

Hruby, Vojtech

Article

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Exploring AI Adoption Dynamics and Entrepreneurial Orientation in Czech Chemical SMEs: A Pilot Study Perspective

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Vojtech Hruby 

Brno University of Technology, Department of Management, The Czech Republic

Abstract

This article outlines a pilot study aimed at exploring the influence of Entrepreneurial Orientation (EO) on Artificial Intelligence (AI) adoption and firm performance within Czech chemical SMEs. With dual aims, the study first evaluates the feasibility of the main research design and secondly develops and validates an innovative instrument for measuring AI adoption. Through a quantitative survey, 107 Czech chemical SMEs were engaged, focusing on the practicality of research methodologies and the initial testing of measurement tools, especially for AI adoption. Despite a modest response rate, the study met its methodological objectives, offering insights into AI integration and EO's complexity within the sector. The initial findings hint at the need for broader engagement strategies in the subsequent study, reflecting the challenges of researching niche markets. Significantly, the creation of the AI adoption tool marks a considerable advancement, addressing a gap in existing research tools. This study not only underscores the importance of pilot testing in social sciences, especially within specialized sectors, but also its findings and methodologies serve as a blueprint for future research, emphasizing the adaptation of strategies to industry-specific and geographical peculiarities. By establishing a methodological foundation for in-depth future research, this pilot study promises enhanced understanding of EO's impact on AI adoption strategies and performance outcomes in the Czech chemical industry, directly addressing a critical research gap.

Keywords

Artificial Intelligence Adoption, Entrepreneurial Orientation, Czech Chemical SMEs, Pilot Study Methodology, Measurement Instrument Development

JEL Classification

L26, O33, L65

Introduction

This article delineates the outcomes of a pilot study, strategically designed as a precursor to a comprehensive investigation into the influence of Entrepreneurial Orientation (EO) on Artificial Intelligence (AI) adoption and firm performance in Czech chemical Small and Medium-sized Enterprises (SMEs). The pilot study's principal objectives encompass: 1) assessing the feasibility of the proposed main research design, 2) developing and validating a key instrument to measure AI adoption, 3) conducting preliminary tests of the developed tool alongside an established EO questionnaire, and 4) collating and analysing initial data.

Entrepreneurial Orientation (EO), a pivotal theoretical construct in entrepreneurship research, has been scrutinized for over three decades. Despite extensive studies, the EO-firm performance nexus remains somewhat ambiguous (Rauch et al., 2009; Wales, 2021). This pilot study lays the groundwork for a main study hypothesizing a positive interplay between EO and firm performance in an unexplored geographical context. The work of Wales (2021) underscores the global imperative to assess EO across diverse settings, thus bolstering EO's relevance as a universally pertinent construct in research and practice.

Further, Wales (2021) validates the feasibility of investigating EO within new domains, such as the Czech Republic's chemical industry. His findings reveal EO's multifaceted role as an influencer, outcome, and mediator in varied scenarios. This underscores the value of extending EO research into new industries and geographical regions. Previous research (Hrubý and Koráb, 2018; Hruby, 2021), have highlighted a notable gap in published research concerning EO's impact within Czech chemical SMEs, affirming the unique focus of the upcoming main study.

The burgeoning interest in AI, propelled by advancements in technologies like OpenAI's ChatGPT (Dell'Acqua et

Corresponding author:

Vojtech Hruby, Kolejni 2906/4, 612 00 Brno, The Czech Republic
Email: xphruby05@vutbr.cz

al., 2023), foregrounds the second thematic pillar of the main study. This author's preliminary survey of two scholarly databases – Scopus and Web of Science - indicates a paucity of research at the intersection of AI and EO, suggesting an underexplored field ripe for scholarly inquiry. Baldegger et al. (2020) notes the propensity of entrepreneurially oriented firms to adopt AI in HRM, hinting at a potentially fruitful area of research. This pilot study, therefore, aims to develop a specialized measuring tool for AI adoption. This tool is designed to facilitate a comprehensive exploration of the relationship between Entrepreneurial Orientation and AI adoption in the main study. By ensuring the tool's validity and reliability in the pilot phase, we aim to lay the groundwork for a detailed and insightful analysis in the subsequent research.

In contrast to medical and healthcare literature, where pilot and feasibility studies are prevalent, such exploratory studies are less common in social sciences. Yet, as argued by Fraser et al. (2018) and Malmqvist et al. (2019), the value of sharing and discussing pilot study findings in social sciences cannot be overstated. Saunders et al. (2023) and De Vaus (2013) advocate for the necessity of pilot testing, especially for validating data collection tools. This pilot study endeavours to fulfil these academic calls by developing and testing an AI adoption tool, examining an existing EO questionnaire (Covin and Slevin, 1989), and assessing the demographic landscape of Czech chemical SMEs. These efforts are geared toward enriching the methodological robustness of the main study and providing actionable insights for researchers, especially PhD candidates working independently or without extensive supervisory support (Malmqvist et al., 2019).

The subsequent sections of this paper delve into the theoretical underpinnings of EO, its measurement, and the role of pilot and feasibility studies in social sciences. The Methodology and Data section chronicles the pilot study's design and execution phases, detailing the selection of data collection tools and control variables. Finally, the paper culminates in a comprehensive presentation and discussion of the results, culminating in a conclusion that encapsulates the pilot study's contributions and implications for the upcoming main research endeavour.

Literature Review

Entrepreneurship and Entrepreneurial Orientation

The concept of entrepreneurial orientation (EO) is paramount in entrepreneurship, as viewed through the lens of social science research. Given the growing uncertainty and complexity in the world, comprehending EO is crucial for organizations to effectively navigate and prosper. Hence, it is imperative for both managers and academics to possess a deep understanding of EO, in order to ensure the survival and success of organizations, regardless of their size or type (Wales, 2021). The renowned economist of the first half of the twentieth century, Joseph Schumpeter, believed that entrepreneurship was the primary catalyst for enhancing a company's productivity and expansion. He viewed entrepreneurs as people who aimed to develop novel amalgamations, specifically by introducing innovative products, and closely associated entrepreneurship with the concept of innovation (Schumpeter, 2013). The two terms - entrepreneurship and innovation - are frequent talking points of governments around the globe seeking to reinvigorate the post-pandemic growth of economies and to solve pressing global problems: "The UK government celebrates entrepreneurship. We are committed to rewarding innovation and hard work. Entrepreneurs bring solutions to problems, such as climate change, whilst creating new jobs and supporting our economic recovery from coronavirus" - UK Government Minister for Scotland, David Duguid during the build-up to the 2021 United Nations Climate Change Conference, more commonly referred to as COP26 in Glasgow, Scotland (Duguid, 2021).

Entrepreneurship is defined as venturing into new territories, which can be accomplished by introducing new products or services to either new or existing markets, or by establishing a new enterprise, be it a start-up, an existing firm, or through internal corporate venturing. The term 'entrepreneurial orientation' refers to the processes, methods, and decision-making actions that lead to the creation of a new business venture (Lumpkin and Dess, 1996). The concept of EO dates back to the early 1980s and has been increasingly popular, as evidenced by Hruby (2021) and Wales (2021). Miller's conceptualisation in 1983 (Miller, 2011) has become the preferred approach for studying EO (White et al., 2021). It views EO as a unidimensional construct composed of three core elements: innovativeness, proactiveness, and risk-taking. The characteristics of these three dimensions are summarised in Table 1.

Efforts have been made to differentiate 'entrepreneurship'—specifically, new entry—from the process of pursuing new entry, known as 'entrepreneurial orientation'. Lumpkin and Pidduck (2021) define entrepreneurship as a multifaceted, value-creating process and entrepreneurial orientation as the combination of autonomous, proactive, innovative, and competitive risk-taking beliefs and behaviours required to create new value under uncertain conditions. Scholars have analysed these two terms from various perspectives, leading to some ambiguity regarding whether EO represents a decision-making tendency, an attitude receptive to entrepreneurial opportunities, or a set of specific entrepreneurial behaviours (Cowden and Tang, 2021). EO is often viewed as a firm-level theoretical construct that describes entrepreneurial activities within a firm. It encompasses an organization's entrepreneurial processes, actions, methods, policies, decision-making styles, and behaviours at the firm level that demonstrate innovation, proactivity, and a readiness to take risks. Historically, it has been

accepted that EO is applicable for assessing all firms, allowing for comparisons between conservative and more entrepreneurial firms. However, the applicability of EO becomes less straightforward when comparing firms that are entrepreneurial in different ways. For instance, consider the comparison between the US retail giant Walmart, known for its creative capital deployment yet not for creating new products, and the innovative approach of Apple (McNaughton and Sembhi, 2021). In light of such discrepancies, some scholars have recognized the need for EO to evolve and adjust to the dynamics of the 21st-century entrepreneurial landscape. The capacity to innovate, take risks, and adapt is no longer a unique marker distinguishing entrepreneurial from conservative firms. In today's rapidly evolving business environment, all firms are required to adopt, to some degree, entrepreneurial behaviours for mere survival.

Table 1. Dimensions of Entrepreneurial Orientation.

Dimension	Definitions
Innovativeness	Willingness to implement new concepts by the means of experimenting and utilising a creative process focused on the development of new products, services, and processes (Dess and Lumpkin, 2005). Represents the propensity of a firm to market new products and/or services by means of creativity and experimentation as well its inclination to strive for technological leadership (Baldegger et al., 2021).
Proactiveness	Forward looking perspective typical for a market leader, who pursues opportunities expecting future demand (Dess and Lumpkin, 2005). Describes an organization's opportunity-seeking and forward-looking attitude. A proactive firm seeks to develop and present new products and/or services ahead of its competition. It acts in expectation in future demand (Baldegger et al., 2021).
Risk-taking	Decision making and execution without a certain knowledge of likely outcomes; some steps may involve a significant resource allocation (Dess and Lumpkin, 2005). Reflects a company's inclination to engage in risky actions such as entering unfamiliar markets, risking heavy financial exposure, and/or committing significant resources to ventures in unstable environments (Baldegger et al., 2021).

