# ARTIFICIAL INTELLIGENCE IN SMALL AND MEDIUM-SIZED FAMILY FIRMS: AN EMPIRICAL STUDY ON THE IMPACT OF FAMILY INFLUENCE

Patrick Ulrich *, Vanessa Frank **, Ricardo Buettner ***

* *Corresponding author,* Aalen University, Aalen, Germany; University of Bamberg, Bamberg, Germany
Contact details: Aalen University, Beethovenstr. 1, 73430 Aalen, Germany
** Aalen University, Aalen, Germany
*** University of Bayreuth, Bayreuth, Germany

OPEN ACCESS

**How to cite this paper:** Ulrich, P., Frank, V., & Buettner, R. (2023). Artificial intelligence in small and medium-sized family firms: An empirical study on the impact of family influence. *Corporate Governance and Organizational Behavior Review, 7*(1), 72–80. https://doi.org/10.22495/cgobrv7i1p7



**ISSN Online:** 2521-1889
**ISSN Print:** 2521-1870

**Received:** 03.05.2022
**Accepted:** 01.02.2023

**JEL Classification:** M00, M15, M40
**DOI:** 10.22495/cgobrv7i1p7

## Abstract

Artificial intelligence (AI) is one of the most important technologies of the future (Crew, 2020). So far, however, AI has been insufficiently deployed. This applies not only to family businesses, but especially to them. In terms of decision-making, these companies have a number of specific characteristics which mean that they find AI less relevant and may also be skeptical. The article discusses specifics of AI use in family businesses on the basis of a German empirical study. The paper shows that family businesses use AI less frequently and are also less open to the technology than non-family businesses. Socioemotional wealth (SEW) (Gómez-Mejia et al., 2007) serves as the theoretical basis. Based on the SEW, it is argued that although family businesses are aware of the need to apply new theories, they have so far underestimated the potentials and tend to be rather skeptical about applying these technologies. This view is supported by the empirical study. In addition, some differences between small and medium-sized enterprises (SMEs) and large companies are also discussed in the paper.

**Keywords:** Artificial Intelligence, Socioemotional Wealth, Family Firms, Empirical Study

**Authors' individual contribution:** Conceptualization — P.U.; Methodology — P.U.; Formal Analysis — P.U. and V.F.; Writing — Original Draft — P.U.; Writing — Review & Editing — P.U., V.F., and R.B.; Visualization — P.U. and V.F.; Supervision — P.U., V.F., and R.B.

**Declaration of conflicting interests:** The Authors declare that there is no conflict of interest.

## 1. INTRODUCTION

Today, artificial intelligence is one of the most researched topics[1] (Crew, 2020) and a driving technology of the "Fourth Industrial Revolution" (Philbeck & Davis, 2018). Artificial intelligence (AI) is believed to have the potential to significantly impact all industries and how business will be conducted in the future (Brynjolfsson & McAfee, 2017; Floridi et al., 2018). New, AI-based business models are spreading rapidly, disrupting and transforming existing market structures (Hahn et al., 2020). Moreover, implementing AI applications is expected to give the respective enterprise an advantage over its competitors (Buer et al., 2021; Lee et al., 2019). However, besides literature glorifying the opportunities implied with AI, questions are raised about accountability (Gualdi & Cordella, 2021), ethical (Kwon et al., 2020), social and financial challenges (Dwivedi et al., 2021; Kaplan & Haenlein, 2020; Nishant et al., 2020). Since small and medium-sized enterprises (SMEs) already lag on digitalization when compared to large enterprises, concerns are voiced that less well-funded businesses might not stand

[1] Google Scholar, top-publications 2020: https://scholar.google.com/citations?view_op=top_venues&hl=de

a chance in the race towards adopting AI applications and could fall even further behind with competitors benefitting from AI (Organisation for Economic Co-operation and Development [OECD], 2017). For family businesses, in particular, raising capital poses a challenge (European Commission, 2016; Michiels & Molly, 2017), and thus keeping up with non-family firms might be especially demanding.

The contribution of this paper is to present the first comprehensive international study on AI adoption in SME family firms, using socioemotional wealth (SEW) as the explanatory theory. In these companies, structural characteristics such as a reduced size interact with the effects of family involvement such as a specific and often informal style of decision-making. On these grounds, a survey examining some of the negative effects AI has on family firms was conducted.

