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ABSTRACT

AI Business Applications Training and Business Outcomes: An Inclusive Intervention for Underrepresented Entrepreneurs

This study investigates the associations between university-led training in AI business applications and business outcomes among small firms, with a focus on underrepresented entrepreneurs in England, Wales, and Scotland. A total of 121 non-native, disabled, and non-heterosexual entrepreneurs participated in a four-month training programme covering AI applications for communication, finance, project management, and other key business functions. Data were collected before the training (2023) and one year later (2024). Using panel data estimates, the findings indicate that, post-training, firms experienced an increase in digital competencies, which were positively associated with customer satisfaction, entrepreneurs' empowerment, and revenue growth. Notably, interaction effects showed that these associations were significantly strengthened following the training. Additional results reveal that, after the training, firms not only adopted a greater number of AI business applications but also used them more frequently. These behaviours were found to be associated with improvements in business outcomes. The study demonstrates how innovative educational interventions can support entrepreneurs in developing digital competencies within technology-driven environments, thereby enabling more inclusive access to tools and fostering equitable participation in the digital economy. The findings suggest that structured, application-focused training, when clearly aligned with business operations, can accelerate firms' technological adoption and effective use.

JEL Classification: L26, M13, O33, I24, I25, J15, J16, M15, D22, C23

Keywords: AI, AI Business Application Training, business education, small firms, digital competencies, customer satisfaction, entrepreneurs' empowerment, revenue growth, inclusive entrepreneurship

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1. Introduction

Artificial Intelligence (AI) is transforming business environments across a range of sectors, enabling firms to operate more efficiently (Wu et al., 2025; Babina et al., 2024; Hansen et al., 2021; Cubric, 2020; Tarafdar et al., 2019). AI has proven particularly impactful in areas such as communication, marketing, customer service, and decision-making processes (Babina et al., 2024; Tarafdar et al., 2019). It facilitates the automation of repetitive tasks, the analysis of large volumes of data in real time, and the prediction of trends. These competencies support firms in optimising resources, personalising customer interactions, and improving overall operational efficiency (Babina et al., 2024; Hansen et al., 2021; Tarafdar et al., 2019).

Realising the potential of AI in practice requires the development of key digital competencies within firms (Hansen et al., 2021; Cubric, 2020). Competencies in data analytics, technical proficiency, and the interpretation of AI-generated insights are considered essential for maintaining competitiveness in an AI-driven marketplace (Aranitou et al., 2025; Qalati et al. 2025; Marti et al., 2024; Peruchini et al., 2024; Prentice et al., 2022; Hansen et al., 2021; Cubric, 2020; Tarafdar et al., 2019).

However, firms that lack digital competencies and do not adopt AI technologies may face significant challenges (Aranitou et al., 2025; Cubric, 2020; Giotopoulos et al., 2017). Without AI integration, businesses risk falling behind in terms of efficiency and innovation, particularly when compared to competitors that automate processes and make real-time, data-driven decisions (Aranitou et al., 2025; Wu et al., 2025; Cubric, 2020). This gap is especially concerning for smaller firms and underrepresented entrepreneurs, as the widening digital divide places those without access to or engagement with AI at an increasing disadvantage in a highly competitive market (Akpuokwe et al., 2024; Hansen et al., 2021; Pidduck and Clark, 2021; Suseno and Abbott, 2021; North et al., 2020; Rolle and Kisato, 2019; Giotopoulos et al., 2017; Casalino et al., 2012).

The primary objective of this study is to examine how AI business applications training relates to changes in digital competencies and key business outcomes among small firms led by underrepresented entrepreneurs. Specifically, the study assesses the extent to which such training enhances firms' digital competencies and investigates how these competencies are associated with customer satisfaction, entrepreneurs' empowerment, and revenue growth.

To achieve these aims, the study addresses the following research questions: (1) What are the associations between AI business applications training and firms' digital competencies? (2) How are digital competencies related to customer satisfaction, and how do these associations change after the training? (3) How are digital competencies associated with entrepreneurs' empowerment, and how do these associations change after the training? (4) How are digital competencies related to firms' revenue growth, and how do these associations shift following the training?

The study focuses on England, Wales, and Scotland during the period 2023 to 2024. The target population includes non-native entrepreneurs, entrepreneurs with disabilities, and non-heterosexual entrepreneurs operating small firms. The training covers a range of AI-supported business applications, including tools for communication, customer relationship management, accounting, project management, and other relevant areas. Data are collected prior to the training and again one year later, enabling the study to examine longitudinal developments. This pre- and post-training design facilitates the observation of how these associations develop over time.

The present study contributes to the literature in several ways. First, a critical gap in the existing research is the limited attention given to underrepresented entrepreneurs (Khoza, 2024; Akpuokwe et al., 2024; Suseno and Abbott, 2021; Pidduck and Clark, 2021; Rolle et al., 2020; Rolle and Kisato, 2019). This study seeks to address that gap. Underrepresented groups remain largely underexamined in studies of digital adoption and technology-driven entrepreneurship, despite growing evidence that they face substantial and intersecting barriers to accessing technology, education, and financial capital (Akpuokwe et al., 2024; Pidduck and Clark, 2021; Rolle and Kisato, 2019). These barriers often stem from discrimination, cultural exclusion, health-related limitations, and biases embedded in support structures (Pidduck and Clark, 2021). As a result, underrepresented entrepreneurs are frequently disadvantaged in their ability to integrate emerging technologies, particularly AI-driven tools, into their business practices (Pidduck and Clark, 2021; Rolle and Kisato, 2019).

Interventions that support the development of digital competencies among underrepresented entrepreneurs remain largely absent from the literature. Addressing this gap is important, as digital divides reflect more than disparities in access to technology; they also reproduce wider social and economic inequalities. This study responds to that concern by examining whether targeted, application-specific training in AI business applications can function as an equalising mechanism for underrepresented entrepreneurial groups. It contributes to the literature by showing how university-led training initiatives can be adapted to meet the evolving AI-related educational needs of underrepresented entrepreneurs, with the aim of supporting their fuller participation in the digital economy. Exclusion from digital opportunities entails the loss of productivity gains, competitive advantages, and innovation potential associated with emerging technologies. There is a risk that AI-driven business transformations will disproportionately benefit already advantaged entrepreneurs, thereby widening existing inequalities (Khoza, 2024; Suseno and Abbott, 2021; Rolle and Kisato, 2019).

By centring underrepresented entrepreneurs, this study contributes to the expanding literature on inclusive digitalisation and the equitable distribution of the advantages associated with AI (Tiasakul et al., 2024; Sodhi and Dwivedi, 2024). Addressing this gap is particularly timely, given the increasing practical relevance of AI in small business contexts. By documenting both the structure and outcomes of a targeted training programme, it enhances understanding of how universities can act as agents of inclusive technological education for underrepresented entrepreneurs. In doing so, it provides a framework for higher education institutions, policymakers, and community partners seeking to reduce inequalities in digital competency development and small business capacity building.

Second, although there is growing interest in the application of AI within business environments, adoption has been led predominantly by large firms. The landscape differs considerably for small firms, which face distinct challenges in developing their digital competencies (Hansen et al., 2021; Cubric, 2020; Giotopoulos et al., 2017). These firms often lack the financial resources, technical expertise, and strategic support required to deploy AI effectively within their operations. This study is therefore of particular relevance, as it offers a structured educational intervention and provides new insights into the associations between digital training and key business outcomes for small firms. It contributes to ongoing debates by encouraging reflection on how such firms can strengthen their digital competencies and integrate AI technologies into routine business practices.

The study explicitly addresses structural barriers by offering free training, employing flexible delivery methods, mobile-accessible tools, and plain-language instruction, while integrating inclusive pedagogical practices and culturally diverse case studies. The training is grounded in a curriculum that reflects the operational realities and lived experiences of small-scale firms and underrepresented entrepreneurs. By centring critical business performance as a complementary outcome of digital competency, the training seeks to expand conventional definitions of business success and inclusion. In doing so, it offers a practical, scalable, and socially responsive framework for promoting fair participation in AI-enabled markets, advancing both entrepreneurial capacity and digital justice.

Third, a key contribution of this study is the conceptualisation of AI business applications training as a distinct category within the digital adoption literature. Existing research in this area typically focuses on foundational technological competencies, such as basic software use, internet navigation, and online communication (Azevedo and Almeida, 2021; Blackburn and Athayde, 2020; European Commission, 2019; Casalino et al., 2012). As AI technologies become increasingly embedded in business environments, there is a need for a framework that captures how entrepreneurs acquire and apply competencies related to interacting with AI-enhanced platforms designed to personalise, automate, and augment decision-making processes. This study addresses that theoretical gap by defining and empirically examining a form of AI training that is business application-specific, decision-focused, and relevant to core business domains.

Accordingly, AI business applications training is conceptually and pedagogically distinct from general digital upskilling, business application training, and AI literacy programmes. It offers a focused intervention that supports the development of applied digital competencies relevant to the use of AI within small business operations, particularly for underrepresented entrepreneurs. General digital upskilling tends to concentrate on basic ICT tasks such as data entry and file management, often aimed at improving general productivity or employability. In contrast, AI business applications training is structured around the practical use of commercially available AI-enabled tools that support key business functions. The AI business application training does not simply introduce participants to digital tools; it embeds AI use within specific business contexts, enabling the development of competencies directly linked to decision-making, automation, and customer engagement.

AI literacy programmes, by comparison, typically aim to build awareness and understanding of what AI is, how it works, and its broader ethical and societal implications. While these programmes are valuable, they are rarely aligned with the operational realities of small businesses or the specific constraints experienced by underrepresented entrepreneurs. The AI business application training framework developed in this study involves hands-on engagement with AI tools that are already integrated into widely used platforms. It enables participants to apply these tools strategically to enhance firm-level performance.

Moreover, AI business applications training introduces a dimension often absent from general digital skills or AI literacy initiatives. The training positions AI not only as a technological asset but also as a means of challenging reputational stigma, increasing market visibility, and strengthening decision-making autonomy for underrepresented entrepreneurs. In doing so, it moves beyond prevailing conceptualisations of the digital divide and repositions AI business applications training as a strategic pathway towards more equitable participation in the digital economy.

Fourth, the study's theoretical contribution lies in its proposal and empirical validation of the AI Business Applications Training Model. This framework assesses how targeted training, focused on AI business applications for decision-making, automation, and customer engagement, can generate measurable improvements in digital competencies, customer satisfaction, entrepreneurs' empowerment, and revenue growth. By situating these improvements within the lived experiences of underrepresented entrepreneurs, the study conceptualises digital competencies as adaptive forms of capital developed under challenging conditions, rather than as simple outcomes of skill acquisition. In doing so, it offers a new conceptual bridge between research on digital inclusion and empirical studies of technology-based business training.

The contribution rests on two central elements: the nature of the intervention (AI business applications training) and the specific group targeted (underrepresented entrepreneurs). Together, these elements form a distinct theoretical and empirical contribution to the literature on entrepreneurship and digital equity. The AI Business Applications Training Model proposes that this form of training enhances firms' digital competencies by equipping underrepresented entrepreneurs with AI-specific knowledge. This knowledge enables them to transform information into actionable insights and streamline key operations. The model further suggests that, following training, enhanced digital competencies are associated with increased customer satisfaction. This is attributed to the ability of AI business applications to support more responsive and personalised services, reduce reputational stigma, and address biases embedded in customer interactions, which underrepresented entrepreneurs often face.

In addition, AI Business Applications Training Model anticipates that, after training, digital competencies are associated with heightened entrepreneurs' empowerment. By enabling entrepreneurs to build confidence and competence in strategic decision-making, the training may help them navigate structural barriers and strengthen their position in digital marketplaces. Furthermore, the model posits that digital competencies are linked to improved financial performance. This is based on the premise that training equips entrepreneurs with the ability to optimise digital tools, expand their market reach, reduce dependence on external support, and improve operational efficiency, thereby supporting revenue growth.

In sum, this study proposes and empirically validates a new, applied model of AI business applications training that is both theoretically grounded and responsive to the lived constraints of underrepresented entrepreneurs. The intervention is designed and delivered in a context-specific and inclusive manner, aligning with the operational constraints, structural exclusions, and strategic aspirations of non-native, disabled, and non-heterosexual entrepreneurs. Its originality lies not only in its population focus and methodological design, but also in the development of a conceptual framework that links practical competencies to customer relations, entrepreneurs' empowerment, and financial outcomes within a digitalising economy. While previous studies have examined digital skills or general AI literacy in isolation, this study introduces a scalable and socially responsive training approach that embeds AI use within core business operations. By advancing a model that explicitly connects targeted training with digital competencies and inclusive growth, the study offers a distinctive and actionable lens through which digital interventions can be reimagined to promote equity in entrepreneurial ecosystems.

The study's findings indicate that, following the training, the associations between firms' digital competencies and customer satisfaction, entrepreneurs' empowerment, and revenue growth strengthened compared to the period prior to the intervention. The results provide clear evidence that AI business applications training contributes not only to improved business performance but also to increased customer satisfaction and greater entrepreneurs' empowerment. These findings strengthen the case for inclusive interventions and offer empirical support for the proposed AI Business Applications Training Model. The study's focus also aligns with broader sustainability objectives, including the reduction of inequality and the promotion of empowerment through technology. This enhances its relevance for policymakers and business leaders seeking to develop more inclusive digital strategies for underrepresented groups.

The remainder of the study is structured as follows. The next section outlines the study's hypotheses. Section Three discusses the recruitment of entrepreneurs and the design of the AI business applications training. Section Four presents the variables and measurement scales used in the analysis, followed by Section Five, which provides a validation of these scales. Section Six covers the descriptive statistics, and Section Seven presents the study's estimates. Section Eight offers a discussion of the findings. Section Nine outlines the study's contributions. Section Ten sets out the policy implications. Section Eleven discusses the study's limitations and offers suggestions for future research. The concluding section brings the study to a close.

2. Theoretical Framework

This section develops a theoretical framework to explain how AI business applications training contributes to the formation of digital competencies, how these competencies relate to three key business outcomes, namely customer satisfaction, entrepreneurs' empowerment, and revenue growth, and how AI business applications training ultimately moderates the relationship between digital competencies and business outcomes. Subsections 2.1 to 2.4 examine each of these relationships in detail, culminating in subsection 2.5, which synthesises the components into a coherent analytical model[1].

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[1] To inform the study's theoretical framework, literature searches were conducted across academic databases, including Scopus, Web of Science, EBSCOhost, and Google Scholar. The reviewed studies were predominantly in English and, to ensure quality standards, the review focused primarily on peer-reviewed publications. Studies were screened based on the clarity of their aims, the appropriateness of their methodology, the transparency of their findings, and their relevance to the context of the present study. The searchable keywords that informed the theoretical framework

2.1 Digital competencies and AI business applications training

Digital skills are essential for firms to leverage the opportunities presented by Information and Communication Technologies (ICT) (ITU, 2020). The diffusion of technology is widely recognised as a catalyst for the development of such skills (Kraus et al., 2022; North et al., 2020; ITU, 2020; Giotopoulos et al., 2017; Yu et al., 2017; Newby et al., 2014; Bruno et al., 2011; Rogers, 2003). However, digital competencies go beyond technical skills; they encompass the ability to apply these skills to transform information into knowledge, streamline operations, and deliver services through analytical and creative uses of ICT (Oberländer et al., 2020; Vieru, 2015).

Firms with strong digital competencies are more adaptable, innovative, and able to improve performance (Qalati et al., 2025; Kraus et al., 2022; North, 2020; Giotopoulos et al., 2017; Millán et al., 2021). When embedded across departments, digital tools, including business applications, enhance productivity and operational efficiency (North et al., 2020; Yu et al., 2017; Newby et al., 2014). Recent conceptual developments highlight the role of AI in strengthening these competencies related to the use of such tools, offering real-time insights, automation, and cognitive support to improve decision-making (Wu et al., 2025; Raees et al., 2024; Soni, 2023; Chen et al., 2023; Ng et al., 2021; Tarafdar et al., 2019).

Within this context, the Artificial Intelligence Capital framework (Drydakis, 2024a) frames AI knowledge and skills as a form of capital that can strengthen organisational competencies through interpretability, automation, and data-driven decisions. Drawing on human capital theory (Becker, 1964) and technological transformation theory (Schumpeter, 1939), it positions AI capital as a strategic resource for competitive growth. Capability theory (Teece, 2007) similarly recognises

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included, among others, combinations of the following terms: “AI in SMEs”; “AI in small enterprises/firms”; “AI for decision-making”; “AI business applications and SMEs”; “AI for customer engagement”; “AI in finance”; “AI in marketing”; “AI literacy”; “AI and entrepreneurship”; “AI training and entrepreneurs”; “AI-assisted forecasting”; “AI and customer experience”; “applied training”; “digital competencies”; “digital divide”; “digital skills”; “digital training”; “digital training programmes”; “digital transformation”; “disabled entrepreneurs”; “entrepreneurs’ empowerment”; “underrepresented entrepreneurs”; “firm/SME performance”; “financial resilience”; “ICT training”; “ICT upskilling”; “inclusive entrepreneurship”; “LGBTQ+ entrepreneurs”; “migrant entrepreneurs”; “revenue growth”; “small businesses”; “structural barriers and entrepreneurship”; “training evaluation in SMEs”; and “women entrepreneurs”.