Measuring EO and Firm Performance

Performance measurement, as defined by Neely et al. (1995), is the process of quantifying the efficiency and effectiveness of actions. Recent studies, including those by Lee and Raschke (2023) and Lee and Suh (2022), highlight the complexity and multi-dimensional nature of measuring firm performance, especially concerning ESG scores. Rehman and Iqbal (2020), along with Gürlek and Çemberci (2020), delve into the dynamic interplay between leadership styles, innovation, and firm performance, underscoring the significance of strategic equilibrium. Additionally, recent viewpoints, such as those of Faturachman (2023), propose a comprehensive view of firm performance that includes both financial and customer aspects. These contemporary studies emphasize the importance of adopting a holistic approach to evaluating firm performance, given its multifaceted and complex nature.

Ipinnaiye et al. (2017) put forth the idea that the performance of SMEs (Small and Medium-sized Enterprises) is influenced by a blend of the firm's inherent characteristics, its strategic approach, as well as the broader macroeconomic environment in which it operates. They suggest that firm growth is a result of the interplay between these firm-specific elements and external macroeconomic conditions. This aligns with the findings of Popa and Ciobanu (2014), who demonstrated that macroeconomic factors, such as inflation, unemployment, economic crises, and changes in GDP, significantly impact SME performance, in addition to microeconomic factors.

The endeavour to quantify human or firm behaviour through measurement instruments has long been a crucial aspect of social science research (Drost, 2011). One notable research strategy employed in this field is the use of surveys, which involves systematically collecting data from a substantial population. This data is then statistically analysed to quantify behaviours.

The term 'survey' is commonly used to describe the collection of data via questionnaires, but it also includes other methods such as structured interviews (Saunders et al., 2023). The term 'questionnaire' refers to a range of data collection techniques that involve asking a standardized set of questions in a specific order (De Vaus, 2013). This pilot study tests an EO (Entrepreneurial Orientation) questionnaire previously utilized in various studies. The objective is to ensure the questionnaire's applicability and effectiveness in gathering necessary information within a particular research context, encompassing a specific geographic region, industry, and language. This methodology aligns with the views of (Malmqvist et al., 2019), who advocate for the use of well-tested instruments in research to achieve deep understanding, thereby enhancing the reliability of the data collected. Questionnaires are particularly effective when they consist of standardized questions that are likely to be interpreted consistently by all respondents (Robson and McCartan, 2015).

Baldegger et al. (2021) discovered that the predominant tool for measuring Entrepreneurial Orientation of

organizations, as conceptualized by Miller (2011) in 1983, is the nine-item scale developed by Covin and Slevin (1989). The distribution of this measure's usage over time is not skewed. Although the majority of researchers have examined EO as a unidimensional construct comprising three dimensions, there have been arguments supporting a multidimensional construct with five dimensions, as proposed by Lumpkin and Dess (1996). Various adaptations of the Covin and Slevin (1989) measure have been attempted. White et al. (2021) caution against promoting modifications to the CS model, as these could compromise its unidimensional structure and theoretical integrity. They argue that ad-hoc modifications might impair the practical and conceptual utility of EO. However, White et al. (2021) also recognize the necessity for EO and its most popular measuring tool to evolve. Entrepreneurship is generally viewed as a dynamic field, yet the measurement of EO predominantly remains static, unable to address the time-sensitive dynamics between EO, organizational growth, and performance. The original CS scale has limited applicability in capturing new market entries. Cowden and Tang (2021) suggest that there is potential in refining the scale to not only encompass various forms of new entry but also to differentiate between them.

Artificial Intelligence and its Adoption in SMEs

In 2023, Artificial Intelligence (AI) has emerged as a widely discussed topic beyond just academic realms. AI can be described as a technology exhibiting human-like capabilities in executing complex tasks (Vrontis et al., 2022), as programs that mimic human intelligence (Chen et al., 2022), or as the ability of a system to accurately analyse external data, learn from this data, and use this learning to achieve specific goals and tasks through adaptable methods (Kaplan and Haenlein, 2019). There are other definitions that link AI with related concepts like the Internet of Things (IoT) and big data. While machine learning is a crucial aspect of AI, the scope of AI is broader, including the system's ability to process data and its capability to control, navigate, and manipulate objects based on learned knowledge. This is applicable in robotics and other interconnected devices. AI leverages external data from sources such as the IoT or large data repositories. It employs this data to identify underlying rules and patterns, primarily using machine learning techniques. These techniques allow computers to gain knowledge and skills without being explicitly programmed (Kaplan and Haenlein, 2019).

Implementing AI presents Small and Medium-sized Enterprises (SMEs) with the opportunity to revolutionize a variety of business processes. AI can assist in optimizing supply chain management, reducing operational costs, lessening the impact of external crises, and facilitating significant operational changes by introducing improved business models (Vrontis et al., 2022). However, the ability of SMEs to quickly adopt new technologies, learn from experience, innovate, and enhance their production processes is often limited by their smaller scale. This limitation can restrict their capacity to fully benefit from the digital economy. Organizational factors, such as management roles, technology strategy, and employee training, significantly influence the adoption of technology in SMEs. Furthermore, macro-environmental factors like industry standards and national support services also play a crucial role in the technological adoption process within SMEs (Wei and Pardo, 2022).

Giuggioli and Pellegrini (2022) examines the evolution of Artificial Intelligence, tracking its development from initial conceptualization to its current state, which encompasses areas such as machine learning and deep learning. The paper further investigates the role of AI within various technological frameworks of Industry 4.0. This includes its critical involvement in intelligent manufacturing, the Internet of Things, Augmented Reality (AR), and blockchain technologies, highlighting AI's essential role in these areas.

Innovative technologies have consistently driven business evolution, and Artificial Intelligence (AI) is the latest example. Characterized by its ability to learn, connect, and adapt, AI offers transformative capabilities that can redefine business operations and strategies (Huang and Rust, 2021). For Small and Medium-sized Enterprises (SMEs), AI represents a double-edged sword. On one hand, it promises significant benefits such as automating mundane tasks and extracting insights from large datasets. On the other, it poses risks and demands substantial resources for implementation (Giotopoulos et al., 2017). However, SMEs with a strong Entrepreneurial Orientation are not only adept at recognizing AI's potential but are also more willing to embrace the inherent risks. Their natural proactiveness and innovativeness drive them to be early adopters, using AI to secure a competitive advantage. Furthermore, an entrepreneurial mindset promotes a culture of ongoing learning and adaptation, essential for utilizing AI's full potential (Huang and Rust, 2021). EO, with its focus on innovation and risk-taking, naturally aligns with the spirit of technological adoption. SMEs with a marked EO are not just reactive to technological changes; they are proactive, striving to integrate these advances before they become standard in the industry (Wiklund and Shepherd, 2005). Therefore, it is plausible to suggest that entrepreneurially oriented SMEs would lead in adopting AI, not merely because it is a trend, but because they recognize its potential to bring transformative changes.

A growing body of scholarly work is focusing on the complexities of AI adoption by SMEs, yet finding a universally applicable measurement tool remains challenging. Alekseeva et al. (2020) identified a positive correlation between AI adoption at the firm level and factors such as firm size, capital expenditure (Capex), research and development (RandD), and total investments. They also noted that AI adoption by managers correlates with increases in sales, market capitalization, RandD, and Capex. However, AI adoption by IT specialists does not demonstrate a strong link with firm outcomes. Chatterjee et al. (2021) examines the factors influencing AI adoption in manufacturing and production firms, emphasizing the significance of socio-environmental and technological factors. Alsheibani et al.

(2018) suggests a research framework for AI adoption at the firm level, integrating the Technology-Organization-Environment (TOE) framework with the Diffusion of Innovation theory (DOI). Yet, none of these studies provide a definitive measuring tool. Baldegger et al. (2020) discovered a significant relationship between a company's entrepreneurial orientation and its propensity to adopt AI in HRM processes, indicating that companies with a stronger EO are more inclined to implement AI tools in HRM. The absence of a specific measuring tool for AI adoption in SMEs, combined with the insights from these studies, motivates the author of this pilot study to attempt creating a straightforward measuring tool for AI adoption. This endeavour aims to fill this research gap and to facilitate exploration of the relationships among EO, AI adoption, and SME performance in the main study.

SMEs in the Czech Chemical Industry

In 2021, global chemical sales amounted to €3,669 billion. China was the top contributor with €1,488 billion, followed by NAFTA states at €570 billion, and the EU27 states at €554 billion. The rest of Europe contributed an additional €168 billion, according to 'Facts and Figures 2022'. This data establishes Europe as the world's second-largest chemical producer, underscoring the European chemical industry's critical role in regional economic growth. The industry is a significant contributor to wealth generation, providing modern products and services across various sectors. Specifically, the Czech chemical industry, which represents about 1% of Europe's total chemical industry and, combined with its pharmaceutical sector, is the third most important industry in the Czech Republic in terms of GDP contribution, accounting for 13% of the country's industrial production ("Chemical and Pharmaceutical Industry in the Czech Republic", 2010). Moreover, SMEs are the cornerstone of the EU economy. According to the (EU27 - SME Fact Sheet 2021, 2021), they make up 99.8% of all businesses, contributing 53% to value addition and 65.2% to employment. This highlights the critical role of SMEs in the European economic framework, particularly within the chemical sector.

In the Czech chemical industry, Small and Medium-sized Enterprises (SMEs) encounter unique challenges and characteristics that shape their operational and competitive environment. Hrubý and Koráb (2018) observe a limited presence of SMEs in this sector, attributing this to the capital-intensive nature of chemical manufacturing. Despite this, they note that these SMEs generally exhibit superior financial performance compared to the broader manufacturing industry (Hrubý and Koráb, 2018). Dasan (2013) underscores the importance of technology and internationalization for these enterprises, highlighting the need for competitive positioning in global markets. Additionally, SMEs face further complexities due to regulatory changes. Maresova et al. (2021) discuss how increased regulatory costs and administrative burdens, particularly in the medical devices industry, pose significant challenges for SMEs. The adaptation to new technologies and globalized markets presents both opportunities and threats. Písar and Bilková (2019) explore this in the context of Industry 4.0 and innovations, illustrating the dual nature of these developments for SMEs in the chemical sector.

