al.* (2016); Dobrinić, 2020
Technology	Williams *et al.* (2019); da Silva *et al.* (2024); Cuylen *et al.* (2016); Dobrinić, 2020; Mantelaers and Zoet (2018)
Strategy and management	Williams *et al.* (2019); da Silva *et al.* (2024); Cuylen *et al.* (2016); Xiang (2022); Dobrinić, 2020
People	Williams *et al.* (2019); da Silva *et al.* (2024); Mantelaers and Zoet (2018)
Accounting data and cybersecurity	Xiang (2022); Mantelaers and Zoet (2018)
Sales to cash	Inspired by Pekkola *et al.* (2015)
Purchase to pay	-“-
General ledger and reporting	-“-

Source(s): Author's own work

professionals who were selected via purposeful sampling, as recommended by Shaheen *et al.* (2018). The aim was to engage individuals with practical experience in intelligent automation. Among the participants, two were intelligent accounting consultants and four were technology representatives from SME-sized accounting firms. All interviewees received a research announcement and provided informed consent. The interviews were conducted and transcribed using Microsoft Teams, following a structured interview guide designed to elicit insights into intelligent accounting practices. The participants were invited to comment on each dimension and maturity level of the IADMM while viewing the model.

After transcription, the interview data were analysed using NVivo qualitative data analysis software. Coding and interpretation were performed by a single researcher, which may limit intercoder reliability. However, the use of predefined dimensions based on the IADMM framework provided a structured and theory-driven basis for the analysis. The eight previously defined dimensions were used as coding categories, resulting in the following number of references: technology (59), strategy and management (35), processes (19), people (47), accounting data and cybersecurity (41), sales to cash (32), purchase to pay (32) and general ledger and reporting (30). In addition, several interviewees suggested the inclusion of a payroll dimension due to its significant automation potential and its relevance to accounting firms that frequently offer payroll services. This dimension was subsequently added to the NVivo coding scheme and received 21 references. The interviews contributed to the enhancement of the model by refining the level descriptions and introducing a new dimension. Furthermore, for clarity and consistency, the maturity levels were renumbered from 0–4 to 1–5.

The third iteration round was relatively brief and led by the author. During this phase, the IADMM underwent a comprehensive internal review, with the primary focus placed on reorganizing the descriptions of each maturity level to ensure logical coherence across all dimensions. This process involved refining both the language and the structural presentation of the model to enhance its intuitiveness, thereby improving its overall clarity and practical applicability.

The fourth iteration round focused on refining the IADMM through expert feedback. Nine interviews were conducted with consultants, software company representatives and managers from large accounting firms (see Appendix 1), selected for their experience in intelligent accounting. The interview and analysis process followed the same protocol as in the second round. Using NVivo, the predefined dimensions received the following number of references: technology (69), strategy and management (57), processes (36), people (26), accounting data and cybersecurity (47), sales to cash (30), purchase to pay (43) and general ledger and reporting (36).

On the basis of the feedback, general ledger and reporting was split into three new dimensions: reporting (35), accountant's role (66) and payments (14). A new dimension, customer service, was also added (9 references). The role of the accountant was emphasized due to the changing nature of accountants' work under automation, while customer service emerged as a key theme in larger firms. Descriptions of existing dimensions and levels were revised to reflect these insights.

The fifth and final iteration round, led by the author, focused on finalizing the IADMM. Interview data were re-analysed and compared with existing literature to ensure consistency across dimensions. Two dimensions were removed: people and skills – due to its emphasis on attitudes, which were considered unsuitable for objective measurement. Key elements from this dimension were integrated into strategy and management, which was renamed vision and leadership based on feedback suggesting that the term "strategy" may feel too formal for small firms. In addition, customer service was merged with reporting, forming the new dimension reporting and customer communication.

3.5 Final intelligent accounting digital maturity model

To answer the research question of what foundational structure an IADMM for SME-sized accounting firms should have, the final model consists of 11 dimensions and five levels. Four of the dimensions are typical for digital maturity models: technology, processes, vision and leadership and data and cybersecurity. The remaining dimensions are tailored to accounting firms, covering the role of the accountant and specific accounting processes: sales to cash, purchase to pay, payments, general ledger, reporting and customer communication and payroll. Each dimension is scaled across five levels: 1 (non-existent), 2 (initial), 3 (proficient), 4 (advanced) and 5 (continuous improvement). The model is explained by dimension in the following paragraphs, and the complete maturity model is presented in Appendix 2.