AI's potential in automating routine processes and improving precision across various functions, including sales, marketing, customer service, and finance (Felsberger et al., 2022; Bernroider et al., 2014; Borch and Madsen, 2007; Hamal and Senvar, 2021; Basri, 2021).

Training interventions have proven effective in building digital competencies and improving firms' readiness for digital transformation (Azevedo and Almeida, 2021; Blackburn and Athayde, 2000; European Commission, 2019; Casalino et al., 2012). Grounded in training transfer theory (Kirkpatrick, 1994; Baldwin and Ford, 1988), technology diffusion (Rogers, 2003), and capability theory (Li et al., 2017; Teece, 2007), such training has been shown to reduce digital skill gaps and mitigate obsolescence.

In this study, AI business applications training is defined as a targeted, applied educational intervention focused on equipping entrepreneurs with practical skills to implement AI tools in business operations, including communication, finance, and customer management. Unlike general ICT training or upskilling initiatives, which focus on software literacy or web navigation (Azevedo and Almeida, 2021; Blackburn and Athayde, 2020; European Commission, 2019; Casalino et al., 2012), this training emphasises the use of AI for prediction, engagement, and planning. Participants engage with domain-specific tools relevant to small business contexts, such as AI-assisted customer segmentation, real-time messaging, automated financial forecasting, and project management applications (Raees et al., 2024; Soori et al., 2024; Barukh et al., 2021).

Delivered through guided activities based on realistic scenarios, the training fosters both technical understanding and strategic application. This training is particularly relevant for small firms that lack in-house expertise to experiment with emerging technologies. It enables firms to identify and engage customers, adapt pricing strategies, manage cash flow, and automate decision-making using AI-enhanced business applications. As a result, the intervention is positioned not merely as a technical training programme but as a strategic investment in applied digital competencies.

Theoretically, this conceptualisation draws on work that presents digital training as a pathway to stronger operational capacity and responsiveness (Li et al., 2017; Rogers, 2003; Blackler and Brown, 1986). The training builds on the AI Capital framework (Drydakis, 2024a) to support the development of business-specific competencies that remain underexplored in broader ICT and generative AI training.

For underrepresented entrepreneurs, digital competencies are more than functional traits, as they represent responses to exclusion from mainstream support systems. These competencies reflect a form of capital that emerges under structural constraints, such as biased lending practices and limited access to elite networks (Khoza, 2024; Akpuokwe et al., 2024; Suseno and Abbott, 2021; Pidduck and Clark, 2021; Rolle et al., 2020). While digitalisation is often portrayed as universally beneficial, evidence shows it can also deepen inequalities by favouring those already embedded in resource-rich ecosystems (Akpuokwe et al., 2024; Pidduck and Clark, 2021; Rolle and Kisato, 2019).

In this light, AI business applications training serves not only to close skills gaps but also to intervene in exclusionary structures. It provides underrepresented entrepreneurs with practical features to improve visibility, reach broader markets, and personalise services (Aranitou et al., 2025; Peruchini et al., 2024; Marti et al., 2024). These outcomes are not typically delivered by general upskilling or generative AI programmes. By enabling independent forecasting, supply chain management, and service delivery, such training strengthens entrepreneurial resilience, particularly in the absence of formal mentoring or crisis support. When aligned with the lived realities of underrepresented groups, digital training becomes a vehicle for both inclusion and structural repair. It positions digital competencies as part of a broader effort to democratise entrepreneurship.

To examine the association between AI business applications training and digital competencies, the following hypothesis is proposed:

Hypothesis 1: Post-AI business applications training, firms experience an increase in digital competencies.

2.2 Digital Competencies, Customer Satisfaction and AI Business Applications Training

Innovation, digital platforms, and AI technologies support improved customer service and evaluation by enabling fast, accurate responses, automated support, and data-informed personalisation (Ibrahim et al., 2025; Aranitou et al., 2025; Peruchini et al., 2024; Qalati et al., 2024; Ibrahim et al., 2023; Kraus et al., 2022; Prentice et al., 2022; North, 2020). Business applications such as chatbots and virtual assistants improve accessibility and ensure customer needs are met promptly, contributing to higher satisfaction (Chen et al., 2023; Chung et al., 2018). AI can also streamline customer records and generate tailored product or service recommendations based on behavioural data (Chung et al., 2018).

Firms that integrate these technologies effectively often benefit from increased loyalty, repeat business, and referrals (Chen et al., 2023; Peruchini et al., 2024; Prentice et al., 2022). The present study suggests that AI business applications training can enable firms to use such tools more strategically, strengthening their ability to anticipate and meet customer needs. Following training, firms are expected to apply AI business applications in ways that enhance the connection between digital competencies and customer satisfaction. This includes managing greater volumes of data, streamlining services, and interpreting AI-generated insights to improve responsiveness (Marti et al., 2024; Chen et al., 2023). These outcomes indicate that training improves not only technical proficiency but also the capacity to sustain high-quality customer experiences.

For underrepresented entrepreneurs, these benefits may be even more significant. Structural biases often influence how professionalism is perceived, regardless of actual performance (Santos et al., 2025; van Merriënboer et al., 2025; Adeeko and Treanor, 2022; Martinez, 2020). AI business applications that automate communication and standardise service processes can help shift customer evaluations away from identity-based assumptions toward performance-based outcomes (Khoza, 2024; Rolle and Kisato, 2019).

The present study indicates that training in these tools provides entrepreneurs with reliable methods of engagement that reduce the risk of reputational stigma and expand access to wider customer segments. In this way, AI business applications training supports both technological advancement and inclusive practice (Tiasakul et al., 2024; Rolle and Kisato, 2019).

To explore the relationship between digital competencies, AI business applications training and customer satisfaction, the following hypotheses are formulated:

Hypothesis 2.a: Firms' digital competencies are associated with increased customer satisfaction.
Hypothesis 2.b: Post-AI business applications training, firms experience an increase in customer satisfaction.
Hypothesis 2.c: Post-AI business applications training, firms' digital competencies are more strongly associated with increased customer satisfaction.

2.3 Digital competencies, entrepreneurs' empowerment and AI business applications training

Empowerment refers to the ability of underrepresented groups to access the knowledge, resources, agency, and competencies required to make strategic decisions in personal and professional contexts (Drydakis, 2024b; Mackey and Petrucka, 2021). Access to digital technologies, particularly ICT, has long been recognised as a driver of empowerment by challenging structural barriers and enabling greater inclusion of groups such as women, migrants, LGBTQ+ individuals, and people with disabilities (Khoza, 2024; Alateeg and Al-Ayed, 2024; Hilbert, 2011; Kelkar and Nathan, 2002).

Within this framework, digital competencies function as enablers of agency. They support market access, service delivery, and leadership development, particularly among women and migrant entrepreneurs (Aranitou et al., 2025; Khoza, 2024; Kraus et al., 2022). The ability to use AI business applications for strategic decision-making and operational oversight enhances entrepreneurs' control over their ventures and strengthens their capacity to navigate complex market environments (Çetin et al., 2021; Mackey and Petrucka, 2021).

Entrepreneurs' empowerment in this study is conceptualised as a dynamic process through which underrepresented entrepreneurs develop confidence, competence, and autonomy to act strategically within digital economies. This definition moves beyond psychological or resource-based interpretations, emphasising empowerment as a form of operational capacity developed through digital competency (Akpuokwe et al., 2024; Hilbert, 2011; Mackey and Petrucka, 2021). AI business applications training contributes to this process by equipping entrepreneurs with the skills to manage AI tools across communication, customer engagement, finance, and team coordination.

Such training is particularly relevant in contexts where underrepresented entrepreneurs are excluded from elite entrepreneurial ecosystems, including formal mentorship and financing networks (Khoza, 2024; Akpuokwe et al., 2024). In these environments, the development of digital competencies becomes a strategic response to constrained opportunity structures. Through the internalisation of analytical, operational, and marketing functions, entrepreneurs establish resilient, data-informed business models (Asongu and Odhiambo, 2020; Cummings and O'Neil, 2015). Access to AI business applications such as predictive analytics, automated workflows, and customer segmentation allows for more responsive and independent business planning. These competencies redistribute informational power and increase entrepreneurs' capacity to act, particularly in resource-constrained or discriminatory environments (Drydakis, 2024b).

Following AI business applications training, it is proposed that the relationship between digital competencies and entrepreneurs' empowerment will be strengthened. This supports the view that digital competencies contribute directly to entrepreneurs' self-efficacy. As entrepreneurs gain autonomy and visibility, they challenge dominant narratives linking success to privileged identities. In this way, empowerment becomes both an economic and symbolic outcome of AI training.

To assess the association between digital competencies, AI business applications training and entrepreneurs' empowerment, the following hypotheses are proposed:

Hypothesis 3.a: Digital competencies are associated with increased entrepreneurs' empowerment.
Hypothesis 3.b: Post-AI business applications training, there is an increase in entrepreneurs' empowerment.
Hypothesis 3.c: Post-AI business applications training, firms' digital competencies are more strongly associated with increased entrepreneurs' empowerment.

2.4 Digital competencies, firms' revenue growth and AI business applications training

Firms that adopt AI business applications and engage in digital skills programmes are more likely to experience increases in revenue, profitability, and overall performance (Aranitou et al., 2025; Ardito et al., 2024; Kraus et al., 2022; North, 2020). These financial indicators are central to assessing a firm’s sustainability, resilience, and competitiveness in evolving markets (Aranitou et al., 2025; Ardito et al., 2024). Revenue growth signals a firm’s market expansion, while profit generation reflects operational efficiency and long-term viability (Bandari, 2019).

AI business applications training is understood as a strategic investment that enhances firms’ digital competencies, thereby supporting improved financial outcomes (Aranitou et al., 2025; Ardito et al., 2024; Kraus et al., 2022). Firms that integrate AI business applications following training may be better positioned to anticipate customer trends, personalise engagement, automate operations, and manage resources efficiently (Kraus et al., 2022; North, 2020). These competencies can lead directly to higher sales and reduced costs (Aranitou et al., 2025).

For underrepresented entrepreneurs, enhanced digital competencies acquired through AI business applications training may offset the disadvantages associated with limited access to financial capital, networks, or institutional support. AI business applications can facilitate data-informed decision-making, reduce reliance on third-party services, and expand customer reach through digital platforms. By enabling engagement with predictive analytics and AI-assisted management applications, training helps develop scalable, profitable business models (Drydakis, 2025a; Ardito et al., 2024).

Moreover, AI business applications support operational efficiency and offer means to compete in markets where underrepresented entrepreneurs may face exclusion due to structural inequities or discriminatory practices (Akpuokwe et al., 2024; Pidduck and Clark, 2021). In this regard, revenue growth and profitability become indicators not only of commercial success but also of inclusive digital empowerment (Drydakis, 2025a; Tiasakul et al., 2024; Sodhi and Dwivedi, 2024).

Given these considerations, the fourth set of hypotheses in the study, assessing the association between digital competencies, AI business applications training and firms’ revenue growth, is presented below:

Hypothesis 4.a: Digital competencies are associated with increased revenue growth for firms.
Hypothesis 4.b: Post-AI business applications training, firms experience an increase in revenue growth.
Hypothesis 4.c: Post-AI business applications training, firms’ digital competencies are more strongly associated with increased revenue growth.

A summary of the study’s hypotheses, expected associations, and the rationale for the moderating role of AI business applications training in the relationship between digital competencies and business outcomes is provided in Appendix Table AI.

[Appendix, Table AI]

The preceding sections establish the theoretical rationale for the study's four sets of hypotheses. The model below integrates these components into a coherent analytical framework.

2.5 AI Business Applications Training Model

The AI Business Applications Training Model brings together the study's hypotheses, demonstrating how training in AI business applications fosters digital competencies that, in turn, support three key outcomes: customer satisfaction, entrepreneurs' empowerment, and improved financial performance.

Distinct from general upskilling initiatives or broad business application frameworks, this model establishes a direct and applied link between AI competencies and inclusive business outcomes. It offers a strategic, context-sensitive framework tailored to the specific circumstances of small firms and underrepresented entrepreneurs operating in digital markets. Unlike conventional generative AI and digital training programmes, which often lack a coherent conceptual foundation and fail to reflect the operational realities of small enterprises, this model provides applied training through AI business applications.

It is grounded in multiple theoretical traditions, including human capital theory, which frames training as a productivity-enhancing investment (Becker, 1964); technological transformation and diffusion theory, which positions technology as a driver of organisational change (Schumpeter, 1939; Rogers, 2003); and capability theory, which defines digital competencies as strategic assets (Teece, 2007). Training transfer theory supports the model's emphasis on applied, context-relevant learning (Kirkpatrick, 1994; Baldwin and Ford, 1988), while the concept of AI capital (Drydakis, 2024a) underpins its focus on interpretability, automation, and decision-making. Finally, inclusive entrepreneurship perspectives highlight how digital competencies function as resilience assets, enabling underrepresented entrepreneurs to overcome systemic barriers (Rolle et al., 2020; Orser et al., 2019).

At its core, the model conceptualises digital competencies as applied, strategic proficiencies that allow entrepreneurs to leverage AI business applications for prediction, automation, and engagement (Oberländer et al., 2020; Vieru, 2015; Tarafdar et al., 2019; Prentice et al., 2022; Peruchini et al., 2024; Marti et al., 2024). These competencies are distinct from general ICT skills, as they involve cognitive engagement with AI-driven systems across business functions.

First, the model predicts that AI business applications training enhances digital competencies by providing underrepresented entrepreneurs with practical skills to convert data into actionable insight and optimise business operations (Azevedo and Almeida, 2021; Blackburn and Athayde, 2020; Casalino et al., 2012; Bruno et al., 2011).

Second, it proposes that, following training, digital competencies are more strongly associated with customer satisfaction. Entrepreneurs equipped with AI business applications can provide personalised, timely services, mitigate reputational bias, and respond to customer needs more effectively (Marti et al., 2024; Prentice et al., 2022; Khoza, 2024; Drydakis, 2024b). AI-enabled engagement shifts the focus from identity-based evaluations to performance-based service delivery.

Third, the model anticipates that enhanced digital competencies, developed through AI business applications training, support entrepreneurs' empowerment. Defined as a combination of confidence, competence, and strategic autonomy (Mackey and Petrucka, 2021), empowerment arises when entrepreneurs are able to plan, forecast, and lead independently, particularly within exclusionary environments (Pidduck and Clark, 2021; Suseno and Abbott, 2021; Asongu and Odhiambo, 2020).

Fourth, it links digital competencies to improved financial performance. By enabling AI-supported pricing, customer analytics, and operational streamlining, the AI business applications training equips entrepreneurs to build scalable, resource-efficient business models (Aranitou et al., 2025; Ardito et al., 2024; Kraus et al., 2022). These competencies help firms adapt to market changes and compete effectively despite resource constraints.

Figure I illustrates the moderated relationship between digital competencies and the three key business outcomes. It shows that, following training, digital competencies are more strongly associated with improvements in customer satisfaction, entrepreneurs' empowerment, and revenue growth.

[Figure I]

The model maintains coherence across levels of analysis by positioning digital competencies as the central mechanism connecting relational (customer satisfaction), individual (entrepreneurs' empowerment), and organisational (financial performance) outcomes. These competencies are enhanced through AI business application training. Increased customer satisfaction stems from enhanced digital competencies, as entrepreneurs are trained to use AI business applications to personalise services and improve interactions. For underrepresented entrepreneurs, this training and the resulting competencies enable participation in digital economies on more equitable terms, leading to greater empowerment. Similarly, financial benefits emerge through the strategic integration of AI business applications into decision-making and planning, as a direct outcome of the training and strengthened digital competencies.

The model also acknowledges the interdependencies among the proposed outcomes. For example, empowered entrepreneurs may be better positioned to engage customers effectively and guide their firms through digital transitions. In turn, increased customer satisfaction may foster loyalty and contribute to financial performance. These positive spillover effects illustrate the model's integrated structure, in which enhanced digital competencies serve as a foundational mechanism for generating multiple, mutually reinforcing benefits across individual, relational, and organisational domains.

Hence, the AI Business Applications Training Model presents a multi-dimensional, theoretically grounded, and practically applicable framework. It highlights how targeted AI business applications training enhances digital competencies that support business outcomes within underrepresented communities. By conceptualising AI business applications training as a vehicle for empowerment, inclusion, and resilience, the model contributes an original perspective to research on AI adoption, the use of AI business applications, and digital and inclusive entrepreneurship.