Linking Theory to Pilot Study Objectives

While numerous research papers mention pilot testing their methodologies and some methodological literature advocates for the use of pilot studies in qualitative research, there is a notable gap in documented research specifically detailing how to conduct these pilot studies (Malmqvist et al., 2019). In their extensive literature review using Medline and the Web of Science, Lancaster et al. (2004) found no formal methodological guidelines defining what constitutes a pilot study. Typically, a pilot or feasibility study is conducted prior to a main study, to which it is closely related. Its primary purpose is to guide the planning process and determine the feasibility of the main study. A pilot study is a small-scale experiment designed to test assumptions, observe outcomes, and collect preliminary data. It includes risk mitigation strategies to minimize the likelihood of failure in a larger-scale project (Fraser et al., 2018). Despite the apparent benefits of pilot and feasibility studies for refining a research design or approach, many researchers are hesitant to use and publish the results of such studies (Tejlingen and Hundley, 2002). Financial and time constraints might deter researchers from conducting pilot studies, which could otherwise prepare them for potential challenges in the primary research project. Consequently, design and planning flaws may go unnoticed and unresolved, meaning that the benefits of a well-organized and managed pilot study in enhancing the quality of the main research are not realized (Malmqvist et al., 2019).

The terms 'pilot study' and 'feasibility study' are sometimes used interchangeably. Chan et al. (2017) define a feasibility study as an evaluation to determine whether a proposed project is doable and whether it is worthwhile to proceed with it. A pilot study, while serving a similar purpose in assessing feasibility, additionally includes a small-scale execution of the main study. Thus, pilot studies encompass aspects of feasibility studies. Eisenhardt (1989) advocates for commencing research without pre-established theories or hypotheses, an approach particularly pertinent to pilot studies focusing on exploring feasibility and refining research methods. Maintaining an open mind during this process can yield more unbiased and authentic insights. This perspective aligns with Gioia (2021), who emphasizes the importance of grounding research in the actual experiences and perceptions of subjects. This approach is vital in a pilot study, especially when its objectives include testing feasibility and honing research methodologies.

The primary goal of a pilot study is not to test specific research questions, but rather to prevent researchers from embarking on a large-scale study without a thorough understanding of the proposed methodologies. In essence, a

pilot study is conducted to avoid potential major flaws in a study that could lead to significant losses of time and resources (Polit and Beck, 2016). Such a study typically lacks the statistical power for formal hypothesis testing, and its results should be considered preliminary and interpreted with caution (Leon et al., 2011). However, if a pilot study is well-planned with clearly defined objectives, it can significantly enhance the relevance of the research, provide a framework for the study, and thus, ensure its scientific validity and potential for publication (Lancaster et al., 2004). Reasons for conducting pilot studies, as identified in the literature, are summarized in Table 2.

Table 2. Motivations for carrying out pilot studies.

No.	Reason	Source
1	Developing and testing adequacy of research instruments	(Lancaster et al., 2004)
2	Assessing the feasibility of a full-scale study or survey	(Leon et al., 2011)
3	Assessing whether the research protocol is realistic and workable	(Tejlingen and Hundley, 2002)
4	Identifying logistical problems which might occur pursuing proposed methods	(Lowe, 2019)
5	Collecting preliminary data	(Arain et al., 2010)
6	Assessing the proposed data analysis techniques to uncover potential problems	(Lancaster et al., 2004)
7	Developing research questions and a research plan	(Tejlingen and Hundley, 2002)
8	Finding out whether the planned recruitment approach would generate volunteers	(Secomb and Smith, 2014)
9	Testing out the tools for collecting data in practice to ensure that they elicit the type and range of responses required	(Tejlingen and Hundley, 2002)
10	Reflecting upon personal skills and abilities as a researcher and explore self	(Kim, 2011)
11	Developing hypothesis for the main study	(Slavec et al., 2017)

This pilot study is designed to address crucial research gaps identified in the theoretical exploration, particularly focusing on Entrepreneurial Orientation, AI adoption, and their interplay within the SMEs of the Czech chemical industry. The development and thorough testing of a new AI adoption measurement tool specifically addresses the lack of instruments tailored for this distinct industry and geographic context. This process not only confirms the tool's efficacy for the main study but also sheds light on the intricacies of AI integration in SMEs, an area not extensively covered in existing literature.

Moreover, the pilot study's in-depth evaluation of EO within this sector aims to enrich our understanding of EO's role in the Czech chemical industry, a subject that has not been extensively explored in prior research. By examining EO within the context of this specific industry, the study sets the stage for a more focused and relevant examination in the main study, potentially revealing new aspects of EO's influence on firm performance and innovation.

In summary, this pilot study acts as a critical link between theoretical concepts and practical application. It verifies the relevance of theoretical models in a real-world context and fine-tunes the research methodologies for use in the main study. The pilot ensures that the ensuing research is not only theoretically valid but also practically significant and methodologically sound. This establishes a strong foundation for a thorough investigation of the relationships between EO, AI adoption, and SME performance in the Czech chemical industry.

Methods

Research Design

This pilot study represents a crucial initial step towards a more extensive examination of the relationship between entrepreneurial orientation, artificial intelligence adoption, and SME performance within the Czech chemical industry. Utilising a carefully designed quantitative survey, this research aims to develop and preliminarily test measurement instruments for AI adoption and to evaluate the efficacy of the existing EO questionnaire by Covin and Slevin (1989), rather than focusing on hypothesis testing or generating statistically significant results. This methodological choice aligns with the study's objectives, drawing inspiration from Churchill (1979) foundational principles for creating a new AI adoption measurement tool. The survey specifically targets a selected group of Czech chemical SMEs, chosen based on criteria similar to those used by Saunila (2017), to ensure the research's relevance and specificity. The following subchapters will elaborate on the development of these instruments, the sample selection process, data collection methods, and an initial analysis of the collected data using descriptive statistics. This methodological summary paves the way for a thorough understanding of the pilot study's efforts to not only achieve its immediate aims but also to establish a solid foundation for the forthcoming main study.

Development of AI Adoption Measurement Tool

The development of the AI Adoption Measurement Tool in this study is anchored in a rigorous and systematic

review of the literature, reflecting a commitment to methodological robustness essential for exploring AI adoption within SMEs. Central to this development is (Churchill, 1979) acclaimed approach to questionnaire design, which emphasizes the creation of tools that are both reliable and valid in marketing and business research. This approach is instrumental in understanding the multifaceted nature of AI adoption and is echoed in Raja Sreedharan et al. (2016), who adeptly adapted Churchill's technique to construct a scale with high content validity.

In an effort to optimize the reliability and applicability of the AI Adoption Measurement Tool, the initial set of 9 items was subjected to a meticulous evaluation process. This began with presenting the items to five academic colleagues, specialists in their respective fields, to gather critical feedback on the face validity of the tool. Their insights were instrumental in ensuring the relevance and clarity of each item, drawing parallels with the methodological approach employed by Dubey et al. (2015). Simultaneously, to further authenticate the tool's validity, five SME managers from the Czech chemical industry, with insider knowledge and practical experience, were engaged to assess the Content Validity Substantive coefficient (CSV). Based on the guidelines established by Anderson and Gerbing (1991), this evaluation focused on identifying and retaining only those items with a substantial validity score, determined by a CSV value of 0.5 or higher.

This rigorous validation process led to the exclusion of 6 items that did not meet the necessary validity threshold, thereby refining the tool to a more concise and targeted set of questions. Additionally, the questionnaire's design incorporated the principles outlined by Converse and Presser (1986), emphasizing clarity in question wording and the elimination of potential biases. This approach was crucial to minimize the risk of misinterpretation and bias among respondents, ensuring the collection of accurate and reliable data. Furthermore, the incorporation of multi-item constructs, as advocated by Endres and Endres (2018), significantly enhanced the measurement accuracy and reliability of our tool.

Lastly, the design process meticulously incorporated strategies to mitigate common-method bias. This included measures such as ensuring respondent anonymity, and varying survey layouts, aligning with best practices in questionnaire design as suggested by De Vaus (2013). This thorough and theoretically informed approach underscores the tool's potential in providing insightful data for comprehensively understanding AI adoption trends, particularly within the context of small and medium-sized enterprises.

Rationale for Questionnaire Items

The formulation of questionnaire items for measuring AI adoption is deeply rooted in the well-established relationship between organizational innovativeness and technology adoption, particularly concerning AI technologies. Studies such as Heinze and Heinze (2020) underscore this connection by demonstrating a positive correlation between perceived organizational innovativeness and the extent of technology adoption. Similarly, Cannavale et al. (2022) emphasized AI's role as an innovative tool in enhancing business relationships and performance, especially in inter-organizational networks. This notion is further supported by Camisón and Villar-López (2014), who established that organizational innovation is a precursor to technological innovation capabilities, ultimately driving improved firm performance.

Building on these insights, Wamba-Taguimdje et al. (2020) explored how AI capabilities enhance organizational performance across various sectors, thus emphasizing the importance of AI adoption in innovative organizations. This body of research collectively reveals a critical trend: firms with a stronger orientation towards innovation are more likely to adopt emerging technologies like AI. Such an inclination is an integral part of Entrepreneurial Orientation, especially its innovativeness dimension. EO, with its facets of innovativeness, proactiveness, and risk-taking, is consistently linked to new technology adoption in diverse organizational settings.

For instance, Akbari and Baharestan (2013) demonstrated the significant impact of information technology on EO in the pharmaceutical industry, reinforcing technology's role in enabling EO. Nasution et al. (2021) further elucidated this by showing how EO dimensions, particularly innovativeness and proactiveness, influence e-commerce adoption in Indonesian SMEs. Upadhyay et al. (2022) also provided evidence of the critical role EO plays in family businesses' decisions to adopt AI. These studies collectively suggest that EO, particularly its aspect of innovativeness, is a key determinant in adopting advanced technologies like AI.

The theoretical underpinnings from these studies lead to the formulation of a pertinent questionnaire item: 'Has your firm adopted AI technologies to innovate your product or service offerings?' This question is designed to directly assess the intersection of AI adoption and organizational innovativeness, a crucial element in understanding the role of EO in facilitating technological advancement in today's business landscape.