When the technology dimension is at level 1 (non-existent), accounting is conducted with locally installed systems or on paper. At level 2 (initial), the firm uses a cloud-based system without automation. At level 3 (proficient), the firm uses a cloud-based system with built-in automations and integrations, providing scalable access to AI and automation (Ma *et al.*, 2021). This level might be optimal for micro or small firms. At level 4 (advanced), the firm develops its own automations with RPA and AI for tasks not covered by the cloud system, focusing on integrations to avoid manual data transfers. At level 5 (continuous improvement), the firm uses the latest technologies and continuously monitors new ones.

The second dimension is processes, aligning with the emphasis of Kokina *et al.* (2021) on the importance of process management in automation projects. At level 1, the firm lacks unified processes, and each employee manages tasks individually, leading to inconsistent client management. At level 2, the firm lists regular tasks, discontinues unnecessary ones, and documents financial management processes with clear responsibilities. At level 3, unified processes are monitored and analysed for simplification, with task schedules tracked using a technical solution. At level 4, processes are analysed for automation potential. At level 5, process automations are regularly developed and maintained.

The third dimension is vision and leadership. This dimension also incorporates people and skills, which was excluded in the final iteration because measuring employee attitudes seemed inappropriate. Instead, management should provide change management activities like communication and training to foster suitable attitudes towards new technologies. At the lowest maturity level, management has no automation plans. At level 2, management has some automation plans and provides open communication and training. Interviewees highlighted the need for pricing models that accommodate automation, suggesting fixed monthly fees or a combination of fixed and transaction-based pricing. At level 3, automation is integral to operations, with employees trusting the automated processes and accepting occasional mistakes as part of development. Automation usage is monitored, aiming to use all possible automations. At level 4, the firm's strategy and business are based on intelligent accounting, with employees acting as automation developers. A budget is available for external software and automation, and employees are trained to enhance their automation skills. At the highest level 5, employees act as citizen developers, creating parts of the automations themselves, supported by either in-house or outsourced automation developers.

The fourth dimension is data and cybersecurity. This dimension covers data use, security and cybersecurity in accounting firms. At level 1, data are unstructured (paper, emails, PDFs). At level 2, the firm uses mainly structured data (e-invoices, digital bank statements) and considers data and cybersecurity elements. At level 3, the firm has a business continuity plan and provides data and cybersecurity training. At level 4, data are used to improve quality and processes, and a data security officer is appointed. At level 5, the firm uses customer accounting data as big data for industry-level insights. While only a few interviewees had experience with this, they saw it as a great opportunity.

The rest of the dimensions focus on accounting processes. The role of the accountant dimension describes how accountants' work changes with automation. At level 1, work focuses on data entry and statutory accounting. At level 2, accountants assist customers with internal reports. At level 3, they take on a consultative role, guiding customers in process development and automation. At level 4, accountants act as business challengers, suggesting improvements. At level 5, accountants specialize in areas such as customer consulting, technology, data security or process management.

The reporting and customer communication dimension evolves from accountants sending statutory reports to customers by email or mail at level 1 to customers themselves using cloud-based software for financial reports at level 2. At level 3, graphical reports and regular customer satisfaction monitoring are introduced. At level 4, AI technologies are incorporated for reporting insights and automation in customer communication, including a customer retention plan. At level 5, reporting includes cause-and-effect analysis, and customer service is available 24 / 7 with AI support.

The evolution of the sales to cash dimension begins at level 1, where customers send paper or PDF invoices, and data from external sales systems are entered manually. At level 2, sales information is processed digitally, and customers create invoices in partially integrated accounting software or sales systems, with invoices sent as e-invoices. At level 3 external sales systems are integrated fully with the accounting system, enabling automatic contract-based invoicing and the use of mobile devices. At level 4, invoicing initiation occurs automatically upon receipt of digital information, though there is also an approval step. Finally, at level 5, invoicing is fully automated using new technologies such as voice recognition, and sales data are accumulated for cost accounting.

The purchase to pay dimension's maturity evolves quite similarly as that of sales to cash. At level 1, the accounting firm's customers receive invoices and pay them manually, with invoices and receipts arriving at the accounting firm in paper or PDF format. At level 2, the accounting software receives structured invoices (e-invoices), which are then sent to the customer for approval, using a receipt management application. At level 3 automatic payments are made for approved invoices on their due date, using default accounts and built-in automations of the accounting software. At level 4, ML is used to enhance invoice processing when built-in automation is insufficient. Finally, at level 5, most purchase invoices and expense receipts are processed without human interaction, and data from purchase invoices are used in cost accounting and inventory management.