The rest of the paper is as follows: initially, Section 2 reviews the literature regarding family businesses, digital technologies and the usage of AI in family businesses. Afterwards, Section 3 explains the methodology of the research. Later on, the analysis has been done in Section 4 followed by the discussions in Section 5. Finally, the conclusions are presented in Section 6.

## 2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

### 2.1. Theoretical background

Family businesses often differ from non-family businesses as their decisions and values are not solely influenced and driven by economic goals (Behringer et al., 2019), but also by non-economic goals, which in the literature are referred to as "socioemotional wealth". This term and the theory around it were introduced by Gómez-Mejía et al. (2007). With the help of the SEW theory, they wanted to explain why the aforementioned differences between family firms and non-family firms exist in various decision-making processes (Behringer et al., 2019). The SEW theory was developed based on the behavioral agency model (BAM) by (Wiseman & Gómez-Mejía, 1998) and wants to offer a framework to show that complexities inside a family firm can arise due to the proximity of family and business (Sluhan et al., 2018).

This connection between family and business is consolidated by the family's identification with the business, the big influence that the family has on everything happening with the firm, and the predominant intention of preserving the business for future (family) generations as management duties are passed on within the family. Because of this close-knit relationship, the families are more risk-averse, in comparison to external management as there is more at stake (Gómez-Mejía et al., 2007).

Berrone et al. (2012) introduced five dimensions to allow a better understanding of these non-economical influences that are an elemental part of the SEW theory. These five dimensions are "family control and influence", "family members' identification with the firm, binding social ties", "emotional attachment" and "renewal of family bonds to the firm through dynastic succession" (Berrone et al., 2012). Members of the family can be influenced by these dimensions to preserve the values or the image of the firm. They will try to avoid any kind of bad publicity or situations that could endanger the family business and therefore have negative repercussions for the family name (O'Boyle et al., 2010), even if the outcome of the decision might lead to weaker performance of the firm (Schepers et al., 2014).

However, when the firm's performance falls to the point where its continued existence is threatened and therefore the family's legacy is endangered, family businesses will push the envelope and will no longer shy away from taking risky (but possibly profitable) actions (Gómez-Mejía et al., 2007). Moreover, with decisions mostly only having to be agreed upon with other family members, the trusting relationship helps to reduce protracted decision-making times and lowers transactions cost (Bromiley & Cummings, 1996).

Although this close connection between family and business explained by the SEW theory is also described as being "a prosocial and positive stimulus" (Kellermanns et al., 2012), there are further downsides. According to (Kellermanns et al., 2012), the emotional link can have negative impacts on shareholders or stakeholders that are not part of the family. Without the family connection, they are likely to have no influence on the biased, possibly bad decisions by the family members; however, the results can still have implications for them. Opposing opinions, although they might be given in the best interest of the business, might be construed as criticism or a direct attack on the family values and incite a "we against them"-mentality. Following this mindset, there is a chance that (external) control mechanisms are eliminated, if this is beneficial for the family (Kellermanns et al., 2012).

One of the most important points to be mentioned is that AI is not limited to a specific task as it can find use in all industries. This makes it a "general-purpose-technology" comparable to technological innovations from the past like the steam engine or electricity (Cockburn et al., 2018). AI allows businesses to automate tasks as systems are becoming "smart" and have, at least up to a certain degree, the capability to teach themselves (Brynjolfsson & McAfee, 2017). When considered by use in different industries, the following statements about AI can be made:

- In the *finance sector*, AI can excel thanks to the amount of data that can be processed and analyzed to support the decision-making process. (Bahrammirzaee, 2010) proposes that AI can be used in "Credit Evaluation" to help in the scoring process of a customer, support "Portfolio management" by finding the perfect individualized fit, and in "Financial prediction and planning" where it can be used for forecasting purposes (Bahrammirzaee, 2010). Furthermore, players in the financial sector have started to implement 'robot advisors as "digital asset manager[s]" (Kruse et al., 2019) to improve customer satisfaction.
- In *manufacturing*, visually inspecting an underlying material remains a key aspect to ensure the quality of the final product. AI, or machine learning to be more specific, has proven to be a reliable and cost-effective approach to automate this process (Koppe & Schatz, 2021).