The rationale for the questionnaire items designed to measure AI adoption in SMEs is strongly anchored in the research linking proactiveness, a key dimension of Entrepreneurial Orientation, with the adoption of emerging technologies like AI. Recent studies underscore the significance of proactive AI adoption in enhancing organizational capabilities and decision-making processes, crucial for competitive Customer Relationship Management (CRM) (Natrajan et al., 2022). Martín-Rojas et al. (2017) further elucidate the role of technological distinctive competencies (TDCs) in corporate entrepreneurship, demonstrating that companies focused on improving technological competencies, particularly in proactiveness, achieve higher organizational performance.

The accelerating pace of AI innovation, as highlighted by Vasant et al. (2022), necessitates the identification and integration of appropriate AI capabilities into decision processes to maintain a competitive edge.

This trend is further supported by Alferyev et al. (2020), who justify the promotion of AI at the state level, emphasizing AI's role in providing a competitive market advantage. Lee et al. (2019) focus on AI's transformative impact on business models, suggesting that proactive AI adoption can drive disruptive innovation. Aligning with these insights, Kavandi and Westerlund (2015) explored how entrepreneurial marketing, underpinned by an EO that includes proactiveness, fosters the adoption of smart technologies. Hughes and Morgan (2007) and Veen and Wakkee (2009) also highlighted the direct correlation between proactiveness and effective technology adoption in high-tech and SME sectors, respectively.

These collective findings demonstrate that proactiveness, as an integral aspect of EO, significantly predicts a firm's inclination to adopt new technologies. Firms with a proactive orientation are more likely to recognize and leverage the potential of emerging technologies like AI, thereby gaining a competitive advantage. This theoretical grounding informs the development of a key questionnaire item: 'Is your firm actively planning to use AI in business operations within the next 12 months?' This question aims to capture the essence of proactiveness in the context of AI adoption, offering valuable insights into how forward-looking strategies influence technological integration in SMEs.

In constructing the questionnaire items for AI adoption, significant emphasis was placed on the interplay between risk-taking and the propensity to invest in innovative technologies like AI. This relationship is underpinned by research indicating that firms exhibiting higher levels of risk-taking are more inclined to invest in disruptive technologies such as AI, even in the absence of immediate financial returns. Cox and Lowrie (2013) and Demary and Goecke (2019) highlight the dual perception of AI as both a risk and an opportunity, underscoring the necessity for firms to engage in risk-taking behaviour to maintain a competitive edge. Similarly, Ernst et al. (2019) discuss AI's potential to enhance productivity while balancing the risks and opportunities it presents, including considerations of inequality and long-term benefits.

The field of ophthalmology and optometry, as explored by Zarkin (2020), provides a compelling example of how the medical sector is embracing AI despite potential uncertainties, further emphasizing the role of risk-taking in the adoption of emerging technologies. Extensive research on Entrepreneurial Orientation reveals that risk-taking, as a fundamental aspect of EO, significantly influences the adoption of technologies like AI. Studies by Pérez-Luño et al. (2011), and Tajeddini et al. (2020) collectively illustrate that risk-taking not only fosters technological adoption but also enhances innovation and competitive positioning in various industries, including IT, hospitality, and more.

These insights inform the development of a key questionnaire item tailored to capture a firm's willingness to embrace emerging and less established AI technologies: 'Is your firm willing to adopt AI technologies that are still emerging and less established?' This question aims to gauge the extent of risk-taking behaviour in the context of AI adoption, reflecting how SMEs' agility and flexibility might influence their approach to new technological advancements. It encapsulates the essence of EO's risk-taking dimension in the decision-making process surrounding AI adoption, offering valuable insights into how SMEs navigate the opportunities and challenges presented by AI.

Finalizing the AI Adoption Measurement Tool

In conclusion, the development of the AI adoption measurement tool, detailed in Table 3, adopts a 7-point Likert scale, a choice that aligns with established academic research standards, particularly in psychology, marketing, and social sciences. This scale not only ensures depth and precision in data collection but also facilitates consistency and comparability within this study, especially since it mirrors the scale used for measuring Entrepreneurial Orientation (EO). The finalized measure, encapsulating key aspects of AI adoption within the EO framework, offers a robust tool for assessing AI integration in SMEs. Reflecting both theoretical underpinnings and practical application, this tool is well-positioned to yield valuable insights into the dynamics of AI adoption in relation to entrepreneurial characteristics.

Table 3. AI Adoption Measurement Tool.

Item	Description	Question	Range
In	Innovativeness	Has your firm adopted AI (Artificial Intelligence) technologies to innovate your product or service offerings?	1=Not at all, 7=Extensively
Pro	Proactiveness	Is your firm actively planning to use AI (Artificial Intelligence) in business operations within the next 12 months?	1=Not at all, 7=Definitely
Ris	Risk-taking	Is your firm willing to adopt AI (Artificial Intelligence) technologies that are still emerging and less established?	1=Not at all, 7=Absolutely

Source: Own Research

Entrepreneurial Orientation Measurement

Understanding the strategic posture of organizations, particularly in SMEs within the Czech chemical industry, is

pivotal for comprehending market dynamics and competitive behaviour. In this regard, the concept of Entrepreneurial Orientation has been instrumental. Predominantly based on Miller (2011) unidimensional construct of three dimensions, EO has been extensively validated globally, underscoring its universal applicability and robustness.

Central to the measurement of EO in this research is the scale developed by Covin and Slevin (1989), a tool that has withstood rigorous testing across diverse industries and regions, earning accolades for its validity and reliability (Rauch et al., 2009). The choice of this scale for our study hinges on several key factors:

- **Cross-National Applicability:** Its proven efficacy in various international contexts, as evidenced by Hansen et al. (2011), makes the Covin and Slevin scale ideally suited for application in the Czech chemical industry, a sector marked by both local nuances and global trends.
- **Relevance to SMEs:** The scale's validation in SME contexts, highlighted in Kreiser et al. (2002) multi-country analysis, aligns perfectly with this study's focus on SMEs in the Czech chemical sector.

The scale, as presented in Table 4, consists of nine items categorized to assess innovation, proactiveness, and risk-taking, using a seven-point Likert scale. This format ensures a nuanced capture of an organization's entrepreneurial tendencies, with higher scores reflecting a stronger entrepreneurial orientation.

In conclusion, the selection of the scale is a strategic decision (Covin and Slevin, 1989), aligning with this research's objectives to deeply understand EO within SMEs in the Czech chemical industry. Its proven track record in diverse contexts, specific relevance to SMEs, and comprehensive nature make it an invaluable tool for this study, despite the scale's general limitations, such as its static nature and narrow scope in new market entry. This tool's application is expected to yield insightful data, crucial for drawing meaningful conclusions about the role of EO in this sector.

Table 4. The EO Measurement Scale.

"In general, the top managers of my firm favour..."		
...a strong emphasis on the marketing of tried-and-true products or services	1 - 2 - 3 - 4 - 5 - 6 - 7	...a strong emphasis on R&D, technological leadership, and innovation"
"How many new lines of products or services has your firm marketed in the past five years?"		
No new lines of products or services	1 - 2 - 3 - 4 - 5 - 6 - 7	Very many new lines of products or services
Changes in product or service lines have been mostly of a minor nature	1 - 2 - 3 - 4 - 5 - 6 - 7	Changes in product or service lines have usually been quite dramatic"
"In dealing with its competitors, my firm..."		
...typically responds to actions which competitors initiate	1 - 2 - 3 - 4 - 5 - 6 - 7	...typically initiates actions which competitors then respond to
...is very seldom the first business to introduce new products/services, administrative techniques, operating technologies, etc.	1 - 2 - 3 - 4 - 5 - 6 - 7	...is very often the first business to introduce new products/services, administrative techniques, operating technologies, etc.
...typically seeks to avoid competitive clashes, preferring a "live-and-let-live" posture	1 - 2 - 3 - 4 - 5 - 6 - 7	...typically adopts a very competitive, "undo-the-competitors" posture"
"In general, the top managers of my firm believe that..."		
...a strong proclivity for low-risk projects (with normal and certain rates of returns)	1 - 2 - 3 - 4 - 5 - 6 - 7	...a strong proclivity for high-risk projects (with chances of very high returns)"
"In general, the top managers of my firm believe that..."		
...owing to the nature of the environment, it is best to explore it gradually via timid, incremental behaviour	1 - 2 - 3 - 4 - 5 - 6 - 7	...owing to the nature of the environment, bold, wide-ranging acts are necessary to achieve the firm's objectives"
"When confronted with decision-making situations involving uncertainty, my firm..."		
...typically adopts a cautious, "wait-and-see" posture in order to minimise the probability of making costly decisions	1 - 2 - 3 - 4 - 5 - 6 - 7	...typically adopts a bold, aggressive posture in order to maximise the probability of exploiting potential opportunities"

Source: Covin and Slevin (1989)

Sample and Data Collection

The initial phase of this research, conducted in May and June 2023, targeted a carefully selected sample of 107 small and medium-sized enterprises within the Czech Republic's chemical industry. This selection was based on the official EU definition of SMEs as set out in the European Commission (2003), considering factors such as company size, workforce, and financial thresholds. The criteria for selection, including NACE code 20 classification

for chemical industries and categorization as medium-high tech, are detailed in Table 5. Micro enterprises were excluded to enhance comparability and focus within the sample. Companies were identified from the Amadeus database, which is known for its exhaustive collection of data on European companies. This methodical approach, following recommendations by Saunila (2017) and Pérez-Luño et al. (2011), was instrumental in providing a comprehensive examination of SMEs within the selected sector.

Table 5. Search Strategy.

Step No.	Description	Step result	Search result
1	"Status: Active companies"	20,957,993	20,957,993
2	"Region/Country/region in country: Czech Republic"	510,466	504,561
3	"NACE Rev. 2 (Primary codes only): 20 - Manufacture of chemicals and chemical products"	47,863	1,031
4	"Number of employees: Last available year, min=10, max=249, exclusion of companies with no recent financial data"	2,615,706	215
5	"Operating revenue (Turnover) (th EUR): Last available year, max=50,000, exclusion of companies with no recent financial data"	920,757	136
6	"Total assets (th EUR): Last available year, min=2,000, max=43,000, exclusion of companies with no recent financial data"	1,402,614	107

Source: Amadeus (1.5.2023)

During the initial data collection, the average company in the sample employed 85 workers and had been in operation for 20 years, with the youngest and oldest companies being 3 and 47 years old, respectively. In terms of financial performance, these firms averaged 12.5 million EUR in annual sales. A notable observation is that 58.88% of these companies were established in the 1990s, a period of significant economic transition in the region.