3. AI business applications training

3.1 Recruitment of entrepreneurs

In 2022, a Google search was conducted to identify organisations, support groups, and networks representing non-native communities, LGBTIQ+, and disability communities across England, Wales, and Scotland. These communities were emailed with information regarding the study. The introductory letter outlined details of the study, emphasising the availability of free online digital training in AI business applications for non-native, LGBTIQ+, and disabled entrepreneurs who own and manage small firms. The communities were requested to circulate the invitation via their mailing lists. Ethics clearance information was included in the opening letter, outlining the aims, procedures, teaching methods, and research protocols associated with the training. Additionally, the letter included details about the research team's affiliations, credentials, and expertise in the field, inviting initial communication.

The invitation specified that prospective entrepreneurs should have access to a PC or laptop, a smartphone, and a free online meeting platform. The research protocol required participants to provide their email addresses to receive training instructions and indicated that e-surveys would be administered before and after the training to gather demographic and business-related information. Ethical clearance assured participants of their anonymity, with the option to withdraw from the training or subsequent data collection at any stage. The declaration of competing interests confirmed that the research team had no financial incentives and was unaffiliated with the developers of the business applications. Information was also provided about the research team's selection and screening of AI business applications, as outlined in section 3.2.

The research team conducted interviews with interested participants, and participants' business credentials were verified. Entrepreneurs confirmed their participation by providing written informed consent and completing e-surveys between January and February 2023, creating a dataset designated as Wave 1, collected prior to the AI business applications training. The training took place between March and June 2023 and consisted of six three-hour, online lecture-oriented sessions. In addition, six further online meetings were provided to address any queries, held one week after each lecture-oriented session. Given the nature of the study, a sufficient interval between data collections was essential to enable meaningful comparisons and trend analysis (Andreß et al., 2013; Lynn, 2009). The follow-up e-survey (Wave 2) was conducted after the AI business applications training, between June and August 2024.

3.2 AI business applications

AI business applications were identified through the Google Play Store. As in Drydakis (2022a; 2024b; 2025a), the applications were grouped into nine categories: (i) communication, (ii) networking, (iii) social media, (iv) customer relationship management, (v) payments, (vi) accounting and finance, (vii) inventory management, (viii) team and time management, and (ix) project management. The applications were categorised into the aforementioned groups to reflect distinct and functionally meaningful areas of AI use in small business settings. This design enables the training to ground its theoretical analysis in the specific ways AI systems support information processing, customer interaction, and business planning, rather than treating AI as a homogeneous or abstract concept (Hansen et al., 2021; Tarafdar et al., 2019). The top three AI business applications in each category, based on performance and user reviews, were selected, resulting in a total of 27 applications. Three personnel evaluated these applications following Martin et al.'s (2013) five-step protocol, which included: (i) identifying all potentially relevant AI-aided business applications[2], (ii) removing outdated versions of each applications, (iii) identifying the main

[2] In the applications' description section, the developers identified AI as a key feature, aligning with the essential technical characteristics typically associated with AI integration. In each case, at least one AI attribute, such as machine learning, deep learning, or neural networks, was required to classify the applications as AI-aided. As the study focused on the three most popular AI applications, these applications provided further substantiation by linking to their developer pages or resources, where they discussed the specific AI technologies employed. Additionally, user

functional requirements and excluding applications that did not meet these criteria, (iv) identifying all secondary requirements, and (v) constructing tasks to test the main functional requirements using keystroke-level modelling and usability heuristic evaluation.

For the keystroke-level modelling, each AI business application was analysed to assess efficiency (Card et al., 1980). As shown in Table 1, the number of interactions required to complete tasks was used as the measure of application efficiency (Martin, 2013). Given that this study focused on the most popular AI business applications in each category, those top-ranked on the Google Play Store, it is unsurprising that the identified applications demonstrated similar levels of efficiency in terms of interactions required. Furthermore, as seen in Table 1, usability heuristic evaluation (Bertini et al., 2009) was carried out, covering the following aspects: (i) visibility of system status and losability/findability of the device, (ii) alignment between the system and real-world expectations, (iii) consistency and mapping, (iv) good ergonomics and minimalist design, (v) ease of input, screen readability, and glanceability, (vi) flexibility, efficiency of use, and personalisation, (vii) aesthetics, privacy, and social conventions, and (viii) realistic error management. The usability heuristic evaluation was conducted using Nielsen's (1994) five-point severity ranking scale. Table 1 indicates that no major usability problems or catastrophes were found in the 27 applications, suggesting that the selected AI business applications are generally appropriate for business training. Additionally, the applications' usability was confirmed by user review rankings on the Google Play Store, which reflected low levels of usability issues.

[Table 1]

During the evaluation stage (Martin et al., 2013), the following operations were assessed across various categories of business applications supported by AI. Communication applications were evaluated on internal and external e-interactions and e-information sharing processes. Networking applications were assessed based on operations such as sending updates on the go, adding new connections, recruiting new hires, following inspirational firms and individuals, and analysing competitor strategies. Social media applications were evaluated on operations related to planning, promoting, and monitoring projects through engagement with social channels.

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reviews referenced the AI functionality in practice, highlighting how proficiently the applications performed decisions, predictions, or personalised suggestions. This aligns with the criteria for AI-powered functional features, such as automation, recommendation systems, and decision support systems, which users commonly encounter. By cross-referencing application descriptions, technical documentation, and user feedback with established AI screening indicators, it is evident that these business applications exhibit several essential characteristics of AI integration.

Furthermore, customer relationship management applications were assessed against a range of processes, including managing customer profiles.

Moreover, payment applications were evaluated based on their ability to review business analytics, monitor sales items, and process credit cards, cheques, and invoices. Accounting and finance applications were examined for their role in bookkeeping processes, including invoicing, expense management, and payroll. In addition, inventory management applications were evaluated on operations involving the creation of product catalogues, tracking and managing stock and sales, and handling purchase orders. Team and time management applications were assessed on operations related to managing payroll, benefits, and payroll tax calculations and filings. Finally, project management applications were evaluated on processes related to managing projects, workflows, and deadlines across different business operations.

By assessing usability and task efficiency across domains, the study ensures that the selected AI business applications are not only accessible and practical for small firms, but also analytically relevant for understanding digital competencies as a dynamic, competency-enhancing construct (Oberländer et al., 2020; Vieru, 2015). Consequently, the heterogeneity of the AI business applications is framed as an operational strength, capturing the diverse yet interrelated roles that AI plays in entrepreneurial workflows.

3.3 AI business applications training structure

The AI business applications training aimed to introduce participants to the fundamental principles underlying AI, guiding them to understand both the benefits and challenges of applying AI in a business environment, and how AI can facilitate business processes (Chen et al., 2023; Hansen et al., 2021; Chung et al., 2018). Furthermore, the training sought to demonstrate how businesses can optimise day-to-day operations and enhance functionality and productivity. The training was structured to provide an introduction to the relevance of each of the nine thematic in a business context, outline the tasks each application could perform, present technical instructions on downloading and installing the applications, offer a practical, manual-oriented presentation on how to use each one, and provide case studies to showcase their functionality.

During the first session, participants were introduced to what AI actually does, how it works, and the challenges associated with it, enabling them to make informed decisions about the use of AI in their businesses. Real-world examples of AI business applications were presented, along with discussions on the opportunities, challenges, ethical considerations, and compliance with data protection laws. In the second session, participants were informed of how the research team selected and screened the applications, and communication and networking applications were introduced.

The third session focused on social media and customer relationship management applications, while the fourth session covered payments and accounting/finance applications. In the fifth session, participants were introduced to managing inventory, team, time, and project management applications. The sixth session provided a comprehensive overview of the training. As mentioned earlier, six additional online meetings were held one week after each lecture-oriented session to address any queries participants had[3].

3.4 Pedagogical justification and curriculum design rational

To ensure the effectiveness and accessibility of the training, the sessions were structured not only thematically around nine distinct categories of AI business applications, but also in accordance with pedagogical principles informed by adult learning approaches (Azevedo and Almeida, 2021; Blackburn and Athayde, 2020; Orser et al., 2019; Marchand and Dijkhuizen, 2018; Casalino et al., 2014), training transfer theory (Kirkpatrick, 1994; Baldwin and Ford, 1988), AI capital and capability-building frameworks (Drydakis, 2024a; Teece, 2007), innovation and technology diffusion theory (Rogers, 2003; Blackler and Brown, 1986), and inclusive entrepreneurship education (Tiasakul et al., 2024; Rolle et al., 2020; Khoza, 2024; Orser et al., 2019). This integrated instructional framework supports not only digital competency acquisition but also aligns with the broader theoretical models outlined in the study, forming the foundation of the AI Business Applications Model. In this sense, the training is positioned not merely as a technical intervention but as a transformative educational strategy aimed at fostering agency, resilience, and equity within AI-enabled business environments.

Each session was guided by clearly defined learning objectives that outlined what trainees should understand or be able to do by the end of the session. These objectives were paired with targeted digital skill-building activities designed to support the development of applied competencies relevant to entrepreneurial contexts, including campaign automation, financial forecasting, customer engagement, inventory tracking, and team coordination.

Active and experiential learning strategies were embedded throughout the training, including case studies, workflow simulations, peer reviews, and interactive demonstrations. These strategies draw on constructivist and situated learning theories, enabling participants to develop understanding through real-time practice and reflection in authentic settings (Dziubaniuk and

[3] Reflecting on the nature of the queries, these were related to how firms could customise a particular application to suit their business needs, how the applications could be integrated with existing business systems, how to resolve installation issues and engage with the provided case studies, and how to optimise certain business tasks using the presented applications.

Nyholm, 2021; Mattar, 2018; Cobb and Bowers, 1999). The pedagogical structure followed a deliberate progression: beginning with conceptual orientation, moving to AI business applications, and culminating in integrative, cross-functional planning exercises that reinforced the transfer of learning across contexts.

Question-answering and feedback mechanisms were incorporated throughout the training to support understanding and encourage reflective learning. These included Q&A activities, formative assessments such as skill-application tasks, self-assessment checklists, group-based evaluations, and scenario-based challenges. Feedback was provided during sessions and through follow-up activities, helping to create a supportive and iterative learning environment.

Importantly, the training was designed according to principles of Universal Design for Learning and inclusive pedagogy, with particular attention given to the structural barriers faced by underrepresented entrepreneurs (Stentiford and Koutsouris, 2021; Capp, 2017; Florian and Black-Hawkins, 2011; Rose, 2000). To ensure that the training was inclusive and practically accessible for small firms led by individuals from marginalised backgrounds, the training incorporated mobile-first design, plain-language delivery, and culturally relevant case studies. AI business applications were selected based on usability and mobile accessibility; instructions were delivered in clear, jargon-free language; and case studies were curated to reflect diverse entrepreneurial experiences, including those of migrants, disabled individuals, non-heterosexual entrepreneurs, and individuals without formal business training.

Flexible participation formats were adopted, including asynchronous task access, voice-to-text functionality, and varied feedback mechanisms. These features enabled equitable engagement among learners with different schedules, digital literacy levels, and learning preferences. By grounding the curriculum in real-world examples that reflect gender, cultural, and business diversity, the training addressed both technological and social barriers to AI adoption, supporting more inclusive forms of digital participation and entrepreneurial development.

Further details of the training structure are provided in Appendix Table AII, which outlines, for each session, the learning objectives, digital skill-building components, digital competencies targeted, AI business applications and practices, pedagogical strategies, assessment and feedback mechanisms, and inclusion and accessibility features.

[Appendix, Table AII]

4. Variables

The e-surveys included questions to capture firms’ characteristics, such as years of operation, number of employees, and sector of operation, alongside the entrepreneurs’ demographic characteristics, including gender, ethnicity, sexual orientation, and disability status.

The study utilised the Digital Competencies Scale (Drydakis, 2022b) to assess firms' levels of digital competency. This scale captures entrepreneurs' reflections on their firm's competency in using digital tools across nine key business domains: (i) communication operations involving internal and external electronic interactions; (ii) networking operations relating to recruitment and the analysis of competitors' strategies; (iii) social media engagement for planning, promoting, and monitoring projects; (iv) customer relationship management through maintaining customer profiles and sending marketing messages; (v) payment services through the analysis of business analytics data; (vi) accounting and finance services for organising bookkeeping processes; (vii) inventory operations for tracking and managing stock and sales; (viii) team and time management services for administering payroll and employee benefits; and (ix) project management services for overseeing business activities. For example, social media engagement is assessed with the question: "How competent is your firm in using social media applications to plan, promote, and monitor business projects or campaigns?" Responses are recorded using a five-point Likert scale ranging from "Very strong" to "Very weak", with higher scores indicating greater digital competency. As highlighted in the literature reviewed in Section 2, AI is now embedded in many of the business applications used across the domains assessed by the Digital Competencies Scale (Babina et al., 2024; Basri, 2021; Hansen and Bogh, 2021; Oberländer et al., 2020; Vieru, 2015). AI functionalities such as automation, predictive analytics, natural language processing, and algorithmic decision support are increasingly integrated into platforms for communication, marketing, financial management, customer relationship management, and project coordination. As such, although the scale does not explicitly reference AI, it remains highly relevant for evaluating competencies that are shaped or enhanced by AI-driven technologies. Accordingly, the scale is used in this study to capture firms' digital competencies prior to the AI business applications training, as well as to assess any improvements in these competencies following the training. This approach enables the identification of changes in firms' digital competencies within operational domains where AI is likely to influence efficiency, adaptability, and strategic decision-making.

To measure customer satisfaction, the Reichheld (2003) Customer Satisfaction Scale was utilised. Study participants received either e-surveys or hard copies to distribute to their customers. Instructions were provided on how to conduct data collection and submit their observations to the research team. Customers provided evaluations based on Reichheld's (2003) five themes related to satisfaction, loyalty, and recommendation behaviour. For instance, they were asked, "How satisfied are you with the products/services you received from us?" and "How likely is it that you will continue to purchase products/services from our firm?". Depending on the question, responses were scored on a ten-point Likert scale, ranging from "Not at all satisfied" to "Completely satisfied", or from "Not at all likely" to "Extremely likely", with higher scores indicating higher levels of customer satisfaction. For each firm, an average score was then calculated based on the responses to the Reichheld (2003) scale, capturing the overall customer satisfaction per firm[4]. Although the scale was originally designed to evaluate customer experience in conventional business environments, its continued relevance is supported by evidence presented in Section 2, which indicates that the core dimensions of customer satisfaction remain central in digitally powered and AI-enabled markets (Peruchini et al., 2024; Chen et al., 2023; Prentice et al., 2020; Chung et al., 2018; Newby et al., 2014). Accordingly, the Customer Satisfaction Scale is employed in this study to measure customer satisfaction both prior to and following the AI business applications training, enabling the analysis to assess whether improvements in firms' digital competencies are reflected in customers' reported satisfaction levels.

The Empowerment scale (Rogers et al., 1997) was used to assess participants' levels of empowerment. This scale consists of 28 items representing five thematic factors: self-esteem, power-powerlessness, community activism and autonomy, optimism and control over the future, and righteous anger. The scale aims to capture participants' perceived ability to make decisions and control their lives, with a focus on developing a positive self-concept and personal competence. Example statements include: "I see myself as a capable person," and "I am often able to overcome barriers". Responses were scored on a four-point Likert scale from "Strongly agree" to "Strongly disagree," with higher scores indicating higher levels of empowerment. As discussed in the literature reviewed in Section 2, empowerment is a multidimensional construct that plays a critical role in enabling underrepresented entrepreneurs to navigate systemic barriers, assert autonomy, and make strategic decisions within competitive market environments (Akpuokwe et al., 2024; Khoza, 2024; Alateeg and Al-Ayed, 2024; Mackey and Petrucka, 2021; Çetin et al., 2021). The Empowerment Scale is particularly well-suited to this study, as it captures both psychological and behavioural dimensions of empowerment through the key thematic factors outlined above. These dimensions are directly relevant to the experiences of underrepresented entrepreneurs, who often operate outside mainstream support structures and face compounding disadvantages linked to discrimination, exclusion, or limited access to financial and social capital. The scale's emphasis on self-efficacy, autonomy, and future orientation aligns with entrepreneurs' perceived ability to make decisions, overcome structural obstacles, and act with confidence in business environments. By administering the scale before and after the training, the study examines whether enhanced digital competencies are associated with greater levels of perceived empowerment. This enables a meaningful exploration of how the development of digital competencies contributes to broader

[4] In Wave 1, approximately 54 customers per firm completed the survey, whereas in Wave 2, approximately 57 customers per firm completed the survey.

shifts in entrepreneurial agency and self-perception, particularly among participants from underrepresented backgrounds.