Payments have their own dimension, with digital bank statements and reference payment automation included from the lowest level, reflecting Finland's long-standing practices (Jaatinen *et al.*, 2021). At level 2, digital, machine-readable bank statements are automatically transferred to the accounting system, with default accounts used for entries. At level 3 software with built-in ML is introduced for recording bank statement transactions. At level 4, payments with incomplete data are allocated using AI. Finally, at level 5, AI examines accounts receivable discrepancies.

The maturity of the general ledger dimension primarily depends on the ability to input data into the accounting system in a structured format. At level 1, accounting-related information is received in various forms and from different channels, with all entries made manually and directly to the general ledger; no sub-ledgers are used. At level 2, information is received in a structured form in a unified location, and system internal audit reports are used. At level 3 system automations are implemented in general ledger processes, such as accruals and allocations. At level 4, custom automations and internal audit reports are developed for general ledger entries. Finally, at level 5, all recurring general ledger processes are automated, including financial statement entries and management report creation.

The final dimension, payroll – although primarily managed by human resources – represents a crucial service offered by accounting firms with substantial automation potential. This dimension encompasses data entry, beginning with unstructured data formats at level 1 and advancing to structured payroll information at level 2. Automation is further enhanced through integrated platforms at level 3. In this level, once data entry is automated, the emphasis shifts to automated payroll calculations, with monthly salaries being relatively straightforward to automate. Integrated data management systems elevate the maturity to level 4. The interviewees in the study observed that even complex salary structures can be automated with precise payroll information and a robust system, as evidenced at level 5.

3.6 Step 5: Evaluation

The evaluation step involved testing the generated maturity model with three cases, similar to Pekkola *et al.* (2015) The objective was to determine if the accounting firms could be classified using the maturity model and if they found it useful. The smallest firm (Firm 1) was a sole proprietorship, the second (Firm 2) employed about 10 people and the third (Firm 3) had around 30 employees. All provided accounting services to their customers. The evaluation was conducted through discussions with the company managers, scaling their companies using the model to assess its applicability. All discussions were conducted through Microsoft Teams, recorded and transcribed (Appendix 1).

Firm 1 was a small enterprise primarily using a locally installed accounting software and delivering services to comply with legal requirements. Accounting documents were received in an unstructured format: such as paper or PDFs, and the accountant keyed in the documents manually into the accounting system:

> They just send the materials to me in a traditional way. Like, some put it in an envelope, and then some might, like, you know, create a Google Drive account for themselves, give me access and rights to it, and I go fetch the materials from there. And then some know how to, like, put the stuff here as a PDF file or something and just email it to me as an attachment. (Firm 1 entrepreneur).

On the basis of discussion, we concluded that the firm primarily operated at maturity level 1 across most dimensions. However, in response to one client's request for modern cloud-based software and more automated services, the firm demonstrated level 3 maturity in several areas. This highlights a potential limitation of the maturity model: If a firm uses varied approaches to serve different clients, then the model may not fully capture the diversity of its practices, and results can vary depending on the customer context.

Firm 2 used a modern cloud-based accounting software with extensive automation features, and they could recognize themselves from the model. They were exclusively seeking clients willing to adopt cloud accounting and would not take "manual clients" anymore:

> Yes, because we really try to make use of all the automation and robotics built into the software. And of course, we also try to streamline things in our own processes. But yeah, there's always room for improvement.[…] Yeah, yeah, it's level 3 where we're at, and we try to make the most out of it. (Firm 2 entrepreneur).

This firm primarily operated at maturity level 3, which could be considered optimal and cost-effective for a small firm, as it used the software's automation without developing its own.

This approach relied on obtaining structured accounting data from clients and leveraging the automation capabilities of advanced accounting software. However, some manual processes remained to keep employees motivated but also because the automation did not work for all companies so well.

Firm 3, also a small accounting firm, started to use modern cloud-based accounting software several years ago and migrated all customers to the system. Automation is part of their strategy, which is followed closely:

> We switched to system X maybe seven or eight years ago. We made the change, forced the clients off the old one, and now systems X and Y are the tools we use. (Firm 2 entrepreneur).

Firm 3 hired in-house developers to enhance automation within the company. The automation technologies are mainly software robotics:

> We did like 95% of it ourselves, and then consultant's team helped us out a bit with the tricky parts. We've been working with software robotics for, what, at least five years, I'd say. (Firm 3 entrepreneur).