- In the *tourism sector*, AI plays an important role not only in companies but also in governments as at the airport there are systems in place that enable a faster entry process at the border using facial recognition technology (Samala et al., 2020). Another advantage of AI is that it is always available and can provide information to a customer, therefore, improving customer service and experience. Hotels are advancing quite similarly to houses and are evolving into "Smart Hotels" where the "Internet of Things" and robots start to take over and there are already hotels where no humans are needed (Law et al., 2019).
- The *retail sector* also garners benefits from AI technology as it can help optimize goods management. AI can react to events and trends faster and can, for example, adjust prices if there is a sudden shift in demand. Additionally, it can be used for sales forecasting or purchasing as well as logistics (Weber & Schütte, 2019).

Although AI has the chance to bring positive effects there also have to be questions raised about the possible negative effects that can result from the increase of AI technology. Especially social and ethical questions are being discussed as AI and robots can replace humans, at least to a certain extent, causing them to lose their jobs. Furthermore, it can be discussed how much influence should be given to an AI in a certain decision process as it may have a different result simply on basis of data (Dwivedi et al., 2021; Kaplan & Haenlein, 2020). The overwhelming majority of studies surrounding AI are focused on the tasks, which AI is performing, or where AI has the potential to improve current processes. Peer-reviewed research on the implementation rate and effectiveness of implemented systems in companies is scarce. However, consulting studies such as those by McKinsey or Deloitte can be referenced.

McKinsey published "The state of AI in 2020" report summarizing the results of an online survey among 2,395 companies, varying in location, size, and industry (McKinsey & Company, 2020). In terms of the distribution of AI, around half indicated that an AI tool is in use. The most common areas of application are product enhancements (24%) and service optimizations (24%). It was further found that enterprises are utilizing AI today more often to increase their revenue than to cut costs (McKinsey & Company, 2020).

In a study conducted amongst 2,737 managers from Australia, Canada, China, France, Germany, Japan, the Netherlands, the UK, and the USA, Deloitte (2020) assessed the "State of AI in the enterprise". When asked about the relevance of AI, 73% indicated that AI was critical for business performance today with numbers rising to 83% within the next two years. Enterprises that had already implemented AI solutions, did so mainly in information technology (IT) (47%), cyber security (22%), production (16%), and product development (15%) (Deloitte, 2020).

A research deficit is also noticeable in the area of SMEs and family firms. Since SMEs account for the largest share of firms and employ the majority of the workforce (Organisation for Economic Co-operation and Development [OECD], 2019), they are often described as the 'backbone of an economy' (Abbasi et al. 2018). Despite their undisputed relevance, SMEs still lack a universal definition (Becker et al., 2019). When trying to section SMEs off of larger enterprises, three approaches are present in the current literature: delimitation by quantitative traits, delimitation by qualitative traits, and a combination of those (Loecher, 2000).

One of the more common standards applied to classify enterprises by quantitative measures was published by the European Commission in 2003. According to their definition, SMEs have up to 250 employees, a maximum of €50 million in sales, and a balance sheet total of not more than €43 million (Commission of the European Community, 2003). The Institut für Mittelstandsforschung (IfM) Bonn, whilst employing the same metrics, has set its threshold for employees and sales at €500 and €50 million, respectively (IfM Bonn, 2016).

Since family firms often match the quantitative criteria of small and medium-sized enterprises, they are commonly deemed a sub-group of SMEs. However, family firms have separate characteristics and are not to be equated with an SME (Becker et al., 2019). In theory, they are understood as an enterprise on which one family is exhibiting a controlling influence. Practically, this may be manifested by holding more than 50% of the voting rights and having one or more family members in top management or supervisory board positions (Koeberle-Schmid, 2008).

When focusing on AI in small and medium-sized companies, Hansen and Bøgh (2021) and Žigienė et al. (2019) provides a theoretical overview. From a practical point of view, especially the "European SME survey 2019" (El Kasmi et al., 2019) gives further insights into AI's distribution and usage. It was conducted via online access panels surveying around 500 SMEs across Germany, France, the UK, Spain, and Poland. The results indicate that only 20% of the considered European SMEs stated that AI is in use. According to the answers given to a question about future developments, however, 29 percent indicated to be planning to implement AI within the next two years (El Kasmi et al., 2019).