Lastly, a question on revenue growth assessed firms' annual performance by comparing revenue from the previous year with that of the current year (Keiningham et al., 2007). Participants were provided with clear instructions on how to calculate this figure, including a simple formula and an illustrative example, to ensure consistency and minimise reporting errors. Revenue growth serves as a key performance indicator, reflecting a firm's capacity to expand its income over time (Aranitou, 2025; Ardito et al., 2024; Bandari, 2019). In the present study, revenue growth is particularly relevant, as it may signal increased customer reach, improved marketing, more efficient operations, and sales directly associated with enhanced digital competencies (Aranitou, 2025; Ardito et al., 2024). Unlike profit or surplus, which may be shaped by discretionary spending, reinvestment strategies, or tax-related decisions, revenue growth provides a more immediate and standardised measure of market performance. It acts as a direct, market-facing signal (Aranitou, 2025; Ardito et al., 2024; Bandari, 2019). This measure is especially pertinent in studies involving small firms and underrepresented entrepreneurs, where low initial profit margins are common (Ardito et al., 2024). As such, revenue growth may offer a useful indication of business scalability and market traction following the AI business applications training intervention.

5. Sample size and validation of scales

Given the pre-post training intervention design of the study, which enables a longitudinal approach, the sample comprises 121 entrepreneurs who provided information both before and after the training, yielding a total of 242 observations[5]. According to Cohen's (1988) guidelines, detecting a medium effect size (d = 0.5) with a statistical power of 0.80 at the 0.05 significance level requires approximately 64 paired observations. The present study, with 121 pairs, exceeds this threshold, offering substantial power to detect meaningful effects and enhancing the reliability of the findings (Ellis, 2010). Additionally, the study includes a diverse sample, representing men and women, non-heterosexual and heterosexual individuals, natives and non-natives, as well as disabled and non-disabled participants. This diversity aligns with recommendations from previous studies, which emphasise the importance of diverse and representative samples for obtaining reliable and generalisable results (Fowler, 2014).

[5] At the first online meeting for the AI business applications training, 139 entrepreneurs participated. During the course of the training, 11 entrepreneurs withdrew from the programme, while seven entrepreneurs, despite completing the training, did not provide follow-up information in the Wave Two survey.

Table 2 presents the scale validations. In Panel I, the firms' Digital Competencies scale shows good internal consistency and fit indices, suggesting it is a reliable and valid measure of digital competencies within firms (Hair et al., 2019; Tavakol and Dennick, 2011; Hu and Bentler, 1999; Bentler and Bonett, 1980). The Construct Reliability (H) value of 0.938 indicates strong construct reliability (values higher than 0.80 are generally considered to reflect strong centrality and model fit). The Cronbach's Alpha (α) value of 0.78 indicates acceptable internal consistency reliability (values above 0.70 are typically considered acceptable). The ratio of the Chi-Square Statistic to Degrees of Freedom (chi2/df) of 2.2 indicates an acceptable fit (values below 3 are generally considered acceptable). The Root Mean Square Error of Approximation (RMSEA) value of 0.069 falls within the acceptable range (0.05–0.08), indicating a reasonable fit. The Standardised Root Mean Square Residual (SRMR) value of 0.048 is below the 0.08 threshold, indicating a good fit. The Normed Fit Index (NFI) value of 0.861 indicates an acceptable fit, though values closer to 0.90 are generally preferred. The values of the Relative Noncentrality Index (RNI), Comparative Fit Index (CFI), and Incremental Fit Index (IFI) are above the recommended threshold of 0.90, indicating a good fit.

[Table 2]

In Panel II, the Customer Satisfaction scale demonstrates good internal consistency and an overall good model fit, making it a highly reliable and valid measure for assessing customer satisfaction.

Similarly, in Panel III, the Entrepreneurs' Empowerment scale shows good internal consistency and good fit indices, making it a reliable and valid measure of entrepreneurs' empowerment.

6. Descriptive statistics

Table 3 provides descriptive statistics for the sample. Female entrepreneurs represent 35.5% of the sample, while 61.9% are non-native entrepreneurs. The table further reveals that 23.1% of the sample consists of entrepreneurs with disabilities, and 24.7% are non-heterosexual entrepreneurs. Nearly half of the sample, at 46.6%, comprises entrepreneurs aged over 40.

Regarding education and business experience, 16.5% of the sample holds higher or vocational education qualifications. A majority of the firms, 61.1%, have been in operation for more than five years. Additionally, 56.1% of the firms employ more than five people. The table also highlights aspects of business ownership and sector distribution. Only 11.5% of the sample consists of business owners who own their business premises. The distribution across various business sectors includes 16.5% in manufacturing, 28.0% in retail and wholesale trade, 27.2% in professional and business services, 14.8% in hospitality and tourism, and 13.2% in construction and real estate.

The regional distribution indicates that 57.8% of the sample is based in England, 24.7% in Wales, and 17.3% in Scotland.

[Table 3]

Prior to the training, participants were given a list of the 27 AI business applications (i.e., those covered during the training) and were asked to indicate both how many they used and how frequently they used them. The same list was provided after the training. Table 4 shows that the mean number of AI business applications used by firms increased from 2.8 before the training to 5.4 afterwards. The difference of 2.6 applications is statistically significant ($t = 26.5$, $p < 0.01$), suggesting that the training programme was effective in expanding the range of AI business applications adopted by participating firms.

In addition, the average frequency of use increased from 2.9 to 3.8 on a five-point scale (ranging from Never to Very Often). This difference of 0.85 is also statistically significant ($t = 10.19$, $p < 0.01$). These results indicate that, beyond increasing adoption, the training also promoted more regular use of AI business applications.

[Table 4]

Table 5 presents the descriptive statistics and the results of tests comparing the means of various metrics before and after AI business applications training. In Panel I, it is observed that, prior to the training, firms had a mean score of 1.9 in digital competencies. Post-training, this increased to 2.4, indicating a statistically significant improvement (t-test = 9.4, $p < 0.01$). The mean customer satisfaction score rose from 6.3 prior to the training to 7.0 afterwards (t-test = 6.1, $p < 0.01$). Additionally, entrepreneurs' empowerment levels increased from a mean of 2.2 before the training to 2.9 afterwards (t-test = 16.9, $p < 0.01$). Revenue growth rates increased from 2.5% before the training to 5% post-training ($z = 11.6$, $p < 0.01$).

[Table 5]

Table 5, in Panels II–IX, presents a tabulation analysis across demographic groups. As shown in Panels II and III, following the AI business applications training, both male and female entrepreneurs exhibit significant improvements in their firms' digital competencies (female entrepreneurs: from 1.6 to 2.2, $t = 12.7$, $p < 0.01$; male entrepreneurs: from 2.1 to 2.5, $t = 6.0$, $p < 0.01$). Similarly, post-training, there is a statistically significant increase in customer satisfaction, entrepreneurs' empowerment, and revenue growth rates for both female and male entrepreneurs. Panels IV and V present relevant information for non-native and native entrepreneurs. Panels VI and VII provide information on entrepreneurs with and without disabilities, while Panels VIII and IX provide information for non-heterosexual and heterosexual entrepreneurs. As observed, post-training, all demographic groups show an improvement in firms' digital competencies, customer satisfaction, empowerment levels, and revenue growth rates.

Table 6 presents a correlation matrix. AI business applications training is positively correlated with the number of AI business applications in use ($r = 0.80$, $p < 0.01$), and the frequency of use of AI business applications by firms ($r = 0.45$, $p < 0.01$). Moreover, positive correlations are found between AI business applications training and firms' digital competencies ($r = 0.52$, $p < 0.01$), customer satisfaction ($r = 0.36$, $p < 0.01$), entrepreneurs' empowerment levels ($r = 0.73$, $p < 0.01$), and firms' revenue growth rates ($r = 0.60$, $p < 0.01$).

In addition, firms' digital competencies are positively correlated with customer satisfaction ($r = 0.59$, $p < 0.01$), the level of entrepreneurs' empowerment ($r = 0.75$, $p < 0.01$), and firms' revenue growth rates ($r = 0.72$, $p < 0.01$). Furthermore, the number of AI business applications in use is also positively correlated with firms' digital competencies ($r = 0.65$, $p < 0.01$), customer satisfaction ($r = 0.40$, $p < 0.01$), entrepreneurs' empowerment levels ($r = 0.68$, $p < 0.01$), and firms' revenue growth rates ($r = 0.62$, $p < 0.01$). Comparable patterns are observed for the frequency of use of AI business applications.

[Table 6]

7. Estimates

7.1 Estimation strategy

This section presents the study's estimates. It begins by examining the association between AI business applications training and the number and frequency of AI business applications used by firms (Section 7.2), before exploring the association between AI business applications training and firms' digital competencies (Section 7.3). It then examines the associations between firms' digital competencies and customer satisfaction (Section 7.4), firms' digital competencies and entrepreneurs' empowerment (Section 7.5), and firms' digital competencies and revenue growth rates (Section 7.6). Evaluations are then offered as to whether the number and frequency of AI business applications are associated with business outcomes (Section 7.7).

In each case, Pooled OLS, Random Effects, and Fixed Effects models are employed to determine whether the estimates hold across alternative empirical specifications (Bell et al. 2019). The study indicates that, given the longitudinal nature of the data, panel specifications may be more suitable than cross-sectional specifications. Additionally, it is suggested that omitted factors may correlate with key predictors in Random Effects models, while Fixed Effects models can address omitted variable bias (Wooldridge 2010; Vaisey and Miles 2017). These alternative empirical specifications function as robustness checks.

The Pooled OLS and Random Effects models control for entrepreneurs' age, gender, ethnicity, presence of disabilities, sexual orientation, education, firms' years of operation, number of employees, ownership of business premises, and fixed effects on business sectors and regions[6]. However, Fixed Effects models do not control for time-invariant information (Andreß et al., 2013). Identification tests are conducted and reported to ascertain which empirical approach may better fit the data (Andreß et al., 2013). The Breusch-Pagan LM test (Morgan, 2013) is employed to evaluate whether Pooled OLS models are more appropriate than Random Effects models, and Hausman tests (Wooldridge, 2010) are used to determine whether Random Effects models are more appropriate than Fixed Effects models.

To mitigate potential sources of estimation bias, several precautions were taken (Clarke, 2005). As outlined, the models are designed to address omitted variable bias by incorporating a broad set of firm- and entrepreneur-level controls. These covariates were selected based on

[6] In the empirical analysis, the regression models do not simultaneously include the pre–post training indicator alongside the number and frequency of AI business applications in use. This decision is driven by multicollinearity concerns (Alin, 2010). As demonstrated in the descriptive results, there is a substantial and statistically significant increase in both the number of AI applications used and the frequency of use following the training. These variables are therefore highly correlated with the pre–post training variable, particularly in the post-training period, where their values shift markedly. Including all three variables in the same regression model would introduce multicollinearity, inflating standard errors and potentially obscuring the interpretation of coefficients. Specifically, diagnostic tests, including variance inflation factors (VIFs) and pairwise correlation coefficients, confirm that the number of applications used, the frequency of use, and the post-training indicator are strongly intercorrelated. In several model specifications, the VIFs for these variables exceed conventional thresholds, indicating that their joint inclusion would compromise the precision of coefficient estimates and the reliability of statistical inference. Moreover, as both the number and frequency of applications in use are likely outcomes of the training intervention, including them alongside the treatment indicator risks introducing post-treatment bias, which may distort the estimated effect of the intervention. To address this issue and preserve the clarity of the empirical specification, the models retain the pre–post training indicator as the primary explanatory variable. This variable captures the full effect of the training intervention and reflects the core interest of the study: to evaluate changes in outcomes attributable to the AI business applications training. This approach ensures model stability, avoids redundancy, and provides a robust estimate of the overall training impact on key business outcomes. The number and frequency of applications in use are tested separately to evaluate whether they are associated with business outcomes.

theoretical considerations and prior empirical research on factors influencing business performance, digital competencies, and technology adoption (Aranitou et al., 2025; Pidduck and Clark, 2021). Their inclusion helps to reduce the risk of bias due to unobserved heterogeneity. Moreover, the use of a pre–post intervention design with repeated measures enables the analysis to capture within-firm changes over time, which further attenuates the influence of time-invariant omitted variables. The study also recognises the possibility of common method bias arising from reliance on self-reported data, particularly with regard to digital competencies, empowerment, and revenue growth. To address this, several strategies were employed. First, procedural remedies were applied during data collection: separate survey instruments were used for different constructs, neutral wording was employed to reduce evaluation apprehension, and respondents were assured of anonymity and the non-evaluative nature of the research. Second, measurement scales were selected based on prior validation and demonstrated reliability, thereby reducing the likelihood of systematic error due to method effects. Finally, triangulation was partially achieved through the use of customer surveys, which provided an external, independent source of data for assessing customer satisfaction. This introduced methodological separation between key independent and dependent variables, further reducing the risk of common method bias. Collectively, these measures strengthen the internal validity of the study and enhance the robustness of the estimated training effects.

In addition to the main effects, the analysis includes interaction terms to examine whether the associations between firms' digital competencies and the outcome variables (customer satisfaction, entrepreneurs' empowerment, and revenue growth) differ according to training status (Balli and Sørensen, 2013). These interaction terms make it possible to identify whether the post-training period moderates the relationship between digital competencies and key business outcomes. This specification is grounded in the theoretical expectation that digital competencies may become more salient or effective following exposure to structured AI training.

A positive and statistically significant interaction effect indicates that the relationship between digital competencies and a given outcome is stronger after the AI business applications training than before. For instance, a significant interaction between digital competencies and the post-training indicator in the customer satisfaction model suggests that digital competencies are more strongly associated with customer satisfaction after firms have completed the training. This implies that AI business applications training enhances the effectiveness of these competencies in driving improved business outcomes.

In this context, the interaction effect is interpreted as a moderating effect, indicating that the relationship between digital competencies and outcomes is conditional on training exposure. This interpretation aligns with the theoretical expectation that AI business applications training improves not only skills acquisition, but also the strategic application of those skills in real-world business contexts. The results therefore offer insight into how the benefits of digital competencies can be amplified through structured, application-specific training, particularly among underrepresented entrepreneurs.

7.2 The association between AI business applications training and the number and frequency of AI business applications used by firms

Table 7 presents a preliminary analysis assessing whether AI business applications training is associated with the number of AI business applications used by firms and the frequency of their use. In Model I, the Pooled OLS estimate suggests that, following the training, the number of AI business applications used by firms increased ($b = 2.582$; $p < 0.01$).

In Model II, the Random Effects estimate yields similar results, indicating a post-training increase in the number of AI business applications in use ($b = 2.567$; $p < 0.01$). Model III, which uses Fixed Effects estimation, also reveals a comparable pattern ($b = 2.526$; $p < 0.01$). The Breusch and Pagan Lagrangian Multiplier test suggests that the Random Effects model provides a better fit than the Pooled OLS model ($p > chibar^2 = 0.000$). The Hausman test indicates that the Random Effects model is preferable to the Fixed Effects model ($p > chi^2 = 0.944$).

[Table 7]

Similarly, in Models IV–VI, the results indicate that AI business applications training is associated with an increased frequency of use of such applications by firms, suggesting that firms use AI business applications more frequently following the training.

7.3 The association between AI business applications training and firms' digital competencies

In Table 8, Model I presents the estimates of firms' digital competencies. In Model I, the Pooled OLS estimate indicates that, following the AI business applications training, there is an increase in firms' digital competencies ($b=0.465$; $p<0.01$). The estimate suggests that, on average, firms' digital competencies rose by 0.465 points post-training compared to their level before the training. The increase of 0.465 points represents approximately 23.8% relative to the pre-training average of firms' digital competencies, which was 1.95 (Table 5, Panel I).

In Model II, the Random Effects estimate shows comparable findings, indicating that post-training, firms' digital competencies increased ($b=0.465$; $p<0.01$). Similarly, in Model III, the Fixed Effects estimate confirms the patterns observed in Models I and II ($b=0.462$; $p<0.01$). The Breusch and Pagan Lagrangian Multiplier test indicates that the Random Effects model is a better fit for the data than the Pooled OLS model ($p > chibar^2 = 0.000$). Additionally, the Hausman test suggests that the Random Effects model is preferable over the Fixed Effects model ($p > chi^2 = 0.974$).

Based on these estimated patterns, and irrespective of the empirical specification, Hypothesis 1 can be accepted.

[Table 8]

7.4 The association between firms' digital competencies and customer satisfaction

In Table 9, estimates on customer satisfaction are presented. As observed, in Model I, the Pooled OLS estimate suggests that firms' digital competencies are associated with an increase in customer satisfaction (b = 1.167; $p < 0.01$). The coefficient indicates that for every one-unit increase in the firm's digital competencies, there is a 1.167-point increase in customer satisfaction, on average (or 18.29%). Similarly, in Model II, the Random Effects estimate corroborates the result of Model I (b = 1.167; $p < 0.01$). Additionally, in Model III, the Fixed Effects estimate aligns with the results of Models I and II (b = 0.979; $p < 0.01$). Based on these estimates, Hypothesis 2.a is accepted.