Despite its small size, this firm could be classified at least at maturity level 4, indicating that they had developed their own automation solutions and operated in a highly modern manner. In some dimensions, the firm even achieved the highest maturity level.

These three evaluation cases indicate that the maturity model works, allowing accounting firms to determine their maturity levels. The firms also found the model to be useful, as it provided insights and suggestions for improving their processes:

> It might really be that people kind of easily get stuck and fall into their own routines, and then they don't even notice any other way of thinking or like, way or style of working. (Firm 1 entrepreneur).

Regarding ease of use, Firm 2 noted that defining their maturity level required the presence of researchers, as they would not have been able to comprehend all the maturity levels or dimensions independently. "[…] if someone's just wondering, like, what level are we actually at? Then, in that case, it should be even simpler. The levels should be defined in a more straightforward way". This suggests that the model should be further developed to facilitate self-assessment especially for non-experienced users, and Firm 3 confirms it: "Not a whole lot of new things, really, but sure, there's definitely a use for the tool – especially if you're still in that more traditional world".

4. Conclusions

This research represents an interdisciplinary effort, combining elements of digital maturity models commonly found in IT literature with the accounting domain. The objective was to develop an IADMM for SME-sized accounting firms. The model was developed using design science methods and especially using Becker *et al.*'s (2009) procedure model. Based on a systematic literature review, 15 specialist interviews and five iteration rounds, the developed model contains 11 dimensions, each with five maturity levels. This digital maturity model has been successfully evaluated with small accounting firms.

This research contributes to the accounting literature in three key ways. Firstly, it builds upon existing maturity models in accounting by developing a model specifically tailored to intelligent accounting processes, addressing a critical need in the evolving landscape of AI and automation. While maturity models are well-established in the field of IT, their application to accounting remains relatively novel. The few existing models indicate growing relevance and interest in this area, yet none have specifically addressed intelligent accounting, which is increasingly topical in the current AI-driven environment. To illustrate the distinction, Hentati and Boulila (2023) developed a diagnostic tool to measure the digital maturity of accounting firms by using a questionnaire-based approach. By contrast, the IADMM advances this concept by offering a structured matrix of dimensions and maturity levels, each with descriptive criteria. This format aligns more closely with traditional maturity models and provides users with clear guidance on how to progress to higher levels of maturity. Similarly, the IADMM shares methodological similarities with the EIPMM developed by Cuylen *et al.* (2016), particularly in its use of a dimension-level structure. However, while the EIPMM focuses narrowly on e-invoicing, the IADMM encompasses the full range of processes typically found in small accounting firms, making it more comprehensive and applicable in practice. Moreover, as Cuylen *et al.*'s model was developed nearly a decade ago, it reflects the technological context of its time. Since then, accounting technologies and AI capabilities have evolved significantly, further highlighting the need for an updated and broader model such as the IADMM.

Secondly, this research provides an incremental contribution to the accounting and organizational change literature by offering insights into how accounting processes in SME-sized accounting firms are conducted across five maturity levels, ranging from non-automation to intelligent automation. This work responds to calls for more empirical studies on technologies applied in accounting (Moll and Yigitbasioglu, 2019) and complements existing literature on the use of RPA and other emerging technologies in accounting (Tiron-Tudor *et al.*, 2024). Although the IADMM was developed with SME-sized accounting firms in mind, its structure and dimensions are applicable to accounting firms of all sizes, and potentially to accounting departments within larger organizations. The model's emphasis on process maturity, technological adoption and organizational readiness makes it a versatile tool for assessing and guiding digital transformation across diverse accounting contexts.

The findings confirm that successful implementation of intelligent accounting technologies leads to significant changes in accountants' work roles, including role expansion and potential deskilling (Coombs *et al.*, 2020; Jaatinen *et al.*, 2021). Thus, the role of the accountant is an essential part of the maturity model. Prior research explored the future skills required in accounting (e.g. Kokina *et al.*, 2021; Igou *et al.*, 2023; Yigitbasioglu *et al.*, 2023) and both accountants and management should actively prepare for these changes. The IADMM's vision and leadership dimension supports change management and employee training, but individual accountants must also ensure their skills and attitudes remain aligned with the evolving work environment. More studies about the change, future role and skills are needed to keep accountants' jobs relevant. In addition, the IADMM developed in this study offers a foundation for future empirical research. It can be used to quantify digital maturity in accounting firms, making it suitable for statistical testing in both longitudinal and cross-sectional studies. Such applications could further illuminate how digital transformation unfolds across different organizational contexts and timeframes, and how it shapes accounting work and organizational structures over time.