Data was gathered using a sophisticated email campaign via (Ecomail.cz, 2023), complemented by follow-up calls to enhance response rates. This methodology yielded a total of 9 complete responses, as detailed in Table 6. To assess non-response bias, a comparative analysis of respondents and non-respondents based on employee count and revenue was conducted, revealing no significant differences, and thus mitigating concerns regarding non-response bias.

Table 6. Data Collection Summary.

Day No.	Action	Responses	% of n
1	Initial emails sent	2	1.87
8 - 15	Follow up calls	3	2.80
16	First email remainder	1	0.93
23 - 30	Follow up calls	2	1.87
31	Second email remainder	0	0.00
38 - 45	Follow up calls	1	0.93
	TOTAL	9	8.40

Source: Own Research

In preparation for the main study and the introduction of AI adoption as a new dependent variable, a second phase of data collection using a newly developed measurement tool was initiated in November 2023. This phase involved re-engaging with the initial respondents to gather additional data pertinent to AI adoption. Despite the time gap between the two phases, this approach was essential for testing the newly developed instrument and obtaining preliminary data for the pilot study. Collins and Graham (2002) highlights the risks of spacing observations too far apart in longitudinal studies; however, in this case, the differing focus of the two data collection phases (initially on EO and subsequently on AI adoption) mitigates potential concerns regarding the time gap. Moreover, as the primary objective of this pilot study was not hypothesis testing but rather the validation of the research plan and instruments, the inclusion of this new dimension aligns well with the study's goals.

In conclusion, the two-phased approach to data collection, while presenting challenges related to the time gap, offers a unique opportunity to understand the evolving dynamics within the sample group. This methodology not only aligns with the overall research objectives but also contributes to a deeper understanding of EO and AI adoption in SMEs within the Czech chemical industry.

Control Variables

The author controlled for the firm's size and age. The data were obtained from the Amadeus database. No control variable for the industry was established as all firms in the sample were from the same industry represented by NACE code 20. The size of the variable was determined based on the number of employees and due to its wide distribution, the variable was subjected to a log transformation.

Results

This chapter presents the findings from the pilot study on Entrepreneurial Orientation (EO) and AI Adoption among small and medium-sized enterprises in the Czech chemical industry. The results are structured into three sections: an overview of the response rate and data collection, descriptive statistics of EO and AI Adoption, and the analysis of internal consistency and correlations between these constructs.

Response Rate and Data Collection Overview

The study initially identified 107 firms fitting the selection criteria, but only 9 responses were received, resulting in a response rate of 8.41%. This low response rate, albeit reasonable given the specificity of the target population, suggests that the Czech SMEs in the chemical sector represent a relatively small pool of potential respondents. Each response was meticulously entered into a spreadsheet, culminating in a comprehensive dataset (Table 7) that encapsulates individual scores across EO dimensions and AI Adoption for each participating firm.

Table 7. Summary of the questionnaire responses.

Var. Dim. Ind.	Entrepreneurial Orientation									AI Adoption		
	Innovativeness			Proactiveness			Risk-taking			AI1	AI2	AI3
	In1	In2	In3	Pr1	Pr2	Pr3	Ri1	Ri2	Ri3			
Firm1	5	5	5	5	2	4	3	5	3	1	1	1
Firm2	3	3	4	4	4	5	5	5	5	1	2	2
Firm3	3	6	4	3	3	4	2	5	5	1	1	1
Firm4	5	2	5	5	5	4	5	5	4	1	1	1
Firm5	4	4	4	6	7	4	5	6	6	1	1	1
Firm6	3	3	3	6	5	3	3	4	4	1	3	4
Firm7	7	7	6	5	6	6	5	6	6	1	1	3
Firm8	5	4	5	5	5	5	4	5	5	2	4	2
Firm9	5	3	5	5	7	4	5	5	5	2	5	3

Source: Own Research

Descriptive Statistics

Descriptive statistics of the collected data are summarized in Table 8. The dimensions of EO, encompassing Innovativeness, Proactiveness, and Risk-taking, along with AI Adoption, exhibited a range of responses, with no visible outliers or missing values. The mean scores for Innovativeness, Proactiveness, Risk-taking, overall EO, and AI Adoption were 13.11, 14.11, 14.00, 41.22, and 5.33, respectively. Notably, the standard deviation values suggest a moderate spread in the responses across firms.

Table 8. Descriptive statistics.

	Mean	Median	Sum	Min.	Max.	Range	Standard Dev.	Cronbach Alpha
Innovativeness	13.11	13.00	118.0	9.00	20.00	11.00	3.18	0.73
Proactiveness	14.11	14.00	127.0	10.00	17.00	7.00	2.47	0.40
Risk-taking	14.00	14.00	126.0	11.00	17.00	6.00	2.29	0.73
EO	41.22	40.00	371.0	34.00	54.00	20.00	6.30	0.77
AI adoption	5.33	5.00	48.0	3.00	10.00	7.00	2.69	0.71

Source: Own Research

Internal Consistency and Correlation Analysis

Cronbach's alpha was calculated to assess the internal consistency of the EO and AI Adoption scales. The results, detailed in Table 2, reveal that the overall EO scale demonstrated satisfactory internal consistency ($\alpha = 0.77$), as did the dimensions of Innovativeness ($\alpha = 0.73$) and Risk-taking ($\alpha = 0.73$). However, the dimension of Proactiveness initially showed lower consistency ($\alpha = 0.40$), which improved to 0.63 upon the exclusion of one

indicator (Pr3). This adjustment aligns with the unidimensional conceptualization of EO by (Miller, 2011). Similarly, the AI Adoption scale showed a satisfactory level of internal consistency ($\alpha = 0.71$).

The correlation analysis (Table 9) revealed interesting patterns. The dimensions of EO (Innovativeness, Proactiveness, and Risk-taking) showed significant positive correlations with each other. However, when correlating these dimensions with AI Adoption, only Proactiveness exhibited a moderate positive correlation ($r = 0.39$), while Innovativeness and Risk-taking showed no significant correlation with AI Adoption.

Table 9. Correlations.

	Means	Std. Dev.	IN	PR	RI	EO	AI
Innovativeness	13.11	3.18	1.00				
Proactiveness	14.11	2.47	0.25	1.00			
Risk-taking	14.00	2.29	0.36	0.79	1.00		
EO	41.22	6.30	0.73	0.81	0.86	1.00	
AI adoption	5.33	2.69	-0.14	0.39	0.00	0.08	1.00

Source: Own Research

Summary of Findings

The results of this pilot study provide valuable insights into the EO and AI Adoption among Czech chemical industry SMEs. While the response rate was lower than anticipated, the richness of the data collected offers a unique window into the entrepreneurial dynamics of this sector. The internal consistency of the scales used, and the correlation results lay a foundational basis for further exploration in the main study, particularly in understanding the nuanced relationship between EO dimensions and AI Adoption.

Discussion

This pilot study lays essential groundwork for a main study hypothesizing a positive correlation between Entrepreneurial Orientation and firm performance in the Czech chemical industry. Additionally, it explores the premise that firms with higher EO are more inclined to adopt AI technology. This exploration aligns with the objectives to assess research feasibility, develop an AI adoption tool, conduct preliminary tests, and analyse initial data.

The modest response rate of 8.40% from a small pool of Czech chemical SMEs suggests challenges in engaging a broader sample, a common issue in social science research (Saunders et al., 2023). This low rate could be attributed to the targeted top managers' busy schedules and a general reluctance to respond to questionnaires. The questionnaire distribution method, via Ecomail.cz, might have also impacted the response rate, potentially being flagged as spam, a challenge noted by Casillas et al. (2011). This raises a concern for the main study: ensuring sufficient response rates for statistical significance.

To address this, expanding the industry focus to include pharma and the plastic industry is considered, aligning with the approach of Svaz chemického průmyslu ČR (2017). Alternatively, capturing EO through innovative research methods is contemplated. This includes measuring firm behaviour through content analysis, Computer-Aided Text Analysis (CATA), and Psychological Assessment via Text Input (PATI), as well as assessing resource allocation via financial statement information (White et al., 2021). These methods could potentially circumvent the challenge of low response rates by deriving insights from content analysis instead of relying solely on questionnaire responses. However, the novelty of these methods presents a limitation, as there are comparatively fewer research papers to guide their application. Additionally, the limited publicly available information on SMEs compared to large corporations could restrict the efficacy of content analysis in SME contexts, potentially rendering this approach challenging or even infeasible.

The descriptive statistics showcased a wide spectrum of responses, reflecting a diverse sample. The Cronbach's alpha of 0.77 for EO aligns with findings in studies like Rauch et al. (2009), confirming the reliability of the EO measurement. The newly developed AI adoption tool's Cronbach's alpha of 0.71 also indicates promising reliability. However, the unexpected low correlation between EO and AI adoption, coupled with low AI adoption scores, contrasts with findings from studies like Baldegger et al. (2020), suggesting the need for further investigation in the main study. The sample's characteristics, such as the average size and revenue, reaffirm SMEs' economic significance, supporting the discussion in the second chapter. The stability of the industry is highlighted by the average age of the companies, with many thriving since the 1990s market transition.

This pilot study, while primarily aimed at guiding the main study, makes significant contributions beyond its immediate objectives. One of the key achievements of this study is the development of a new measurement tool for AI adoption. This tool not only aids in addressing the gap in existing literature but also provides a valuable resource for future research in various contexts. The creation of the AI adoption tool is particularly impactful as it

offers a novel method for quantifying AI integration within organizations, a topic that has not been extensively explored in the context of entrepreneurial orientation. This tool can be instrumental for other researchers seeking to understand the dynamics of AI adoption in different industries or geographical settings.

Additionally, the pilot study contributes to the broader understanding of EO's relationship with firm performance and AI adoption, particularly in the underexplored context of Czech chemical SMEs. By providing preliminary insights into these relationships, the study lays a foundation for more extensive research in these areas. It also opens avenues for future studies to build upon the initial findings and explore the nuances of EO and AI adoption across various business environments.