In Model IV, the Pooled OLS estimate shows that post-training, there is an increase in customer satisfaction (b = 0.543; $p < 0.01$). The coefficient indicates that, on average, post-training, customer satisfaction increased by 0.543 points (or 8.51%). Moreover, in Model V, the Random Effects estimate (b = 0.542; $p < 0.01$) and in Model VI, the Fixed Effects estimate (b = 0.588; $p < 0.01$) reinforce the pattern in Model IV. Consequently, Hypothesis 2.b is accepted.

In Model VII, the Pooled OLS interaction estimate suggests that post-training, firms' digital competencies are associated with a more substantial increase in customer satisfaction compared to the patterns before the training (b = 1.777; $p < 0.01$). This indicates that post-training, firms' digital competencies are associated with a greater increase in customer satisfaction by 1.777 points (or 27.8%) compared to the pre-training period. In Model VIII, the Random Effects estimate (b = 1.777; $p < 0.01$) and in Model IX, the Fixed Effects estimate (b = 1.781; $p < 0.01$) confirm the finding in Model VII. Thus, based on these estimates, Hypothesis 2.c is accepted.

[Table 9]

7.5 The association between firms' digital competencies and entrepreneurs' empowerment

Table 10 presents estimates on entrepreneurs' empowerment. In Model I, the Pooled OLS estimate indicates that firms' digital competencies are associated with increased entrepreneurs' empowerment (b = 0.808; $p < 0.01$). That is, the increase in entrepreneurs' empowerment from a one-unit increase in firms' digital competencies is 0.808 points (or 36.73%). Similarly, in Model II, the Random Effects estimate (b = 0.808; $p < 0.01$), and in Model III, the Fixed Effects estimate (b = 1.175; $p < 0.01$), also show that firms' digital competencies are associated with increased entrepreneurs' empowerment. Based on these outcomes, Hypothesis 3.a can be accepted.

In Model IV, the Pooled OLS estimate shows that post-training, there is an increase in entrepreneurs' empowerment (b = 0.715; $p < 0.01$). This signifies that the increase in entrepreneurs' empowerment post-training is 0.715 points (or 32.5%). In Model V, the Random Effects estimate (b = 0.717; $p < 0.01$), and in Model VI, the Fixed Effects estimate (b = 0.750; $p < 0.01$), corroborate the findings of Model IV. Hence, Hypothesis 3.b is accepted.

In Model VII, the Pooled OLS interaction term demonstrates that post-training, firms' digital competencies are more strongly associated with entrepreneurs' empowerment compared to pre-training patterns (b = 0.310; $p < 0.01$). This indicates that post-training, firms' digital competencies are associated with an additional 0.310-point increase (or 14.09%) in entrepreneurs' empowerment compared to before the training. Moreover, in Model VIII, the Random Effects estimate (b = 0.304; $p < 0.01$), and in Model IX, the Fixed Effects estimate (b = 0.294; $p < 0.01$), further support the finding in Model VII. Thus, Hypothesis 3.c is accepted.

[Table 10]

7.6 The association between firms' digital competencies and revenue growth rates of the firms

Table 11 presents the revenue growth rate estimates. In Model I, the Pooled OLS estimate shows that firms' digital competencies are associated with higher revenue growth rates (b = 3.137; $p < 0.01$). The estimate indicates that a one-unit increase in firms' digital competencies is associated with a 3.1 percentage point increase in the revenue growth rate. In Model II, the Random Effects estimate (b = 3.137; $p < 0.01$) and in Model III, the Fixed Effects estimate (b = 3.227; $p < 0.01$) also demonstrate that firms' digital competencies are associated with higher revenue growth rates. Based on the estimates, Hypothesis 4.a is accepted.

In Model IV, the Pooled OLS estimate shows that post-training, there is an increase in firms' revenue growth rates (b = 2.483; $p < 0.01$). That is, post-training, the revenue growth rate increases by 2.4 percentage points. In Model V, the Random Effects estimate (b = 2.469; $p < 0.01$) and in Model VI, the Fixed Effects estimate (b = 2.448; $p < 0.01$) support Model IV's estimate. Hence, given the estimates, Hypothesis 4.b is accepted.

In Model VII, the Pooled OLS interaction association shows that post-training, firms' digital competencies are associated with an increase in revenue growth rate compared to the pre-training period (b = 0.984; $p < 0.05$). The interaction association indicates that post-training, firms' digital competencies are associated with a 0.9 percentage point greater increase in revenue growth rate compared to the pre-training period. Similarly, in Model VIII, the Random Effects estimate (b = 1.053; $p < 0.01$) and in Model IX, the Fixed Effects estimate (b = 0.930; $p < 0.05$) continue to support the findings of Model VII. Thus, Hypothesis 4.c is accepted.

[Table 11]

7.7 Further insights: Number and frequency of AI business applications in use and associated business outcomes

Finally, Table 12 presents insights into how the number and frequency of AI business applications used by firms may be associated with business outcomes. In all cases, Fixed Effects estimates are reported, as they were found to provide the best fit for the data.

The number of AI business applications used by firms is positively associated with firms' digital competencies (Model I, $b = 0.139$, $p < 0.01$), customer satisfaction (Model II, $b = 0.166$, $p < 0.01$), entrepreneurs' empowerment (Model III, $b = 0.231$, $p < 0.01$), and firms' revenue growth rates (Model IV, $b = 0.751$, $p < 0.01$).

Similarly, the frequency of use of AI business applications by firms is positively associated with digital competencies (Model V, $b = 0.198$, $p < 0.01$), customer satisfaction (Model VI, $b = 0.203$, $p < 0.01$), entrepreneurs' empowerment (Model VII, $b = 0.331$, $p < 0.01$), and revenue growth rates (Model VIII, $b = 1.016$, $p < 0.01$).

[Table 12]

8. Discussion

This section evaluates the outcomes of the study by presenting three thematic areas: the increased use of AI business applications post-training; the reported improvements in digital competencies, customer satisfaction, entrepreneurs' empowerment, and revenue growth; and the acquisition of skills and their integration into business operations.

8.1 Increased use of AI business applications

The study's findings indicate an increase in both the number and frequency of AI business applications used by firms following the training, demonstrating a measurable improvement in digital engagement. These patterns suggest that AI business applications training enhances access to AI tools by embedding learning within realistic, task-oriented business scenarios. The results reinforce the view that structured, application-focused training, when clearly aligned with business operations, can accelerate firms' technological uptake and usage (Azevedo and Almeida, 2021; Blackburn and Athayde, 2020; Casalino et al., 2012; Bruno et al., 2011; Kirkpatrick, 1994).

The study's outcomes align with learning and training frameworks that emphasise the importance of contextual practice and reinforcement in supporting long-term skill acquisition and the development of digital competencies (Kirkpatrick, 1994; Baldwin and Ford, 1988). This shift in AI business application use is particularly significant given the time-bound nature of the intervention. That such measurable changes in adoption and usage patterns occurred between pre-and post-training assessments indicates a strong level of demand among small firms for accessible, applied digital competencies development. This responsiveness highlights the importance of tailored interventions that position digital inclusion not as a peripheral concern, but as a central element of entrepreneurial capability building (Teece, 2007), particularly for underrepresented entrepreneurs (Rolle et al., 2020; Orser et al., 2019).

8.2 Improvements in digital competencies, customer satisfaction, empowerment, and revenue growth

The findings from this study indicate that AI business applications training is positively associated with improvements in small firms' digital competencies, customer satisfaction, entrepreneurs' empowerment, and revenue growth. These associations were found to be statistically significant and became more pronounced following the training, lending empirical support to the proposed AI Business Applications Training Model. The results align with existing research that highlights the critical role of digital competencies in enhancing firms' ability to navigate dynamic market environments, improve operational efficiency, and remain competitive in an increasingly digitised economy (Babina et al., 2024; Hansen et al., 2021; Oberländer et al., 2020; North et al., 2020; Cubric, 2020; Tarafdar et al., 2019).

AI business applications training contributes to the development of digital competencies by equipping entrepreneurs with AI-specific knowledge, skills, and exposure, and by providing practice with AI-driven tools. As outlined in the training structure, each session targets a distinct business domain, embedding technical elements and reinforcement learning within practical business activities through relevant applications.

Through structured exposure to these AI-powered business applications, entrepreneurs gain hands-on experience in automating routine functions, optimising communication processes, managing customer relationships, analysing financial data, and coordinating team operations. For example, Session 2 introduces an AI recommendation application within realistic communication scenarios, while Session 4 focuses on the use of AI business applications for cash flow forecasting. These practical applications offer a clear mechanism through which participants translate technical knowledge into functional, decision-oriented business competencies. This supports previous findings suggesting that AI integration can enhance firms' efficiency, responsiveness, and adaptability (Wu et al., 2025; Babina et al., 2024; Cubric, 2020; Tarafdar et al., 2019).

The study found that, following AI business application training, the relationship between digital competencies and customer satisfaction became stronger. These improvements can be directly attributed to the learning-by-doing components of the training, such as the use of AI-powered customer relationship management software for customer segmentation and campaign automation, and the implementation of AI-assisted messaging platforms. These AI business applications support the delivery of tailored customer experiences by predicting needs, adapting language, and optimising outreach strategies. This finding aligns with existing evidence that digital competencies enable firms to deploy AI-enhanced systems, such as chatbots, customer relationship management software, and predictive analytics, to deliver personalised and high-quality customer experiences (Peruchini et al., 2024; Kraus et al., 2022; Prentice et al., 2022; Chung et al., 2018). Such tools contribute to customer loyalty and satisfaction, particularly by enabling firms to anticipate customer needs and deliver responsive, reliable service. In this way, customer satisfaction is not only a reflection of service quality, but also a product of firms' capacity to translate AI-enabled insights into meaningful customer value.

The study also finds that AI business applications training significantly strengthens the relationship between digital competencies and entrepreneurs' empowerment. In this context, empowerment encompasses not only confidence and decision-making ability, but also the capacity to overcome barriers and exercise strategic agency. The training sessions support entrepreneurs in developing competencies for using AI business applications to interpret business data, anticipate risk, and make informed decisions, thereby enhancing both self-efficacy and control. These findings align with empowerment theory and the broader literature on digital empowerment, which argue that digital skills and competencies enable underrepresented individuals to navigate constraints and access new economic opportunities (Mackey and Petrucka, 2021; Wajcman, 2010; Rogers et al., 1997).

For non-native, disabled, and non-heterosexual entrepreneurs, who often face exclusion from mainstream support systems, AI business applications training can offer a means of building resilience and developing enabling competencies (Pidduck and Clark, 2021; Orser et al., 2019). These digital competencies enable underrepresented entrepreneurs not only to manage their businesses more effectively, but also to claim space and credibility in environments where they may otherwise face bias.

The study demonstrates a strengthened association between digital competencies and firms' revenue growth following the training. This is likely explained by multiple interrelated mechanisms embedded within the training. Sessions on customer relationship management, accounting, finance, and operational management expose entrepreneurs to AI business applications that support targeting the right customers, improving customer retention, streamlining budgeting, detecting anomalies, optimising inventory, and allocating resources efficiently.

AI business applications used for detection and forecasting can enhance cash flow management, while scheduling systems and reinforcement learning models can improve workforce efficiency and resource allocation. As previous studies have shown, firms that integrate advanced technologies into their business models are more likely to experience improved profitability and long-term growth by boosting efficiency, enhancing customer experience, reducing error, and enabling data-informed decision-making in areas such as pricing and production planning (Aranitou et al., 2025; Kraus et al., 2022; North et al., 2020).

For underrepresented entrepreneurs, these revenue effects may be particularly important, as digital competencies can help to reduce disadvantages in access to traditional capital, networks, and institutional support.

8.3 Skill acquisition and operational integration

The study's findings provide empirical support for the AI Business Applications Training Model. The training is associated with measurable improvements in firms' digital competencies, as well as stronger associations between those competencies and key performance indicators. These strengthened relationships underscore the potential of AI business applications training to serve not only as a means of skill acquisition but also as a catalyst for structural transformation.

In particular, for underrepresented entrepreneurs who face multifaceted challenges, AI training offers a viable and scalable strategy to enhance customer satisfaction, build entrepreneurs' empowerment, and improve financial performance. Crucially, the observed increase in both the number and frequency of AI business applications used by firms following the training plays a central role in supporting and reinforcing the enhanced relationships identified in this study.

These shifts demonstrate that the training not only introduces new digital tools but also enables their application across key business domains, an indication of digital competency. By expanding the repertoire of AI business applications and embedding them more routinely into operational activities, entrepreneurs are better positioned to activate and realise the potential of their digital competencies.

In this way, increased use of AI business applications functions as a conduit through which digital competencies are translated into tangible outcomes. The study's findings support these arguments, as both the number and frequency of AI business applications in use are positively associated with business enhancements. The adoption of a broader range of AI business applications allows for more comprehensive and responsive approaches to customer service and business planning, thereby contributing to higher levels of customer satisfaction and revenue growth. Furthermore, the routine use of AI business applications likely fosters greater familiarity and confidence, strengthening entrepreneurs' sense of control and empowerment.

9. Contributions

This section outlines the study's conceptual, theoretical, empirical, and practical contributions, providing the basis for the policy implications presented in the following section.

9.1 Integrating AI training and inclusive entrepreneurship

This study addresses a significant gap in the literature by integrating two typically siloed streams of research: AI business applications training and inclusive entrepreneurship. While previous studies have examined digital upskilling in SMEs (Azevedo and Almeida, 2021; Blackburn and Athayde, 2020; European Commission, 2019; Yu et al., 2017; Newby et al., 2014; Casalino et al., 2012; Bruno et al., 2011), and others have explored the systemic barriers faced by underrepresented entrepreneurs (Akpuokwe et al., 2024; Pidduck and Clark, 2021; Rolle and Kisato, 2019), limited research has examined how targeted AI business applications training can function as an inclusive intervention. Specifically, there is little evidence on how such training supports both digital competency and business outcomes for underrepresented groups.

The study introduces AI business applications training as a distinct and original conceptual category that moves beyond conventional approaches to digital upskilling. Unlike general ICT training, which typically focuses on foundational skills such as basic software use or internet navigation, the AI training examined here is framed as a structured, application-specific process that equips underrepresented entrepreneurs with the competencies required to engage with intelligent, decision-support systems. These include AI business applications designed for automating workflows, generating real-time insights, and enhancing customer interaction.

Digital competencies are reconceptualised not as fixed technical skills, but as dynamic and responsive features that develop in reaction to the exclusion from mainstream educational and economic systems experienced by underrepresented entrepreneurs. This reconceptualisation deepens understanding of how the development of digital competencies unfolds within underrepresented entrepreneurial contexts, and how it may function as a response to barriers (Akpuokwe et al., 2024; Pidduck and Clark, 2021; Rolle et al., 2020).

This approach aligns with emerging perspectives that interpret digital competencies as responses to exclusion from conventional business support, financing, and digital literacy infrastructure. In contexts shaped by exclusion, the digital competencies developed through AI business applications training can serve a uniquely enabling function. They may assist underrepresented entrepreneurs in addressing persistent informational, operational, and relational barriers, thereby enhancing their capacity to adapt, innovate, and succeed.

Post-training improvements in digital competencies are therefore not merely incremental enhancements in ICT use, but represent qualitatively distinct developments that reflect the acquisition of AI-informed strategic enablers. This reframing broadens prevailing conceptualisations of digital skill development by highlighting its intersection with inclusion, resilience, and structural transformation in resource-constrained entrepreneurial environments. As such, the study's positioning offers a significant contribution to the literature on inclusive entrepreneurship (Tiasakul et al., 2024; Sodhi and Dwivedi, 2024).

9.2 Advancing theory through the AI Business Applications Training Model

With regard to its theoretical contribution, the AI Business Applications Training Model establishes a novel link between AI business applications training and four core business outcomes: digital competencies, customer satisfaction, entrepreneurs' empowerment, and revenue growth. The model advances existing theory by moving beyond efficiency-focused perspectives on technological integration. It instead positions AI business applications training as a mechanism for inclusion, resilience, and strategic agency.

It proposes that AI-specific training contributes not only to the acquisition of technical skills, but also to enhanced entrepreneurial confidence, decision-making capacity, and the ability to navigate exclusionary market structures (Khoza, 2024; Suseno and Abbott, 2021; Pidduck and Clark, 2021). By integrating insights from interrelated theories, including human capital theory (Becker, 1964), structural technological transformation theory (Schumpeter, 1939), diffusion of innovation (Rogers, 2003), training transfer theory (Kirkpatrick, 1994; Baldwin and Ford, 1988), dynamic capabilities theory (Teece, 2007), and frameworks on AI capital (Drydakis, 2022a) and inclusive entrepreneurship (Orser et al., 2019; Rolle et al., 2020), the model conceptualises digital competencies as strategic resources.