Thirdly, this paper makes methodological contributions; the design science-based development method used in this research is quite rare in the accounting literature. The design science research methodology focuses on creating new useful artifacts (concepts, models, methods) for practical purposes (Geerts, 2011; Eulerich *et al.*, 2022).

In addition, this research holds significant practical relevance. The maturity model offers a valuable tool for accounting firms planning to adopt new technologies. By applying the model, firms can evaluate their current level of maturity in intelligent accounting and receive guidance on how to advance to higher levels. At present, the maturity model is manual, with no accompanying questionnaires or tools for assessment. To implement it within an accounting firm, management and/or those responsible for technology should review the model systematically, asking at each point: “Are we doing this?” This allows organizations to identify practices already in place. Once the current state is mapped, the firm can refer to the descriptions of the next level to plan its progression.

Like all research, this study has some limitations that should be acknowledged. Firstly, the maturity model was based on theoretical literature, and the practical data used to develop the maturity model were sourced from Finland, where digitalization and development levels are high (Bezrukova *et al.*, 2022). In Finland, electronic payment and information transfers between firms, banks and public authorities are common and electronic methods have been allowed in accounting since 1997 without any specific permission. E-invoices are common (Jaatinen *et al.*, 2021) and form the core of the IADMM’s first levels, although accounting documents can be transferred into a structured format in other ways as well. The model contains five maturity levels. If accounting practices are not that developed, then the lowest level should accurately describe such scenarios. While some of the interviewees operated in a global environment and had an understanding beyond Finland, this geographic limitation may still affect the generalizability of the findings to other regions with different economic, regulatory and technological environments. In particular, the applicability of the IADMM may vary depending on national regulations, the availability of digital infrastructure and cultural attitudes towards automation and change. For example, in countries where electronic invoicing is not yet widely adopted or where regulatory frameworks are less supportive of digital transformation, firms may progress through the maturity levels at a different pace. Similarly, organizational hierarchies and employee roles may influence how change is managed and how technologies are implemented. These contextual factors should be considered when applying the model internationally.

Secondly, the maturity model was evaluated using only three case companies. While these cases provided valuable insights into the model’s applicability and effectiveness, and similar or more limited evaluation has been performed with previous maturity models (Pekkola *et al.*, 2015; Cuylen *et al.*, 2016), the limited sample size restricts the generalizability of the maturity model. Moreover, the small number of cases affects the robustness of the results, as broader patterns and variations in accounting practices may not be fully captured. In particular, the diversity of practices within individual firms – such as tailoring services to different client needs – suggests that maturity levels may vary even within a single organization.

Thirdly, with regard to newer technologies, blockchain is only considered at the highest maturity level of the model’s technology dimension, as none of the interviewees had practical accounting experience with it. However, as accounting documents become blockchain based, as seen in countries such as the UAE (Abdennadher *et al.*, 2022) or other disruptive technologies appear, the IADMM should be updated. These limitations do not invalidate the findings but highlight the need for further research. Future studies should aim to test the model in broader and more diverse contexts, refine its dimensions, and explore how digital maturity evolves over time in different organizational environments.

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Appendix 1

Table A1. List of the interviews

Purpose	Interviewee	Method	Duration
Iteration 2	Consultant 1 and 2	MS Teams	64 min
Iteration 2	Head of technology 1	MS Teams	55 min
Iteration 2	Head of technology 2	MS Teams	50 min
Iteration 2	Head of technology 3	MS Teams	58 min
Iteration 2	Head of technology 4	MS Teams	57 min
	Total		*4 h 44 min*
Iteration 4	Accounting consultant 1	MS Teams	37 min
Iteration 4	Accounting consultant 2	MS Teams	42 min
Iteration 4	Accounting consultant 3	MS Teams	45 min
Iteration 4	Accounting consultant 4	MS Teams	46 min
Iteration 4	Accounting consultant 5	MS Teams	66 min
Iteration 4	Accounting firm manager 1	MS Teams	60 min
Iteration 4	Accounting firm manager 2	MS Teams	41 min
Iteration 4	Software specialist 1	MS Teams	48 min
Iteration 4	Software specialist 2	MS Teams	57 min
	Total		*7 h 22 min*
Purpose	Interviewee		
Evaluation	Accounting firm 1	MS Teams	42 min
Evaluation	Accounting firm 2	MS Teams	47 min
Evaluation	Accounting firm 3	MS Teams	73 min
	Total		*2 h 42 min*