Furthermore, the methodology and approach adopted in this pilot study offer a template for similar research endeavours in small and niche markets. The challenges and solutions identified in conducting this pilot study, such as addressing low response rates and exploring alternative data collection methods, provide valuable lessons for conducting effective research in specialized industry segments.

Limitations

This study, while laying foundational groundwork for future research into the interplay between Entrepreneurial Orientation, Artificial Intelligence adoption, and performance within Czech chemical SMEs, acknowledges several limitations that warrant careful consideration.

Firstly, the small sample size, although common in niche market research, limits the generalizability of our findings. This constraint impacts our ability to conduct extensive statistical analyses and necessitates caution in extrapolating our results to the broader SME context. Future studies should aim to expand the sample size to enhance the robustness and applicability of the findings.

Secondly, the AI adoption measurement tool developed for this study prioritizes simplicity, featuring a limited number of indicators. While this approach aids in the tool's applicability across different settings, it may constrain the depth of insights into AI adoption dynamics. Future iterations of this tool would benefit from incorporating a broader array of indicators, allowing for a more nuanced understanding of AI adoption processes.

Additionally, the temporal gap between the two phases of data collection introduces a methodological concern. Although this study manages the gap effectively given its pilot nature, such intervals could affect response consistency. Future research endeavours should seek to minimize these time delays to ensure a more coherent and reliable data collection process.

The reliance on self-reported data, typical of questionnaire-based research, introduces the potential for subjective bias, affecting the data's objectivity. To mitigate this, future studies might consider triangulating findings with alternative data sources, such as observational or qualitative data, to strengthen the validity of the conclusions drawn.

Lastly, the focus on Czech chemical SMEs, while providing valuable localized insights, restricts the study's broader applicability. Extending the research to encompass other industries or geographical areas could offer a more comprehensive understanding of EO and AI adoption's interplay.

Directions of Future Research

In light of these limitations, future research is encouraged to explore the application of the AI adoption tool in varied settings, particularly focusing on larger sample sizes and considering potential advancements in its development. Emphasis should be on employing diverse research designs to thoroughly examine the interplay between entrepreneurial orientation, AI adoption, and performance within narrowly defined segments characterised by small populations. Innovative research methodologies, such as sequential sampling (Ulrich and Miller, 2021), generalization adjustments (Tipton et al., 2017), and strategies for increasing sample sizes (Dolnicar et al., 2016), present valuable alternatives to conventional questionnaire-based approaches in these specific contexts. These methods are particularly beneficial in overcoming the inherent limitations associated with traditional survey techniques when dealing with such specialised segments. Furthermore, future studies could benefit from integrating mixed methods approaches, combining quantitative tools like the AI adoption measure with qualitative analyses. This could involve in-depth interviews, case studies, or observational research to complement and enrich the quantitative data, providing a more holistic understanding of the dynamics at play. Lastly, considering the evolving nature of both entrepreneurial orientation and AI technology, longitudinal studies could offer valuable insights into how these relationships develop and change over time. Such studies would be particularly beneficial in capturing the long-term impacts and trends in AI adoption and entrepreneurial behaviour.

In summary, this pilot study not only aids in refining the main study's approach but also enhances the author's understanding of the subject matter, setting a solid foundation for future research in this domain.

Conclusion

This pilot study presents a pioneering exploration into the dynamic interplay between Entrepreneurial Orientation,

Artificial Intelligence adoption, and the performance of SMEs within the Czech chemical industry. Through this pilot study, I have addressed a significant gap in existing research by developing and preliminarily testing a novel measurement instrument for AI adoption, a critical step forward given the identified scarcity of such tools in the literature. Our study not only validates the feasibility of the proposed main research design but also enriches the theoretical and practical understanding of EO's role in fostering AI integration within this specific industrial context.

By focusing on a niche yet economically vital sector, this thesis contributes to a nuanced understanding of how SMEs in the Czech chemical industry navigate the challenges and opportunities of AI adoption, informed by their entrepreneurial orientations. This contribution is particularly salient against the backdrop of our findings, which suggest a complex relationship between EO, AI adoption, and SME performance, diverging from the more straightforward correlations posited in broader research.

Moreover, this work lays a robust foundation for subsequent comprehensive investigations, providing a methodological blueprint for engaging with specialized industries and geographical contexts. By doing so, it underscores the importance of adapting research strategies to fit the unique characteristics of the subject matter, ensuring both relevance and impact.

In summary, this thesis not only bridges a critical research gap by introducing a tailored AI adoption measurement tool but also illuminates the multifaceted influences of EO in the context of technological innovation within SMEs. As such, it offers valuable insights for academics, practitioners, and policymakers aiming to leverage the synergies between entrepreneurial orientation and technological advancement to enhance firm performance.

References

- Ashraf, N., Camerer, C. F., & Loewenstein, G. (2005). Adam Smith, Behavioral Economist. *Journal of Economic Perspectives*, 19(3), 131-145.
- Finney, J. (1970). *Time and again*. New York, NY: Simon and Schuster.
- Gravetter, F. J., Wallnau, L. B., Forzano, L. A. B., & Witnauer, J. E. (2020). *Essentials of Statistics for the Behavioral Sciences*. Cengage Learning.
- Krishnamachari, B., Wicker, S. B., Bejar, R., & Pearlman, M. (2002). Critical Density Thresholds in Distributed Wireless Networks. Book chapter. In *Communications, Information and Network Security*.
- Razumova, I., & Kalimullina, O. (2017). Research of Innovation Cycles and the Peculiarities Associated with the Innovations Life Cycle Stages. In Proceedings of the 29th International Business Information Management Association Conference 2017 (pp. 1853-1862).
- Akbari, P., & Baharestan, O. (2013). The Analysis of the Impact of Information Technology and Social Capital on Entrepreneurial Orientation in Iran Pharmaceutical Industry. *International Journal of Management and Business Research*, 2013(3), 215-232.
- Alekseeva, L., Gine, M., Samila, S., & Taska, B. (2020). AI Adoption and Firm Performance: Management versus IT. *SSRN Electronic Journal*, 2020(1), 1-40. <https://doi.org/10.2139/ssrn.3677237>.
- Alferyev, D., Khusainova, E., Fedyukhin, A., & Dixit, S. (2020). Ai Technologies as a Factor of Competitiveness of a Business Entity at the Present Stage of Human Development. *E3S Web of Conferences*, 220(1), 1-11. <https://doi.org/10.1051/e3sconf/202022001006>.
- Alsheibani, S., Cheung, Y., & Messon, C. (2018). Artificial Intelligence Adoption: AI-readiness at Firm-Level. *PACIS*, 2018(1), 1-9. <https://aisel.aisnet.org/pacis2018/37>.
- Anderson, J. C., & Gerbing, D. W. (1991). Predicting the performance of measures in a confirmatory factor analysis with a pretest assessment of their substantive validities. *Journal of Applied Psychology*, 76(5), 732-740. <https://doi.org/10.1037/0021-9010.76.5.732>.
- Arain, M., Campbell, M. J., Cooper, C. L., & Lancaster, G. A. (2010). What is a pilot or feasibility study? A review of current practice and editorial policy. *BMC Medical Research Methodology*, 10(1). <https://doi.org/10.1186/1471-2288-10-67>.
- Baldegger, R., Caon, M., & Sadiku, K. (2020). Correlation between Entrepreneurial Orientation and Implementation of AI in Human Resource Management (HRM). *Technology Innovation Management Review*, 10(4), 72-79. <https://doi.org/http://doi.org/10.22215/timreview/1348>.
- Baldegger, R., Wild, P., & Schueffel, P. (2021). The Effects of Entrepreneurial Orientation in a Digital and International Setting. In A. C. Corbett, P. M. Kreiser, L. D. Marino, and W. J. Wales, *Entrepreneurial Orientation: Epistemological, Theoretical, and Empirical Perspectives* (22nd ed., pp. 145-174). Emerald Publishing Limited.
- Camisón, C., & Villar-López, A. (2014). Organizational innovation as an enabler of technological innovation capabilities and firm performance. *Journal of Business Research*, 67(1), 2891-2902. <https://doi.org/10.1016/j.jbusres.2012.06.004>.
- Cannavale, C., Esemio Tamaro, A., Leone, D., & Schiavone, F. (2022). Innovation adoption in inter-organizational healthcare networks – the role of artificial intelligence. *European Journal of Innovation Management*, 25(6), 758-774. <https://doi.org/10.1108/EJIM-08-2021-0378>.
- Casillas, J. C., Moreno, A. M., & Barbero, J. L. (2011). Entrepreneurial orientation of family firms: Family and environmental dimensions. *Journal of Family Business Strategy*, 2(2), 90-100. <https://doi.org/10.1016/j.jfbs.2011.03.002>.
- Chan, C. L., Leyrat, C., & Eldridge, S. M. (2017). Quality of reporting of pilot and feasibility cluster randomised trials: a systematic review. *BMJ Open*, 7(11), 1-14. <https://doi.org/10.1136/bmjopen-2017-016970>.
- Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, 170(1), 1-14. <https://doi.org/10.1016/j.techfore.2021.120880>.
- Chemical and Pharmaceutical Industry in the Czech Republic. (2010). *Czech Business and Trade*, 2010(4), 8-10.

<http://search.ebscohost.com.ezproxy.lib.vutbr.cz/login.aspx?direct=true&db=bth&AN=55697534&lang=cs&site=ehost-live>.