Integrating these theories is essential for understanding how AI-specific training shapes both technical and strategic entrepreneurial capacities. Human capital theory and training transfer theory explain how learning translates into performance, while structural transformation and innovation diffusion frameworks contextualise how technologies disrupt and reconfigure markets. Dynamic capabilities theory and AI capital frameworks highlight the strategic value of adaptability in rapidly evolving digital environments. Inclusive entrepreneurship theory adds a critical dimension by addressing the structural barriers faced by underrepresented groups. Together, these perspectives support a holistic model in which digital competencies are both functional skills and a resilience asset, enabling more equitable participation. These competencies enable underrepresented entrepreneurs to overcome barriers and engage more equitably in digital markets. In doing so, the model reflects a broader transformation in which digital competitiveness becomes a strategic resource for underrepresented groups.

9.3 Addressing an empirical gap through longitudinal research

The empirical contribution of the study lies in its pre–post longitudinal design involving 121 entrepreneurs operating small firms across England, Wales, and Scotland. This methodological approach enables the examination of changes in business outcomes before and after participation in a targeted AI training programme, by testing and confirming the aforementioned moderating relationships. The study's findings are supported by multiple econometric specifications, which collectively enhance the reliability and internal validity of the estimates.

This contribution is particularly significant given the limited availability of longitudinal data on AI training among underrepresented entrepreneurs running small firms. The study therefore fills an important empirical gap by providing evidence on how AI-focused education influences business performance in real-world, resource-constrained settings.

9.4 Delivering a practical, replicable and inclusive training model

The practical contribution of the study lies in the development of a replicable training model that offers actionable insights for policymakers, universities, and development organisations. The internal diversity of the sample, including entrepreneurs from a wide range of demographic backgrounds, firm sizes, and business sectors, adds to the robustness of the study's findings. This variation enhances the analytical relevance of the results and strengthens the applicability of the AI Business Applications Training Model as both a conceptual framework and a practical tool for policy and implementation.

The model and its associated outcomes reflect processes of inclusion, resilience-building, and digital transformation that hold relevance across diverse national and international contexts. Importantly, the training is designed to be inclusive of underrepresented entrepreneurs and small-scale firms by adopting flexible delivery methods through mobile-accessible tools and plain-language instruction. It also integrates inclusive pedagogical practices and culturally diverse case studies, ensuring that participants from varied backgrounds can engage meaningfully with the content. Hence, the curriculum is grounded in the operational realities and lived experiences of both small firms and underrepresented entrepreneurs.

By demonstrating that tailored AI business application training can enhance not only digital competencies but also key business performance indicators, the study provides a compelling case for increasing public investment in AI education. Moreover, it underscores the strategic role that higher education institutions can play in bridging digital divides and promoting inclusive entrepreneurship through context-sensitive pedagogy and community engagement (Orser et al., 2019; UNESCO, 2018).

10. Policy implications

The following section outlines the broader significance of the study by identifying its theoretical, managerial, and practical implications. It reflects on how AI business applications training contributes to inclusive entrepreneurship, strategic business development, and policy design aimed at supporting underrepresented entrepreneurs in digitally transforming and competitively sustaining their small firms.

10.1 Theoretical implications: AI business applications training as adaptive capital

This study has a clear theoretical implication, as it conceptualises AI business applications training as a form of adaptive capital. This capital is developed not through general exposure to technology, but through structured, inclusive, and applied learning that reflects the realities of small business operations and the barriers faced by underrepresented entrepreneurs (Drydakis, 2024b). The study demonstrates that digital competencies should be understood as strategic assets that enable entrepreneurs to adapt, make informed decisions, and respond effectively to business challenges. These competencies are especially critical when developed under conditions of exclusion, limited resources, or unequal access to institutional support.

For researchers, the AI Business Applications Training Model provides a theoretically grounded and empirically validated framework that can be applied in multiple research contexts. It invites scholars to move beyond binary measurements of digital inclusion, such as internet access or tool adoption, and instead focus on how digital competencies are acquired and strategically used. The model facilitates empirical studies that explore the role of targeted training in enabling entrepreneurs to deliver personalised services, streamline operations, and enhance credibility in competitive markets.

The AI Business Applications Training Model is particularly suited to longitudinal and intervention-based designs, as it accounts for how the impact of training evolves over time. It can also be employed in comparative studies across regions, sectors, or social groups to assess how different forms of AI training influence business outcomes under varying conditions. Researchers can build upon this model to test how digital competencies are shaped by the content, delivery method, and contextual relevance of training programmes. This creates opportunities to examine not only whether training works, but also why it works, for whom, and under what circumstances. In addition, the model prompts scholars to centre social context in their analyses. It encourages the integration of variables such as identity, access to capital, prior exposure to digital tools, and structural barriers into theoretical frameworks. Rather than treating entrepreneurs as a homogeneous category, the model offers pathways for differentiating experiences and outcomes based on intersecting forms of exclusion. In doing so, it contributes to the development of more inclusive and grounded theories of digital entrepreneurship.

The AI Business Applications Training Model also opens pathways for theoretical refinement in related fields, including technology adoption, business education, and inclusive innovation. Researchers may use it to challenge and extend current assumptions about how digital competencies are formed and how they function as assets in the context of business growth. This includes exploring the conditions under which digital competencies translate into economic resilience, reputational gains, or strategic autonomy.

10.2 Managerial implications: Strategic integration, training design, and inclusion in practice

The findings offer several important implications for managers of small firms who are navigating the demands of digital transformation. First, managers are encouraged to treat digital training as a strategic investment that directly influences business performance (Wu at el., 2025). AI business applications training, when designed to align with core operational goals, supports the development of internal competencies in areas such as customer relationship management, financial forecasting, project oversight, inventory control, and marketing automation (Qalati et al, 2025; Drydakis, 2022a). These functions are central to competitiveness in digitally driven markets. Rather than viewing training as a standalone activity, managers should embed it into their broader business development strategies.

Second, the results show that structured, application-focused training supports more consistent and effective use of AI business applications. Managers should prioritise programmes that are based on practical instruction, including case studies, simulations, and real-time demonstrations. These approaches help ensure that digital skills are relevant to daily operations and that learning translates into measurable improvements in service delivery, communication, and decision-making. In resource-constrained settings, where time and staffing may be limited, training that targets specific business functions can help maximise the return on learning efforts.

Third, the study highlights the value of inclusive training design. Managers who create learning environments that reflect the experiences and needs of diverse staff are more likely to build digital confidence and long-term capacity across their teams. This involves selecting training tools that are accessible by mobile devices, delivered in clear and straightforward language, and supported by examples that reflect different cultural and business backgrounds.

In practice, this means managers should assess training programmes not only for their technical content but also for their usability, cultural sensitivity, and adaptability to different learner profiles. Firms that actively support inclusive training may also enhance their reputation among customers, improve internal morale, and create opportunities for broader participation in innovation. Digital competency is not simply an outcome of training; it becomes a strategic asset when developed across the organisation and supported by inclusive, practical, and well-structured learning opportunities.

Managers are therefore encouraged to adopt a long-term view of digital competency building. By aligning training investments with business goals, operational realities, and workforce diversity, firms can strengthen their ability to respond to technological change, improve performance, and support inclusive growth.

10.3 Practical implications: institutional delivery, financial access, and community-led scale-up

This study offers a practical framework for advancing inclusive digital transformation, highlighting the crucial role of policymakers, educational institutions, and universities in designing, delivering, and sustaining AI business applications training for small firms. The AI Business Applications Training Model provides an actionable, scalable template that supports not only technical upskilling, but also the broader objectives of inclusive innovation and entrepreneurial resilience.

Policymakers are central to creating the enabling conditions required for the widespread adoption of such training (Wu et al., 2025). To promote equitable participation, public authorities should invest in targeted grant schemes for AI training, establish funding pipelines for underrepresented entrepreneurs, and remove financial and infrastructural barriers that inhibit digital inclusion. This may involve subsidised access to AI-enabled tools, support for mobile-first training platforms, and incentives for firms to engage in ongoing digital competency development. In aligning with broader governance objectives, national and regional governments are encouraged to integrate this training model within economic development strategies, small business support policies, and digital equity agendas (Fülöp, 2014). Such alignment can strengthen the management systems of small firms, enhance their capacity for innovation under board-level oversight, and contribute to long-term resilience and competitiveness in digitally evolving markets (Hoang et al., 2024).

Universities and vocational colleges play a critical delivery role. As trusted institutions with expertise in curriculum design, pedagogy, and research, they are uniquely positioned to provide structured, context-sensitive training that meets both the technological and practical needs of small businesses. Universities can use the model developed in this study to design modules focused on AI applications across marketing, finance, customer engagement, and operations. These institutions should also ensure that training materials are accessible, culturally relevant, and informed by the lived experiences of underrepresented entrepreneurs. By adopting inclusive instructional practices, universities can build institutional leadership in the area of socially responsive innovation.

Community-based institutions and local partnerships also serve an essential function in reaching underserved groups and supporting long-term engagement. These actors can identify training needs, connect entrepreneurs with support networks, and facilitate trust-building between participants and training providers. Through collaboration with universities and local authorities, community institutions can help deliver follow-up support, such as peer-led workshops, sector-specific mentoring, and refresher sessions designed to keep pace with technological change. Practical and localised delivery mechanisms ensure that digital competency building is not limited to a one-time event, but becomes part of a broader ecosystem of inclusive entrepreneurial support.

To achieve sustained impact, it is essential that policymakers and institutional actors treat digital competency development as an ongoing process. AI applications evolve rapidly, and small firms require continued access to learning communities and technical support to adapt. Policymakers are therefore encouraged to fund longitudinal training programmes and to support universities in maintaining publicly accessible learning resources tailored to businesses' needs.

By embedding the AI Business Applications Training Model into policy frameworks, institutional curricula, and regional innovation plans, key stakeholders can collectively contribute to a more inclusive and resilient digital economy. The study provides a practical and replicable model that can strengthen local business ecosystems, reduce barriers to digital participation, and support underrepresented entrepreneurs in navigating and shaping AI-enabled markets.

11. Limitations and future research

This section outlines key limitations of the study and proposes directions for future research. It addresses issues of sample representativeness, causal attribution, measurement validity, and the sustainability of outcomes. Suggestions are offered to strengthen methodological rigour, enhance generalisability, and deepen understanding of how AI training supports diverse entrepreneurial contexts.

11.1 Sample characteristics, generalisability, and scope

Caution is required in generalising the outcomes of this study. The relatively modest number of participating firms may limit the extent to which the findings can be generalised to other regions or industry sectors. Furthermore, while the exclusive focus on underrepresented entrepreneurs addresses a critical gap in both the literature and practice, it also narrows the scope for comparative analysis. The findings may not fully reflect the experiences of more advantaged entrepreneurs or those operating medium-sized enterprises. Comparative research examining differences in outcomes across demographic groups, firm sizes, or sectors would provide valuable insights into how AI training programmes might be better tailored to meet a broader range of needs and challenges.

Issues of self-selection may also constrain the generalisability of the findings. Interest in technology may be correlated with participation in training. The sample consists of entrepreneurs who voluntarily responded to an invitation to join the AI business applications training programme and are therefore likely to be motivated learners with relatively high levels of digital readiness. In addition, recruitment was limited to individuals already connected to a specific community organisation, further narrowing the scope of generalisability.

Future studies should expand recruitment beyond community partner channels to include entrepreneurs identified through business registries, social media advertisements, or field outreach in underserved regions. Incorporating stratified sampling approaches could also ensure greater representation of firms across sectors, rural and urban areas, and levels of digital maturity. Additionally, future studies could integrate baseline screening tools to assess participants' digital readiness prior to training and control for this factor in subsequent analysis. These steps would help capture a broader spectrum of entrepreneurial contexts and improve the empirical validity and applicability of findings across different business types and digital inclusion levels.

11.2 Design, attribution, measurement bias, and instrument limitations

By design, the study did not include a non-treated comparison group. However, fixed-effects models were employed to control for unobserved, time-invariant characteristics at the firm level that might otherwise confound the relationship between training and business outcomes. In addition, the analysis of time-related interaction effects aimed to account for economic conditions before and after the AI business application training. Given the adverse economic climate in the UK during the study period, marked by the cost-of-living crisis, rising societal discrimination against underrepresented groups (Drydakis, 2025b), and macroeconomic volatility, it is unlikely that natural business growth in 2024 alone could explain the observed improvements.

Between 2023 and 2024, the UK experienced an increase in interest rates from 4.5% to 4.9%. This financial tightening contributed to growing business distress, with the number of firms in critical distress rising by 50%, and nearly one-third of businesses postponing expansion plans compared to the previous year (UK Finance, 2025; British Business Bank, 2024; Bank of England, 2024). These conditions suggest that underrepresented entrepreneurs continue to face significant external constraints, reinforcing the argument that the observed improvements in business performance are more plausibly associated with the training intervention and the increased use and frequency of AI business applications following the training, rather than with broader economic recovery.

It is important to note that, as the analysis relies in part on self-reported measures of digital competencies, and empowerment, there is a possibility that the observed improvements reflect participants' awareness of having undergone training, rather than actual behavioural or performance changes, due to social desirability and recall bias (Chung and Monroe, 2003). Participants may have provided responses they perceived to be socially desirable or aligned with the objectives of the training programme. While steps were taken to ensure the clarity and neutrality of survey items, drawing on validated scales, and while the study's longitudinal design mitigates some recall concerns by comparing pre- and post-training data, these forms of bias cannot be entirely ruled out.

To strengthen causal attribution in future research, it would be valuable to include placebo outcome variables that are theoretically unaffected by the AI business applications training, as this could help determine whether change is specific to the targeted outcomes. Propensity score matching could be used to create a comparison group of firms that did not participate in the training but share similar observable characteristics, such as sector, size, level of digital readiness, and the demographic background of the entrepreneur. In addition, difference-in-differences analysis could be used to track both treated and untreated firms over time and to compare changes in outcomes across groups. Quasi-experimental matching designs could also be employed by making use of naturally occurring differences in training access, such as geographic availability or the timing of programme rollout. These strategies would improve the robustness of future findings and support stronger causal interpretation of the impact of AI business applications training.

Collecting objective performance data such as customer retention rates, transaction volumes, or AI tool usage logs could also complement self-reports and reduce reliance on subjective indicators. Employing blinded third-party assessments or incorporating multiple respondent perspectives may enhance the validity of the findings and help to control for expectancy bias. Together, these strategies would provide a more robust basis for identifying the distinct contribution of AI business applications training to observed business outcomes.

Moreover, while the study employed validated and widely used scales to assess business outcomes, limitations remain. Although most measurement models demonstrated acceptable internal consistency and fit indices, the Normed Fit Index for the customer satisfaction and digital competencies scale marginally fell below the more conservative threshold, suggesting that model fit could be further improved. In addition, in this study, the use of existing scales, while enabling comparability with prior research, limited opportunities to develop context-specific or AI-specific measurement innovations that might have captured nuances introduced by the training intervention.

These limitations should be taken into account when interpreting the magnitude of observed gains, and they highlight the value of future research that incorporates more independent performance verification and newly tailored instruments for post-AI training contexts.

11.3 Long-term impact, mechanisms of change, and contextual factors

The study evaluates post-training outcomes one year after the intervention. While this allows for the observation of medium-term effects, the longer-term sustainability of gains in business outcomes remains uncertain. To better understand the durability of these outcomes, longitudinal research tracking firms over multiple years is recommended. Future studies should also incorporate more detailed and objective measures of AI-related competencies. These may include direct assessments of skills in data analytics, and the integration of AI-supported decision-making within core business processes. Identifying which specific digital competencies are most strongly associated with improved business performance would support the design of more targeted and impactful training programmes.

Although this study demonstrates associations between AI business applications training and improved business outcomes, it does not fully account for the underlying mechanisms driving these changes. In particular, the pathways through which enhanced digital competencies contribute to increased customer satisfaction and entrepreneurs' empowerment remain insufficiently explored. Future research should aim to investigate these processes in greater depth, for example by employing analytical models that examine potential mediating relationships between training and business outcomes. Further work is also needed to identify the contextual factors that influence the effectiveness of AI business applications training. These may include business sector, firm size, the entrepreneur's prior experience with digital technologies, and access to complementary resources such as funding or additional educational support. A clearer understanding of these influences would help ensure that AI training initiatives are responsive to the varied needs of different firms and deliver meaningful, inclusive benefits across diverse entrepreneurial settings.

Multiple-criteria decision-making approaches (Cui et al., 2023) could be used to model the complex relationships between entrepreneurial orientation, digital competency development, and business outcomes with greater precision. Such modelling would support the evaluation of how entrepreneurs adopt new technologies, how trainers and trainees explore the links between business training, digital skills, and business improvements, and help identify which types of entrepreneurs and individuals benefit most from AI training (Drydakis, 2025c). This would make the findings more accuracy, reliability, and applicability of findings across diverse business settings.