Source(s): Authors’ own work

Appendix 2

Table A2. Intelligent accounting digital maturity model for small and medium-sized accounting firms

Level/ dimension	1. Non-existent	2. Initial	3. Proficient	4. Advanced	5. Continuous improvement
Technology	Primarily using on-premise software or paper-based processes	Cloud-based financial system in use with built-in AI and some system integrations	Rule-based and AI features of the cloud system actively used; initial RPA/AI experiments conducted	Established RPA and AI use; AIS gaps filled; systems well-integrated	Leveraging latest technologies; continuously monitoring and evaluating new tools
Processes	Each employee manages clients independently with personal methods	Regular tasks listed; unnecessary ones removed. Processes documented and standardized. Roles clarified with clients	Employees skilled in process management. Uniform execution monitored and improved. Tasks scheduled and tracked	Automation opportunities analysed; development plans created	Automations actively maintained and continuously improved
Vision and leadership	Automation is not part of management's plans	Automation is planned; staff engaged through communication and training. Management supports new work methods. Pricing reflects automation use	Automation is trusted and actively used. New solutions are tested. Plans are clearly communicated and tracked with metrics	Operations rely on automation. Staff involved in development. Automation development is budgeted, and staff skills are enhanced through training	Some employees act as citizen developers. Company has dedicated or outsourced IT resources and a tech development lead
Data and cybersecurity	Data mainly in paper or PDF format; its value to operations is unclear	Cybersecurity and customer data protection documented and acknowledged	Business continuity and risk plans in place. Internal monitoring active. Staff trained in data security	Data used to improve quality, processes and communication. Data security officer appointed	Data seen as a key resource. Financial data used across company boundaries for analysis and consulting
Reporting and customer communication	Statutory reports sent via email or mail	Customers access reports directly from the system. Reporting schedule agreed upon	Dashboards available. Customer and partner satisfaction monitored regularly	AI provides insights, alerts and forecasts. Automation used in communication. Customer retention plan in place	Cause-and-effect reports used. 24 / 7 service enabled by AI. Quotation, purchase and onboarding automated

(*continued*)

Table A2. Continued

Level/ dimension	1. Non-existent	2. Initial	3. Proficient	4. Advanced	5. Continuous improvement
Role of the accountant	Focus on data entry, statutory accounting and tax returns	Helps clients understand financials and enables internal reporting	Communicates insights and guides clients in process and automation development	Challenges and supports clients in identifying improvements and suggesting solutions	Accountant specializes in consulting, technology, data security or process management
Sales to cash	Billing data is unstructured; invoices sent as paper or PDFs. External sales data entered manually	Invoices created in accounting or sales systems. E-invoicing used. Partial system integration	External systems integrated. Contract billing automated. Mobile billing supported	Billing starts automatically from digital data. E-invoice approval in place	Billing initiated via new tech (e.g. voice recognition). Data used for cost accounting
Purchase to pay	Invoices are received and paid manually. Documents arrive as paper or PDFs	Invoices received in structured format. Sent for customer approval via accounting software. Receipt app in use	Approved invoices paid automatically. Default accounts and built-in automations used	ML improves invoice processing beyond built-in automation capabilities	Most invoices and receipts processed without human input. Data used for cost accounting and inventory
Payments	Paper or PDF bank statements used. Reference payments recorded manually	Machine-readable bank statements imported automatically to AIS. Default accounts used for entries	Software uses built-in machine learning to record transactions	AI allocates payments with incomplete data	AI identifies and analyses accounts receivable discrepancies
General ledger	Information received in various formats and channels. Entries made directly to the general ledger	Data received in structured form Internal audit reports used	Automations used for tasks like accruals and allocations	Tailored automations and internal audit reports support ledger entries	Recurring ledger tasks and financial statement entries automated. Management reports generated automatically

(*continued*)

Table A2. Continued

Level/ dimension	1. Non-existent	2. Initial	3. Proficient	4. Advanced	5. Continuous improvement
Payroll	Payroll info received in various formats. Customers send paper or PDF documents	Payroll data received in structured format. Payroll separated from accounting. Data transferred via integration	Customers update payroll info via portal. Monthly salaries processed automatically	Time tracking system integrated. Hourly wages calculated automatically. Payroll clerk reviews before payment	All salaries calculated automatically. Automation checks and suggests corrections. Payroll clerk approves for payment

Source(s): Authors' own work

About the author

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