- Chen, D., Esperança, J. P., & Wang, S. (2022). The Impact of Artificial Intelligence on Firm Performance: An Application of the Resource-Based View to e-Commerce Firms. *Frontiers in Psychology*, 13(1), 1-14. <https://doi.org/10.3389/fpsyg.2022.884830>.
- Churchill, G. A. (1979). A Paradigm for Developing Better Measures of Marketing Constructs. *Journal of Marketing Research*, 16(1), 64-73. <https://doi.org/10.2307/3150876>.
- Collins, L. M., & Graham, J. W. (2002). The effect of the timing and spacing of observations in longitudinal studies of tobacco and other drug use: temporal design considerations. *Drug and Alcohol Dependence*, 68(1), 85-96. [https://doi.org/10.1016/S0376-8716\(02\)00217-X](https://doi.org/10.1016/S0376-8716(02)00217-X).
- Converse, J. M., and Presser, S. (1986). *Survey Questions Handcrafting the Standardized Questionnaire* (1st ed.). Sage.
- Covin, J. G., & Slevin, D. P. (1989). The strategic management of small firms in hostile and benign environments. *Strategic Management Journal*, 10(1), 75-87.
- Cowden, B., & Tang, J. (2021). Enhancing Entrepreneurial Orientation Research: From Theorizing to Measuring. In A. C. Corbett, P. M. Kreiser, L. D. Marino, and W. J. Wales (Eds.), *Entrepreneurial Orientation: Epistemological, Theoretical, and Empirical Perspectives* (pp. 69-86). Emerald Publishing Limited. <https://doi.org/10.1108/S1074-754020210000022003>.
- Cox, T., & Lowrie, K. (2013). From the Editors. *Risk Analysis*, 33(6), 945-947. <https://doi.org/10.1111/risa.12075>.
- Dasan, P. (2013). Small and Medium enterprise assessment in Czech Republic and Russia using marketing analytics methodology. *Central European Business Review*, 2(4), 1-14. <https://www.ceeol.com/search/article-detail?id=10486>.
- De Vaus, D. (2013). *Surveys In Social Research* (6 ed.). Routledge. <https://doi.org/10.4324/9780203519196>.
- Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Kraymer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality. *SSRN Electronic Journal*, 2023(24-013), 1-58. <https://doi.org/10.2139/ssrn.4573321>.
- Demary, V., & Goecke, H. (2019). Artificial Intelligence: German companies between risk and opportunity. *Econstor*, 46(4), 3-18. <https://doi.org/10.2373/1864-810X.19-04-01>.
- Dess, G. G., & Lumpkin, G. T. (2005). The Role of Entrepreneurial Orientation in Stimulating Effective Corporate Entrepreneurship. *Academy of Management Perspectives*, 19(1), 147-156. <https://doi.org/10.5465/AME.2005.15841975>.
- Dolnicar, S., Grün, B., & Leisch, F. (2016). Increasing sample size compensates for data problems in segmentation studies. *Journal of Business Research*, 69(2), 992-999. <https://doi.org/10.1016/j.jbusres.2015.09.004>.
- Drost, E. A. (2011). Validity and Reliability in Social Science Research. *Education Research and Perspectives*, 38(1), 105-124. <https://doi.org/10.3316/informit.491551710186460>.
- Dubey, R., Gunasekaran, A., Childe, S. J., Fosso Wamba, S., & Papadopoulos, T. (2015). Enablers of Six Sigma: contextual framework and its empirical validation. *Total Quality Management and Business Excellence*, 27(11-12), 1346-1372. <https://doi.org/10.1080/14783363.2015.1075877>.
- Duguid, D. (2021). *£11 million boost for energy entrepreneurs to turn green dreams into reality: Press Release*. Gov.uk. Retrieved January 22, 2022, from <https://www.gov.uk/government/news/11-million-boost-for-energy-entrepreneurs-to-turn-green-dreams-into-reality>.
- Ecomail.cz. (2023). Retrieved February 14, 2023, from www.ecomail.cz.
- Eisenhardt, K. M. (1989). Building Theories from Case Study Research. *Academy of Management Review*, 14(4), 532-550. <https://doi.org/10.5465/amr.1989.4308385>.
- Endres, H., & Endres, H. (2018). A New Empirical Study. In *Adaptability Through Dynamic Capabilities* (1st ed., pp. 97-132). Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-20157-9_6.
- Ernst, E., Merola, R., & Samaan, D. (2019). Economics of Artificial Intelligence: Implications for the Future of Work. *IZA Journal of Labor Policy*, 9(1), 1-14. <https://doi.org/10.2478/izajolp-2019-0004>.
- EU27 - SME Fact Sheet 2021. (2021). European Commission. Retrieved January 23, 2022, from <https://ec.europa.eu/docsroom/documents/46060>.
- European Commission. (2003). Commission Recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises (2003/361/EC). *Official Journal of the European Union*, 20(1), 36. <http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:124:0036:0041:en:PDF>.
- Faturachman, D. (2023). The Effect of Innovation on Company Performance. *Journal Akuntansi dan Keuangan Indonesia*, 20(2), 1-5. <https://doi.org/https://doi.org/10.21002/jaki.2023.11>.
- Fraser, J., Fahlman, D. W., Arscott, J., & Guillot, I. (2018). Pilot Testing for Feasibility in a Study of Student Retention and Attrition in Online Undergraduate Programs. *The International Review of Research in Open and Distributed Learning*, 19(1). <https://doi.org/10.19173/irrodl.v19i1.3326>.
- Gioia, D. (2021). A Systematic Methodology for Doing Qualitative Research. *The Journal of Applied Behavioral Science*, 57(1), 20-29. <https://doi.org/10.1177/0021886320982715>.
- Giotopoulos, I., Kontolaimou, A., Korra, E., & Tsakanikas, A. (2017). What drives ICT adoption by SMEs? Evidence from a large-scale survey in Greece. *Journal of Business Research*, 81(1), 60-69. <https://doi.org/10.1016/j.jbusres.2017.08.007>.
- Giuggioli, G., & Pellegrini, M. M. (2022). Artificial intelligence as an enabler for entrepreneurs: a systematic literature review and an agenda for future research. *International Journal of Entrepreneurial Behavior and Research*, 29(4), 816-837. <https://doi.org/10.1108/IJEBr-05-2021-0426>.
- Gürlek, M., & Çemberci, M. (2020). Understanding the relationships among knowledge-oriented leadership, knowledge management capacity, innovation performance and organizational performance. *Kybernetes*, 49(11), 2819-2846. <https://doi.org/10.1108/K-09-2019-0632>.
- Hansen, J. D., Deitz, G. D., Tokman, M., Marino, L. D., & Weaver, K. M. (2011). Cross-national invariance of the entrepreneurial orientation scale. *Journal of Business Venturing*, 26(1), 61-78. <https://doi.org/10.1016/j.jbusvent.2009.05.003>.

- Heinze, K. L., & Heinze, J. E. (2020). Individual innovation adoption and the role of organizational culture. *Review of Managerial Science*, 14(3), 561-586. <https://doi.org/10.1007/s11846-018-0300-5>.
- Hruby, V. (2021). Structural Equation Modelling in the Research of Entrepreneurial Orientation: A Systematic Literature Review. In *DOKBAT 2021 - 17th International Bata Conference for Ph.D. Students and Young Researchers* (pp. 215-229). Univerzita Tomase Bati ve Zline. <https://doi.org/10.7441/dokbat.2021>.
- Hrubý, V., & Koráb. (2018). Performance of Small and Medium-sized Enterprises in the Chemical Industry in the Czech Republic – An Exploratory Analysis. *Trends, Economics and Management*, 2018(31), 9-18. <https://doi.org/https://doi.org/10.13164/trends.2018.31.9>.
- Huang, M. H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science*, 49(1), 30-50. <https://doi.org/10.1007/s11747-020-00749-9>.
- Hughes, M., & Morgan, R. E. (2007). Deconstructing the relationship between entrepreneurial orientation and business performance at the embryonic stage of firm growth. *Industrial Marketing Management*, 36(5), 651-661. <https://doi.org/10.1016/j.indmarman.2006.04.003>.
- Ipinnaie, O., Dineen, D., & Lenihan, H. (2017). Drivers of SME performance: a holistic and multivariate approach. *Small Business Economics*, 48(4), 883-911. <https://doi.org/10.1007/s11187-016-9819-5>.
- Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, 62(1), 15-25. <https://doi.org/10.1016/j.bushor.2018.08.004>.
- Kavandi, H., & Westerlund, M. (2015). Using Entrepreneurial Marketing to Foster Reseller Adoption of Smart Micro-Grid Technology. *Technology Innovation Management Review*, 5(9), 5-16. <https://timreview.ca/article/925>.
- Kim, Y. (2011). The Pilot Study in Qualitative Inquiry. *Qualitative Social Work*, 10(2), 190-206. <https://doi.org/10.1177/1473325010362001>.
- Kreiser, P. M., Marino, L. D., & Weaver, K. M. (2002). Assessing the Psychometric Properties of the Entrepreneurial Orientation Scale: A Multi-Country Analysis. *Entrepreneurship Theory and Practice*, 26(4), 71-93. <https://doi.org/10.1177/104225870202600405>.
- Lancaster, G. A., Dodd, S., & Williamson, P. R. (2004). Design and analysis of pilot studies: recommendations for good practice. *Journal of Evaluation in Clinical Practice*, 10(2), 307-312. <https://doi.org/10.1111/j.2002.384.doc.x>.
- Lee, J., Suh, T., Roy, D., and Baucus, M. (2019). Emerging Technology and Business Model Innovation: The Case of Artificial Intelligence. *Journal of Open Innovation: Technology, Market, and Complexity*, 5(3), 44-52. <https://doi.org/10.3390/joitmc5030044>.
- Lee, M. T., & Raschke, R. L. (2023). Stakeholder legitimacy in firm greening and financial performance: What about greenwashing temptations? *Journal of Business Research*, 155, 113393-113403. <https://doi.org/10.1016/j.jbusres.2022.113393>.
- Lee, M. T., & Suh, I. (2022). Understanding the effects of Environment, Social, and Governance conduct on financial performance: Arguments for a process and integrated modelling approach. *Sustainable Technology and Entrepreneurship*, 1(1), 100004 - 100014. <https://doi.org/10.1016/j.stae.2022.100004>.
- Leon, A. C., Davis, L. L., & Kraemer, H. C. (2011). The role and interpretation of pilot studies in clinical research. *Journal of Psychiatric Research*, 45(5), 626-629. <https://doi.org/10.1016/j.jpsychires.2010.10.008>.
- Lowe, N. K. (2019). What Is a Pilot Study? *Journal of Obstetric, Gynecologic and Neonatal Nursing*, 48(2), 117-118. <https://doi.org/10.1016/j.jogn.2019.01.005>.
- Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. *Academy of Management Review*, 21(1), 135-172. <https://doi.org/10.5465/AMR.1996.9602161568>.
- Lumpkin, G. T., & Pidduck, R. J. (2021). Global Entrepreneurial Orientation (GEO): An Updated, Multidimensional View of EO. In A. C. Corbett, P. M. Kreiser, L. D. Marino, & W. J. Wales (Eds.), *Entrepreneurial Orientation: Epistemological, Theoretical, and Empirical Perspectives* (pp. 17-68). Emerald Publishing Limited. <https://doi.org/10.1108/S1074-754020210000022002>.
- Malmqvist, J., Hellberg, K., Möllås, G., Rose, R., & Shevlin, M. (2019). Conducting the Pilot Study: A Neglected Part of the Research Process? Methodological Findings Supporting the Importance of Piloting in Qualitative Research Studies. *International Journal of Qualitative Methods*, 18. <https://doi.org/10.1177/1609406919878341>.
- Maresova, P., Rezny, L., Peter, L., Hajek, L., & Lefley, F. (2021). Do Regulatory Changes Seriously Affect the Medical Devices Industry? Evidence From the Czech Republic. *Frontiers in Public Health*, 9(2), 1-14. <https://doi.org/10.3389/fpubh.2021.666453>.
- Martín-Rojas, R., Fernández-Pérez, V., & García-Sánchez, E. (2017). Encouraging organizational performance through the influence of technological distinctive competencies on components of corporate entrepreneurship. *International Entrepreneurship and Management Journal*, 13(2), 397-426. <https://doi.org/10.1007/s11365-016-0406-7>.
- McNaughton, R. B., & Sembhi, R. S. (2021). Developing an Entrepreneurial Orientation: Capabilities and Impediments. In A. C. Corbett, P. M. Kreiser, L. D. Marino, and W. J. Wales (Eds.), *Entrepreneurial Orientation: Epistemological, Theoretical, and Empirical Perspectives* (pp. 121-143). Emerald Publishing Limited. <https://doi.org/10.1108/S1074-754020210000022005>.
- Miller, D. (2011). Miller (1983) Revisited: A Reflection on EO Research and Some Suggestions for the Future. *Entrepreneurship Theory and Practice*, 35(5), 873-894. <https://doi.org/10.1111/j.1540-6520.2011.00457.x>.
- Nasution, M. D. T. P., Rafiki, A., Lubis, A., & Rossanty, Y. (2021). Entrepreneurial orientation, knowledge management, dynamic capabilities towards e-commerce adoption of SMEs in Indonesia. *Journal of Science and Technology Policy Management*, 12(2), 256-282. <https://doi.org/10.1108/JSTPM-03-2020-0060>.
- Natrajan, N. S., Singh, S. K., & Sanjeev, R. (2022). Fostering CRM Through Artificial Intelligence. In S. Singh (Ed.), *Adoption and Implementation of AI in Customer Relationship Management* (2022nd ed., pp. 70-91). IGI Global. <https://doi.org/10.4018/978-1-7998-7959-6.ch005>.
- Neely, A., Gregory, M., & Platts, K. (1995). Performance measurement system design. *International Journal of Operations and Production Management*, 15(4), 80-116. <https://doi.org/10.1108/01443579510083622>.
- Pérez-Luño, A., Wiklund, J., & Cabrera, R. V. (2011). The dual nature of innovative activity: How entrepreneurial orientation