Finally, there is a need to examine how macroeconomic volatility, including inflation shocks, interest rate fluctuations, and associated policy responses, interacts with digital transformation initiatives. Understanding how AI training performs under varying economic, urban–rural, and environmental conditions that affect firms (Drydakis, 2024c) would enhance its credibility as a resilience-building framework and support the development of tailored support strategies by policymakers and educators in response to an evolving financial landscape.

12. Conclusion

This study examined the associations between AI business applications training and key business outcomes among small firms led by underrepresented entrepreneurs, including non-native, disabled, and non-heterosexual individuals. Drawing on longitudinal data from 121 entrepreneurs across England, Wales, and Scotland, it explored how digital competencies were related to customer satisfaction, entrepreneurs' empowerment, and revenue growth one year after completing a four-month training programme. The findings indicate that digital competencies increased following the training and were positively associated with improvements across all three outcome domains. The training is found to play a moderating role in the relationship between digital competencies and business outcomes, as this relationship becomes stronger following the training.

The study introduces a theoretically informed and empirically grounded AI Business Applications Training Model, which conceptualises digital competencies as the central mechanism linking the training to individual, customer-facing, and organisational outcomes. Its originality lies in its focus on the lived constraints of underrepresented entrepreneurs, its inclusive and context-specific design, and its development of a practical, scalable intervention that embeds AI use within key business operations. By integrating applied digital competencies with inclusion goals, the model positions AI training as a pathway to empowerment, reputational legitimacy, and business growth in structurally constrained environments.

Taken together, the findings contribute to ongoing debates on digital participation and inclusion. They offer a distinctive and actionable perspective through which digital interventions can be designed and delivered to promote equity within entrepreneurial ecosystems. In doing so, the study highlights a scalable, application-specific strategy for advancing more inclusive digital economies through targeted educational interventions.

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Table 1. Evaluation of AI business applications

Categories of AI business applications:	Number of interactions to complete tasks*	Visibility of system status and losability/ findability of the device**	Match between system and the real world**	Consistency and mapping**	Good ergonomics and minimalist design**	Ease of input, screen readability and glanceability**	Flexibility, efficiency of use and personalization**	Aesthetic, privacy and social conventions**	Realistic error management**
Panel I. Communication									
Application 1	4.6 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.6 (0.5)
Application 2	4.6 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)
Application 3	4.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.0 (0.0)	1.0 (0.0)	1.3 (0.5)
Panel II. Networking									
Application 1	4.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)
Application 2	4.6 (1.1)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)
Application 3	4.6 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)
Panel III. Social media									
Application 1	5.0 (1.0)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)
Application 2	4.3 (1.1)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)
Application 3	4.6 (1.1)	1.3 (0.5)	1.6 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.6 (1.1)	1.6 (0.5)
Panel IV. Customer relationship management									
Application 1	4.0 (1.0)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.6 (0.5)	1.6 (0.5)	1.0 (0.0)	1.3 (0.5)
Application 2	5.0 (1.0)	1.0 (0.0)	1.3 (0.0)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)	1.6 (0.5)	1.6 (0.5)
Application 3	4.6 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.6 (0.5)	1.6 (1.1)	1.0 (0.0)	1.0 (0.0)	1.6 (1.1)
Panel V. Payments									
Application 1	7.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.0 (0.0)
Application 2	7.6 (1.1)	1.0 (0.0)	1.6 (0.5)	1.3 (0.5)	1.6 (0.5)	1.6 (0.5)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)
Application 3	7.0 (2.6)	1.0 (0.0)	1.0 (0.0)	1.0 (0.0)	1.0 (0.0)	1.3 (0.5)	1.0 (0.0)	1.0 (0.0)	1.0 (0.0)
Panel VI. Accounting and finance									
Application 1	6.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)	1.6 (0.5)	1.6 (0.5)	1.0 (0.0)	1.3 (0.5)
Application 2	7.6 (1.1)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)	1.6 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)
Application 3	6.6 (1.1)	1.0 (0.0)	1.6 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.6 (0.5)	1.0 (0.0)	1.6 (0.5)
Panel VII. Managing inventory									
Application 1	6.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.0 (0.0)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.0 (0.0)	1.0 (0.0)
Application 2	7.0 (1.7)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)	1.6 (1.1)
Application 3	7.3 (0.5)	1.0 (0.0)	1.0 (0.0)	1.3 (0.5)	1.6 (0.5)	1.0 (0.03	1.3 (0.5)	1.0 (0.0)	1.0 (0.0)
Panel VIII. Team and time management									
Application 1	7.3 (1.5)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.0 (0.0)	1.6 (0.5)
Application 2	7.3 (1.5)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)
Application 3	6.6 (0.5)	1.6 (1.1)	1.6 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.6 (0.5)	1.0 (0.0)	1.3 (0.5)
Panel IX. Project management									
Application 1	6.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.0 (0.0)	1.0 (0.0)	1.0 (0.0)
Application 2	7.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.6 (0.5)	1.6 (0.5)	1.6 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)
Application 3	6.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.3 (0.5)	1.0 (0.0)	1.6 (0.5)

Notes: The sample consists of 27 AI business applications. (*) Keystroke-level modelling. (**) The Usability Heuristic Evaluation was conducted using Nielsen's five-point severity ranking scale. Each AI business application was assessed by three evaluators. Standard deviations shown in parentheses.

Table 2. Validation of scales			
	Panel I Digital Competencies of the firms	**Panel II** Customer Satisfaction	**Panel III** Entrepreneurs' Empowerment
Construct Reliability (H)	0.938	0.642	0.977
Cronbach's Alpha (α)	0.78	0.96	0.92
Ratio of the Chi-Square Statistic to the Degrees of Freedom (chi2/df)	2.2	1.4	3.2
Root Mean Square Error of Approximation (RMSEA)	0.069	0.050	0.095
Standardized Root Mean Square Residual (SRMSR)	0.048	0.047	0.018
Normed Fit Index (NFI)	0.861	0.813	0.981
Relative Noncentrality Index (RNI)	0.919	0.919	0.987
Comparative Fit Index (CFI)	0.919	0.919	0.987
Incremental Fit Index (IFI)	0.921	0.920	0.987
Items	9	28	5
Observations	242	242	242

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Table 3. Descriptive statistics

Variables	Percentages and standard deviations
Female entrepreneurs	35.53 (0.47)
Non-native entrepreneurs	61.98 (0.48)
Entrepreneurs with disabilities	23.14 (0.42)
Non-heterosexual entrepreneurs	24.79 (0.43)
Entrepreneurs older than 40 years of age	46.69 (0.49)
Entrepreneurs with higher or vocational education	16.52 (0.37)
Firms operating for more than five years	61.15 (0.48)
Firms with more than five employees	56.19 (0.49)
Business owners of the premises	11.57 (0.32)
Business sector: Manufacturing	16.52 (0.37)
Business sector: Retail and wholesale trade	28.09 (0.45)
Business sector: Professional and business services	27.27 (0.44)
Business sector: Hospitality and tourism	14.87 (0.35)
Business sector: Construction and real estate	13.22 (0.33)
Region: England	57.85 (0.49)
Region: Wales	24.79 (0.43)
Region: Scotland	17.35 (0.37)

Notes: The sample consists of 242 observations. All variables are presented as percentages. Standard deviations are provided in parentheses.

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Table 4. Descriptive statistics: Number and frequency of AI business applications in use. Means and Standard deviations

	Before AI business applications training	After AI business applications training	Difference
Number of AI business applications in use by firms (c.) (^)	2.86 (0.79)	5.47 (1.11)	d=2.61; t=26.52, p<0.01
Frequency of use of AI business applications by firms (c.) (^^)	2.97 (0.97)	3.82 (0.67)	d=0.85; t=10.19, p<0.01

Notes: (^) Refers only to the AI business applications covered in the training programme (27 in total). (^^) Refers to how frequently the AI business applications from the training programme are used. Responses are given on a five-point scale: Never, Rarely, Sometimes, Often, and Very Often. (c.) Continuous data. Standard deviations are shown in parentheses.

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Table 5. Descriptive statistics. Tabulation analysis among demographic groups. Means and standard deviations

	Before AI business applications training	After AI business applications training	Difference
Panel I. Total sample			
Digital Competencies of the firms (c.)	1.95 (0.40)	2.42 (0.36)	d=0.47; t=9.43, p<0.01
Customer Satisfaction (c.)	6.38 (0.65)	7.03 (0.96)	d=0.65; t=6.13, p<0.01
Entrepreneurs' Empowerment (c.)	2.20 (0.29)	2.93 (0.36)	d=0.73; t=16.97, p<0.01
Revenue Growth Rates of the firms (%)	2.53 (1.42)	5.00 (1.84)	d=2.47; z=11.69, p<0.01
Observations	121	121	
Panel II. Female entrepreneurs			
Digital Competencies of the firms (c.)	1.66 (0.20)	2.28 (0.24)	d=0.62; t=12.74, p<0.01
Customer Satisfaction (c.)	6.22 (0.73)	6.77 (0.66)	d=0.55; t=3.65, p<0.01
Entrepreneurs' Empowerment (c.)	1.92 (0.18)	2.80 (0.35)	d=0.88; t=14.39, p<0.01
Revenue Growth Rates of the firms (%)	1.74 (0.69)	3.81 (1.02)	d=2.07; z=10.93, p<0.01
Observations	43	43	
Panel III. Male entrepreneurs			
Digital Competencies of the firms (c.)	2.12 (0.40)	2.50 (0.40)	d=0.38; t=6.03, p<0.01
Customer Satisfaction (c.)	6.47 (0.58)	7.18 (1.07)	d=0.71; t=5.07, p<0.01
Entrepreneurs' Empowerment (c.)	2.36 (0.21)	3.00 (0.35)	d=0.64; t=13.62, p<0.01
Revenue Growth Rates of the firms (%)	2.97 (1.53)	5.66 (1.87)	d=2.69; z=9.82, p<0.01
Observations	78	78	
Panel IV. Non-native entrepreneurs			
Digital Competencies of the firms (c.)	1.90 (0.42)	2.44 (0.38)	d=0.54; t=8.08, p<0.01
Customer Satisfaction (c.)	6.32 (0.57)	7.08 (0.98)	d=0.76; t=5.76, p<0.01
Entrepreneurs' Empowerment (c.)	2.19 (0.28)	3.00 (0.36)	d=0.81; t=15.14, p<0.01
Revenue Growth Rates of the firms (%)	2.33 (1.33)	5.09 (1.76)	d=2.76; z=10.72, p<0.01
Observations	75	75	
Panel V. Native entrepreneurs			
Digital Competencies of the firms (c.)	2.03 (0.37)	2.41 (0.34)	d=0.38; t=4.95, p<0.01
Customer Satisfaction (c.)	6.49 (0.75)	6.96 (0.95)	d=0.47; t=2.66, p<0.01
Entrepreneurs' Empowerment (c.)	2.22 (0.31)	2.82 (0.34)	d=0.60; t=8.63, p<0.01
Revenue Growth Rates of the firms (%)	2.86 (1.51)	4.89 (1.98)	d=2.03; z=5.5, p<0.01
Observations	46	46	
Panel VI. Entrepreneurs with disabilities			
Digital Competencies of the firms (c.)	1.95 (0.31)	2.34 (0.27)	d=0.39; t=4.97, p<0.01
Customer Satisfaction (c.)	6.36 (0.71)	6.85 (0.60)	d=0.49; t=2.79, p<0.01
Entrepreneurs' Empowerment (c.)	2.16 (0.37)	2.80 (0.39)	d=0.64; t=6.28, p<0.01
Revenue Growth Rates of the firms (%)	2.89 (1.68)	5.14 (1.99)	d=2.25; z=4.55, p<0.01
Observations	28	28	
Panel VII. Entrepreneurs without disabilities			
Digital Competencies of the firms (c.)	1.96 (0.43)	2.45 (0.38)	d=0.49; t=8.19, p<0.01
Customer Satisfaction (c.)	6.39 (0.63)	7.09 (1.05)	d=0.70; t=5.48, p<0.01
Entrepreneurs' Empowerment (c.)	2.21 (0.26)	2.96 (0.34)	d=0.75; t=16.37, p<0.01
Revenue Growth Rates of the firms (%)	2.43 (1.33)	4.96 (1.80)	d=2.53; z=10.90, p<0.01
Observations	93	93	
Panel VIII. Non-heterosexual entrepreneurs			
Digital Competencies of the firms (c.)	2.05 (0.41)	2.47 (0.37)	d=0.42; t=4.08, p<0.01
Customer Satisfaction (c.)	6.52 (0.70)	6.98 (1.07)	d=0.46; t=1.98, p<0.10
Entrepreneurs' Empowerment (c.)	2.24 (0.24)	2.87 (0.30)	d=0.63; t=8.86, p<0.01
Revenue Growth Rates of the firms (%)	2.46 (1.10)	4.76 (1.81)	d=2.30; z=5.93, p<0.01
Observations	30	30	
Panel IX. Heterosexual entrepreneurs			
Digital Competencies of the firms (c.)	1.92 (0.40)	2.41 (0.36)	d=0.49; t=8.56, p<0.01
Customer Satisfaction (c.)	6.34 (0.63)	7.05 (0.93)	d=0.71; t=6.01, p<0.01
Entrepreneurs' Empowerment (c.)	2.19 (0.31)	2.95 (0.38)	d=0.76; t=14.63, p<0.01
Revenue Growth Rates of the firms (%)	2.56 (1.52)	5.08 (1.85)	d=2.52; z=10.03, p<0.01
Observations	91	91	

Notes: (c.) Continuous data. Standard deviations provided in parentheses.

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Table 6. Correlation matrix

	Digital Competencies of the firms	Customer Satisfaction	Entrepreneurs' Empowerment	Revenue Growth Rates of the firms	AI business applications training	Number of AI business applications in use by firms	Frequency of use of AI business applications by firms
Digital Competencies of the firms	1						
Customer Satisfaction	0.59 (0.00)***	1					
Entrepreneurs' Empowerment	0.75 (0.00)***	0.60 (0.00)***	1				
Revenue Growth Rates of the firms	0.72 (0.00)***	0.48 (0.00)***	0.70 (0.00)***	1			
AI business applications training	0.52 (0.00)***	0.36 (0.00)***	0.73 (0.00)***	0.60 (0.00)***	1		
Number of AI business applications in use by firms	0.65 (0.00)***	0.40 (0.00)***	0.68 (0.00)***	0.62 (0.00)***	0.80 (0.00)***	1	
Frequency of use of AI business applications by firms	0.44 (0.00)***	0.25 (0.00)***	0.39 (0.00)***	0.39 (0.00)***	0.45 (0.00)***	0.60 (0.00)***	1

Notes: P-values are provided in parentheses. (***) Statistically significant at the 1% level.

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Table 7. Estimates. Number and frequency of AI business applications used by firms

	Model I. Pooled OLS	Model II. Random effects	Model III. Fixed effects	Model IV. Pooled OLS	Model V. Random effects	Model VI. Fixed effects
	Number of AI business applications in use by firms (^)			Frequency of use of AI business applications by firms (^^)		
AI business applications training	2.582 (0.127)***	2.567 (0.107)***	2.526 (0.121)***	0.832 (0.112)***	0.814 (0.092)***	0.805 (0.104)***
F	31.25	-	116.58	5.39	-	17.18
Prob>F	0.000	-	0.000	0.000	-	0.000
R-sq	0.689	-	0.638	0.277	-	0.168
Wald chi^2	-	729.34	-	-	118.08	-
Prob> chi^2	-	0.000	-	-	0.000	-
R-sq	-	0.689	-	-	0.276	-
Breusch and Pagan Lagrangian multiplier	$chibar^2$=10.90; Prob> $chibar^2$=0.000			$chibar^2$=14.15; Prob> $chibar^2$=0.000		
Hausman	chi^2=1.70; Prob> chi^2=0.944			chi^2=2.52; Prob> chi^2=0.866		
Number of firms	242	242	242	242	242	242

Notes. (^) Refers only to the AI business applications covered in the training programme. (^^) Refers to how frequently the AI business applications from the training programme are used. The Pooled OLS and Random Effects models control for entrepreneurs' age, gender, ethnicity, presence of disabilities, sexual orientation, education, firms' years of operation, number of employees in the firms, ownership of the business premises, and fixed effects on business sectors and regions. The Fixed Effects models control for entrepreneurs' age, education, firms' years of operation, number of employees in the firms, and ownership of the business premises. (***) Statistically significant at the 1% level.

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Table 8. Estimates. Digital competencies of the firms			
	Model I: Pooled OLS	**Model II: Random effects**	**Model III: Fixed effects**
AI business applications training	0.465 (0.046)***	0.465 (0.032)***	0.462 (0.036)***
F	12.58	-	42.01
Prob>F	0.000	-	0.000
R-sq	0.434	-	0.262
Wald chi^2	-	308.78	-
Prob> chi^2	-	0.000	-
R-sq	-	0.417	-
Breusch and Pagan Lagrangian multiplier	$chibar^2$=33.45; Prob> $chibar^2$=0.000		
Hausman	chi^2=1.24; Prob> chi^2=0.974		
Number of firms	242	242	242

Notes. The Pooled OLS and Random Effects models control for entrepreneurs' age, gender, ethnicity, presence of disabilities, sexual orientation, education, firms' years of operation, number of employees in the firms, ownership of the business premises, and fixed effects on business sectors and regions. The Fixed Effects models control for entrepreneurs' age, education, firms' years of operation, number of employees in the firms, and ownership of the business premises. (***). Statistically significant at the 1% level.

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Table 9. Estimates. Customers Satisfaction									
	Model I: Pooled OLS	**Model II: Random effects**	**Model III: Fixed effects**	**Model IV: Pooled OLS**	**Model V: Random effects**	**Model VI: Fixed effects**	**Model VII: Pooled OLS**	**Model VIII: Random effects**	**Model IX: Fixed effects**
Digital competencies of the firms	1.167 (0.110)***	1.167 (0.110)***	0.979 (0.289)***	-	-	-	0.321 (0.151)**	0.321 (0.151)**	0.398 (0.244)
AI business applications training	-	-	-	0.543 (0.107)***	0.542 (0.104)***	0.588 (0.118)***	-3.892 (0.458)***	-3.893 (0.454)***	-3.830 (0.520)***
Digital competencies of the firms × AI business applications training	-	-	-	-	-	-	1.777 (0.204)***	1.777 (0.202)***	1.781 (0.225)***
F	11.39	-	11.08	4.90	-	10.10	17.61	-	22.76
Prob>F	0.000	-	0.000	0.000	-	0.000	0.000	-	0.000
R-sq	0.447	-	0.090	0.258	-	0.015	0.587	-	0.195
Wald chi^2	-	182.16	-	-	79.23	-	-	316.62	-
Prob> chi^2	-	0.000	-	-	0.000	-	-	0.000	-
R-sq	-	0.447	-	-	0.258	-	-	0.587	-
Breusch and Pagan Lagrangian multiplier	$chibar^2$=0.01; prob> $chibar^2$=0.999			$chibar^2$=0.01; prob> $chibar^2$=0.454			$chibar^2$=0.53; prob> $chibar^2$=0.232		
Hausman	chi^2=12.32; Prob> chi^2=0.055			chi^2=12.23; Prob> chi^2=0.057			chi^2=12.59; Prob> chi^2=0.126		
Number of firms	242	242	242	242	242	242	242	242	242

Notes. The Pooled OLS and Random Effects models control for entrepreneurs' age, gender, ethnicity, presence of disabilities, sexual orientation, education, firms' years of operation, number of employees in the firms, ownership of the business premises, and fixed effects on business sectors and regions. The Fixed Effects models control for entrepreneurs' age, education, firms' years of operation, number of employees in the firms, and ownership of the business premises. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level.

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Table 10. Estimates. Entrepreneurs' Empowerment

	Model I: Pooled OLS	**Model II: Random effects**	**Model III: Fixed effects**	**Model IV: Pooled OLS**	**Model V: Random effects**	**Model VI: Fixed effects**	**Model VII: Pooled OLS**	**Model VIII: Random effects**	**Model IX: Fixed effects**
Digital competencies of the firms	0.808 (0.051)***	0.808 (0.051)***	1.175 (0.078)***	-	-	-	0.333 (0.060)***	0.341 (0.060)***	0.458 (0.095)***
AI business applications training	-	-	-	0.715 (0.039)***	0.717 (0.036)***	0.750 (0.042)***	-0.187 (0.184)	-0.175 (0.179)	-0.161 (0.202)
Digital competencies of the firms × AI business applications training	-	-		-	-	-	0.310 (0.082)***	0.304 (0.079)***	0.294 (0.087)***
F	22.46	-	55.68	28.03	-	75.63	44.89	-	85.77
Prob>F	0.000	-	0.000	0.000	-	0.000	0.000	-	0.000
R-sq	0.615	-	0.570	0.665	-	0.436	0.783	-	0.615
Wald chi^2	-	359.36	-	-	514.03	-	-	842.61	-
Prob> chi^2	-	0.000	-	-	0.000	-	-	0.000	-
R-sq	-	0.615	-	-	0.665	-	-	0.783	-
Breusch and Pagan Lagrangian multiplier	$chibar^2$=0.01; Prob> $chibar^2$=0.999			$chibar^2$=1.80; Prob> $chibar^2$=0.089			$chibar^2$=0.04; Prob> $chibar^2$=0.421		
Hausman	chi^2=61.31; Prob> chi^2=0.001			chi^2=5.69; Prob> chi^2=0.453			chi^2=15.41; Prob> chi^2=0.051		
Number of firms	242	242	242	242	242	242	242	242	242

Notes. The Pooled OLS and Random Effects models control for entrepreneurs' age, gender, ethnicity, presence of disabilities, sexual orientation, education, firms' years of operation, number of employees in the firms, ownership of the business premises, and fixed effects on business sectors and regions. The Fixed Effects models control for entrepreneurs' age, education, firms' years of operation, number of employees in the firms, and ownership of the business premises. (***) Statistically significant at the 1% level.

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Table 11. Estimates. Revenue Growth Rates of the firms

	Model I: Pooled OLS	Model II: Random effects	Model III: Fixed effects	Model IV: Pooled OLS	Model V: Random effects	Model VI: Fixed effects	Model VII: Pooled OLS	Model VIII: Random effects	Model IX: Fixed effects
Digital competencies of the firms	3.137 (0.226)***	3.137 (0.226)***	3.227 (0.366)***	-	-	-	1.683 (0.319)***	1.475 (0.314)***	0.049 (0.460)
AI business applications training	-	-	-	2.483 (0.197)***	2.469 (0.155)***	2.448 (0.174)***	-0.674 (0.967)	-0.745 (0.894)	0.214 (0.980)
Digital competencies of the firms × AI business applications training	-	-		-	-	-	0.984 (0.431)**	1.053 (0.398)***	0.930 (0.423)**
F	18.73	-	24.35	16.04	-	51.18	18.73	-	40.22
Prob>F	0.000	-	0.000	0.000	-	0.000	0.000	-	0.000
R-sq	0.571	-	0.456	0.532	-	0.317	0.571	-	0.418
Wald chi^2	-	299.74	-	-	360.83	-	-	451.67	-
Prob> chi^2	-	0.000	-	-	0.000	-	-	0.000	-
R-sq	-	0.541	-	-	0.531	-	-	0.658	-
Breusch and Pagan Lagrangian multiplier	$chibar^2$=0.01; Prob> $chibar^2$=0.999			$chibar^2$=18.64; Prob> $chibar^2$=0.000			$chibar^2$=1.89; Prob> $chibar^2$=0.084		
Hausman	chi^2=12.68; Prob> chi^2=0.048			chi^2=3.92; Prob> chi^2=0.687			chi^2=31.09 ; Prob> chi^2=0.001		
Number of firms	242	242	242	242	242	242	242	242	242

Notes. The Pooled OLS and Random Effects models control for entrepreneurs' age, gender, ethnicity, presence of disabilities, sexual orientation, education, firms' years of operation, number of employees in the firms, ownership of the business premises, and fixed effects on business sectors and regions. The Fixed Effects models control for entrepreneurs' age, education, firms' years of operation, number of employees in the firms, and ownership of the business premises. (***) Statistically significant at the 1% level. (**) Statistically significant at the 5% level.

Table 12. Fixed Effects Estimates. Business Outcomes

	Model I: Digital competencies of the firms	Model II: Customers satisfaction	Model III: Entrepreneurs' empowerment	Model IV: Revenue growth rates of the firms	Model V: Digital competencies of the firms	Model VI: Customers satisfaction	Model VII: Entrepreneurs' empowerment	Model VIII: Revenue growth rates of the firms
Number of AI business applications in use by firms (^)	0.139 (0.015)***	0.166 (0.043)***	0.231 (0.018)***	0.751 (0.072)***	-	-	-	-
Frequency of use of AI business applications by firms (^^)	-	-	-	-	0.198 (0.036)***	0.203 (0.092)***	0.331 (0.050)***	1.016 (0.186)***
F	25.62	8.07	31.14	30.80	12.90	5.95	15.54	13.55
Prob>F	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R-sq	0.327	0.032	0.433	0.316	0.074	0.036	0.153	0.072
Number of firms	242	242	242	242	242	242	242	242

Notes. (^) Refers only to the AI business applications covered in the training programme. (^^) Refers to how frequently the AI business applications from the training programme are used. The estimates control for entrepreneurs' age, education, firms' years of operation, number of employees in the firms, and ownership of the business premises. (***) Statistically significant at the 1% level.

Appendix.

Table AI. Summary of Hypotheses

Hypothesis	Independent Variable(s)	Dependent Variable(s)	Expected Association	Rationale
H1	AI business applications training	Digital competencies	AI business applications training is associated with increased digital competencies	The training offers practical, domain-specific instruction designed to enhance digital competencies
H2.a	Digital competencies	Customer satisfaction	Digital competencies are associated with increased customer satisfaction	Greater digital competencies support the effective use of AI business applications for personalisation, automation, and responsive customer service
H2.b	AI business applications training	Customer satisfaction	AI business applications training is associated with increased customer satisfaction	The training enables firms to deploy AI business applications that improve service quality, increase operational speed, and strengthen customer engagement
H2.c	Digital competencies × AI business applications training	Customer satisfaction	Digital competencies are more strongly associated with customer satisfaction post-AI business applications training	The training improves entrepreneurs' competency to strategically apply AI business applications in customer interactions, helping to mitigate identity-based bias and foster trust-based engagement
H3.a	Digital competencies	Entrepreneurs' empowerment	Digital competencies are associated with increased entrepreneurs' empowerment	Digital competencies support informed decision-making, strategic autonomy, and adaptive leadership
H3.b	AI business applications training	Entrepreneurs' empowerment	AI business applications training is associated with increased entrepreneurs' empowerment	The training builds confidence, self-efficacy, and agency, particularly for underrepresented entrepreneurs excluded from traditional support systems
H3.c	Digital competencies × AI business applications training	Entrepreneurs' empowerment	Digital competencies are more strongly associated with entrepreneurs' empowerment post-AI business applications training	The training enhances the strategic use of AI business applications, thereby strengthening the link between digital competencies and entrepreneurs' empowerment
H4.a	Digital competencies	Revenue growth	Digital competencies are associated with increased revenue growth	Firms with stronger digital competencies are better positioned to use AI business applications to optimise operations, reduce costs, and improve sales
H4.b	AI business applications training	Revenue growth	AI business applications training is associated with increased revenue growth	The training enables firms to apply AI business applications in areas such as forecasting, pricing, and market expansion, thereby strengthening financial performance
H4.c	Digital competencies × AI business applications training	Revenue growth	Digital competencies are more strongly associated with revenue growth post-AI business applications training	The training improves firms'competency in applying AI business applications for financial planning and operational scaling, thereby reinforcing revenue gains

Notes: The ten hypotheses presented in the table form the basis of the study's AI Business Applications Training Model.

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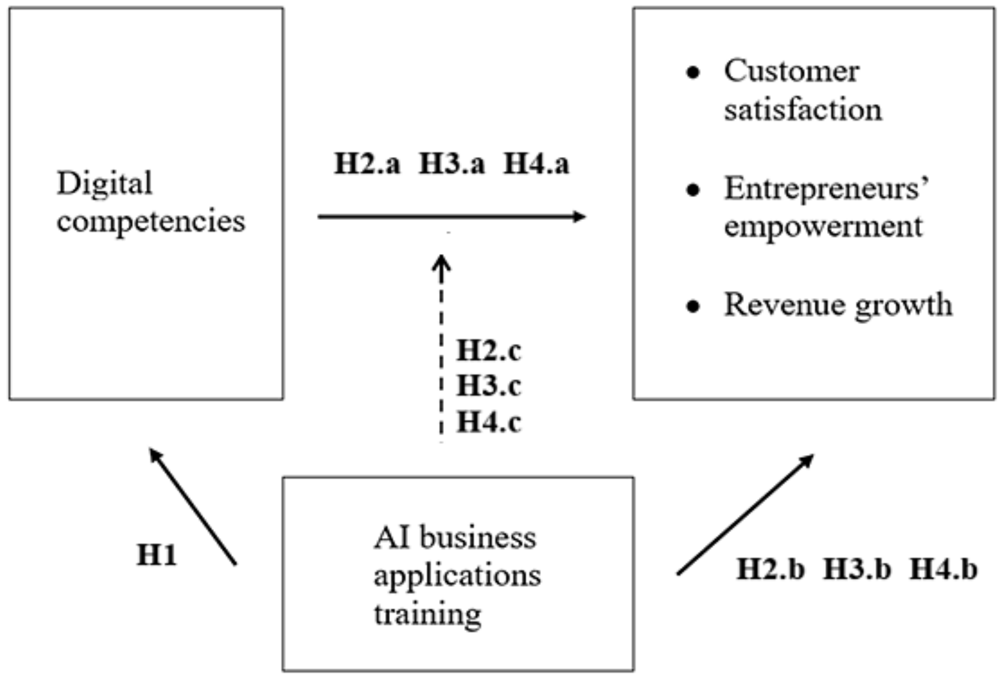
Appendix Table AII. AI Business Applications Training Structure								
Session	**Learning objectives**	**Digital skill building**	**Digital competencies development**	**Learning by doing**	**Pedagogical strategy**	**AI technical elements introduced**	**Assessment and feedback**	**Inclusion and small-firm relevance**
Session 1. Introduction to AI in business	Understand core AI concepts, business relevance, and ethical/legal issues	Basic AI terminology (e.g., machine learning, natural language processing NLP, pattern recognition), ethical AI design	Foundational AI literacy, strategic insight, compliance with data laws	Explore case studies of firms using AI in marketing, finance, and operations	Scaffolded introduction, contextualised examples, peer-supported Q&A	Supervised and unsupervised learning, NLP, algorithmic bias, and model explainability, linked to real-world business tasks	Self-assessment checklist, quiz, group reflection	Free-of-charge training, mobile-accessible tools, simplified language, examples from diverse industries and firm types
Session 2. Communication and networking	Use AI applications for internal/external communication and outreach	AI email drafting, team messaging, smart contact suggestions	Digital fluency, communication efficiency, networking	Draft business emails, simulate AI-enhanced messaging, generate contact suggestions	Scenario-based learning, peer-supported Q&A	NLP text generation, autocomplete, speech-to-text	Peer-reviewed messaging task, scenario reflection	Voice-to-text functionality, mobile compatibility, inclusive case studies
Session 3. Social media and customer relationship management (CRM)	Build visibility and retain customers using AI applications	Campaign automation, behaviour analysis, sentiment detection	Customer engagement, personalisation, digital branding	Segment customers, analyse sentiment, automate marketing	Hands-on CRM setup, walkthroughs, peer-supported Q&A	Sentiment analysis, clustering, predictive analytics	Practical CRM task, group discussion	Video guides, culturally relevant examples, adaptable user interface
Session 4. Payments and accounting/finance	Improve financial tracking and decisions using AI applications	Invoice automation, fraud detection, AI-supported cash flow projections	Financial autonomy, budgeting, cost management	Generate invoices, detect anomalies, forecast cash flow	Simulations, dashboards, forecasting tasks, Q&A	Anomaly detection, time-series forecasting, rule-based automation	Scenario-based tasks, finance quiz	Dashboards, spreadsheet exports, gender-diverse case studies
Session 5. Inventory, time, and project management	Optimise logistics, workflows, and productivity using AI applications	Inventory tracking, shift planning, deadline alerts	Workflow design, resource use, team coordination	Track inventory, plan projects, monitor productivity	Simulations, real-time planning, games, peer-supported Q&A	Basic principles of AI-based scheduling and optimisation	Planning scenarios, live feedback	Offline access, mobile-first tools
Session 6. Strategic integration	Integrate AI applications across business functions	Cross-tool planning, insight synthesis, strategic thinking	Multi-domain problem-solving, decision readiness	Develop and present a cross-functional business plan using AI applications	Capstone challenge, reflection, strategic alignment	AI dashboard use, integrated decision support	Live feedback during final session	Flexible feedback formats, accessibility adjustments

Figure 1. AI Business Applications Training Model



Notes: The figure illustrates that AI business applications training is positively associated with digital competencies (H1). Digital competencies are positively associated with customer satisfaction (H2.a), entrepreneurs' empowerment (H3.a), and revenue growth (H4.a). In addition, AI business applications training is positively associated with customer satisfaction (H2.b), entrepreneurs' empowerment (H3.b), and revenue growth (H4.b). The dashed arrow indicates that AI business applications training positively moderates the relationship between digital competencies and business outcomes. In other words, following the training, digital competencies are more strongly associated with improvements in customer satisfaction (H2.c), entrepreneurs' empowerment (H3.c), and revenue growth (H4.c).