- influences innovation generation and adoption. *Journal of Business Venturing*, 26(5), 555-571. <https://doi.org/10.1016/j.jbusvent.2010.03.001>.
- Pisar, P., & Bilkova, D. (2019). Controlling as a tool for SME management with an emphasis on innovations in the context of Industry 4.0. *Equilibrium*, 14(4), 763-785.
- Polit, D. F., & Beck, C. T. (2016). *Nursing research: Generating and assessing evidence for nursing practice* (10 ed.). Wolters Kluwer.
- Popa, A. E., & Ciobanu, R. (2014). The Financial factors that Influence the Profitability of SMEs. *International Journal of Academic Research in Economics and Management Sciences*, 3(4), -. <https://doi.org/10.6007/IJAREMS/v3-i4/1117>.
- Raja Sreedharan, V., Raju, R., Rajkanth, R., & Nagaraj, M. (2016). An empirical assessment of Lean Six Sigma Awareness in manufacturing industries: construct development and validation. *Total Quality Management and Business Excellence*, 29(5-6), 686-703. <https://doi.org/10.1080/14783363.2016.1230470>.
- Rauch, A., Wiklund, J., Lumpkin, G. T., & Frese, M. (2009). Entrepreneurial Orientation and Business Performance: An Assessment of Past Research and Suggestions for the Future. *Entrepreneurship Theory and Practice*, 33(3), 761-787. <https://doi.org/10.1111/j.1540-6520.2009.00308.x>.
- Rehman, U. U., & Iqbal, A. (2020). Nexus of knowledge-oriented leadership, knowledge management, innovation and organizational performance in higher education. *Business Process Management Journal*, 26(6), 1731-1758. <https://doi.org/10.1108/BPMJ-07-2019-0274>.
- Robson, C., & McCartan, K. (2015). *Real World Research* (4 ed.). Wiley.
- Saunders, M., Lewis, P., & Thornhill, A. (2023). *Research Methods for Business Students* (9th). Pearson.
- Saunila, M. (2017). Understanding innovation performance measurement in SMEs. *Measuring Business Excellence*, 21(1), 1-16. <https://doi.org/10.1108/MBE-01-2016-0005>.
- Schumpeter, J. A. (2013). *Capitalism, Socialism and Democracy*. Taylor and Francis.
- Secomb, J. M., & Smith, C. (2014). A mixed method pilot study: The researchers' experiences. *Contemporary Nurse*, 39(1), 31-35. <https://doi.org/10.5172/conu.2011.39.1.31>.
- Slavec, A., Drnovšek, M., & Hisrich, R. D. (2017). Entrepreneurial openness: Concept development and measure validation. *European Management Journal*, 35(2), 211-223. <https://doi.org/10.1016/j.emj.2016.09.003>.
- Svaz chemického průmyslu ČR. (2017). *Ročenka 2016 o vývoji chemického průmyslu v ČR*. Svaz chemického průmyslu ČR. Retrieved November 21, 2017, from <https://www.schp.cz/info/schp>.
- Tajeddini, K., Martin, E., & Ali, A. (2020). Enhancing hospitality business performance: The role of entrepreneurial orientation and networking ties in a dynamic environment. *International Journal of Hospitality Management*, 90(1), 1-14. <https://doi.org/10.1016/j.ijhm.2020.102605>.
- Tejlingen, E. van, & Hundley, V. (2002). The importance of pilot studies. *Nursing Standard (through 2013)*, 16(40), 33-36.
- Tipton, E., Hallberg, K., Hedges, L. V., & Chan, W. (2017). Implications of Small Samples for Generalization: Adjustments and Rules of Thumb. *Evaluation Review*, 41(5), 472-505. <https://doi.org/10.1177/0193841X16655665>.
- Ulrich, R., & Miller, J. (2021). Alternative sequential methods in statistical testing: A reply to Lakens (2021) and Erdfelder and Schnuerch (2021). *Psychological Methods*, 26(4), 507-512. <https://doi.org/10.1037/met0000420>.
- Upadhyay, N., Upadhyay, S., Al-Debei, M. M., Baabdullah, A. M., & Dwivedi, Y. K. (2022). The influence of digital entrepreneurship and entrepreneurial orientation on intention of family businesses to adopt artificial intelligence: examining the mediating role of business innovativeness. *International Journal of Entrepreneurial Behavior and Research*, 29(1), 80-115. <https://doi.org/10.1108/IJEBR-02-2022-0154>.
- Vasant, P., Munapo, E., Thomas, J. J., & Weber, G. W. (Eds.). (2022). *Artificial Intelligence in Industry 4.0 and 5G Technology* (2022nd ed.). Wiley. <https://doi.org/10.1002/9781119798798>.
- Veen, M., & Wakkee, I. (2009). Value creation and the internet: entrepreneurial behaviour in Dutch SMEs, 8(1), 411-430. <https://www.inderscience.com/offers.php?id=25089>.
- Vrontis, D., Chaudhuri, R., & Chatterjee, S. (2022). Adoption of Digital Technologies by SMEs for Sustainability and Value Creation: Moderating Role of Entrepreneurial Orientation. *Sustainability*, 14(13), 1-19. <https://doi.org/10.3390/su14137949>.
- Wales, W. J. (2021). The status quo of research on entrepreneurial orientation: Conversational landmarks and theoretical scaffolding. *Journal of Business Research*, 2021(128), 564-577. <https://doi.org/https://doi.org/10.1016/j.jbusres.2020.10.046>.
- Wamba-Taguimdje, S. L., Wamba, S. F., Kamdjoug, J. R. K., & Wanko, C. E. T. (2020). Impact of Artificial Intelligence on Firm Performance: Exploring the Mediating Effect of Process-Oriented Dynamic Capabilities. In R. Agrifoglio, R. Lamboglia, D. Mancini, and F. Ricciardi (Eds.), *Digital Business Transformation* (2020 ed., pp. 3-18). Springer International Publishing. https://doi.org/10.1007/978-3-030-47355-6_1.
- Wei, R., & Pardo, C. (2022). Artificial intelligence and SMEs: How can B2B SMEs leverage AI platforms to integrate AI technologies? *Industrial Marketing Management*, 107(1), 466-483. <https://doi.org/10.1016/j.indmarman.2022.10.008>.
- White, J. V., Chaudhary, S., & Gupta, V. K. (2021). *Measurement of entrepreneurial orientation: A systematic critical synthesis of the empirical literature* (1st ed.). Emerald Publishing.
- Wiklund, J., & Shepherd, D. (2005). Entrepreneurial orientation and small business performance: a configurational approach. *Journal of Business Venturing*, 20(1), 71-91. <https://doi.org/10.1016/j.jbusvent.2004.01.001>.
- Zarbin, M. A. (2020). Artificial Intelligence: Quo Vadis? *Translational Vision Science and Technology*, 9(2), 1-15. <https://doi.org/10.1167/tvst.9.2.1>.