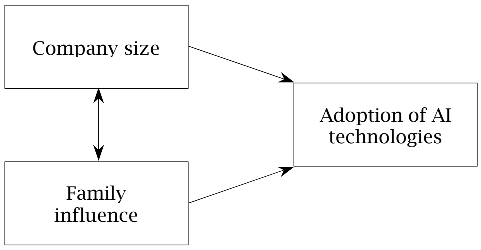
One important study about AI in family firms was published by the Institute of Family Business and Mittelstand at WHU, Vallendar, Germany. The basis of this report was a quantitative survey covering 1,727 German companies. Only 4.9% of the surveyed family businesses have indicated using AI in their day-to-day business. Reasons for this can be found in the identified family business-specific barriers, namely: a missing interface between new technology like AI and existing IT structures, paternalism, static structures, corporate culture, communication problems, the resistance of employees, and shortage of skilled labor (Soluk et al., 2020).

## 2.2. Hypothesis development

The evaluation of variables influencing the perception of AI is approached on basis of a theoretically grounded research framework. According to the contingency theory, the influencing variables in question are company size and family influence. In Figure 1 the research model for the subsequent survey is shown.

It is presumed that the company size and family influence have negative implications for the commitment and capacity to adopt AI. The idea, based on the SEW, that family businesses do not use technologies that are positive for the business because they jeopardize their position in the business network is likely to be even stronger for AI than for other technologies such as enterprise resource planning (ERP) systems. After all, ERP systems are mainly about making things more transparent and supporting decisions. From the perspective of the family owners, this can be seen as a restriction of their sphere of influence. AI-based technologies may drive this even further from the owners' subjective point of view, in that in the final stage they can make the decision all by themselves and thus make the owners obsolete as decision-makers.

**Figure 1.** Research framework




To further examine this suggestion, hypotheses are formulated. According to the literature, crucial factors to the successful usage of AI are "management, implementation, and business imagination" (Brynjolfsson & McAfee, 2017). Internal resistance within the implementation step can originate from your staff. Reasons for this may be unengaged or unskilled employees (Brock & Wangenheim, 2019) that are reluctant to change, as it disturbs the balance (Strebel, 1996). Since workforce loyalty is valued comparably higher in family firms (Deloitte, 2019) and their employment strategy is long-term focused (Le Breton-Miller & Miller, 2006), it can be assumed they have more long-time staff with more traditional values and more established routines. Therefore, internal resistance against new technologies might be especially present for family businesses.

*H1: Artificial Intelligence is less relevant for family firms than non-family firms.*

Further reasons might be found in the size and resources of family firms. The majority of family firms can be classified as small or medium-sized companies (Andersson et al., 2018) and thus have fewer resources available to realize costly and time-consuming projects of adopting AI.

Successful implementation of AI also often hinges on the surrounding IT infrastructure (Davenport & Ronanki, 2018), which poses another challenge for family businesses as they tend to use more non-standardized technologies since family firms are, generally speaking, more hesitant in the external technology acquisition (Kotlar et al., 2013). Smaller enterprises have also been observed to lack IT expertise (Hansen & Bøgh, 2021).

*H2: In family firms, AI technologies are less common than in non-family firms.*

One approach to explaining why AI might be less common in family businesses could be related to the differences in strategies between family firms and non-family firms. Firstly, family firms, consistent with the SEW theory, have shown a tendency to have a less formalized strategy (Basly & Bendaoud, 2020). Secondly, the majority of family firms operate in more traditional markets (Ernst & Young [EY], 2019) and therefore inherit a traditional business model (Kraus et al., 2012; Ward, 2004) for which AI might not be as applicable as for data- or platform-based business models.

*H3: A family firm's strategy is less connected to AI than a non-family firms.*

Since in family businesses, the family exerts a controlling influence on the management (Koeberle-Schmid, 2008), the decision-making power for strategic acquisitions (such as AI) is also in the hands of the family. As there is less willingness to invest money in external specialists (Kotlar et al., 2013), ownership might act as a bottleneck on the way to successful AI adoption. Family businesses traditionally have a recognizable tendency to pay more attention to some areas of the business than others. For example, the focus tends to be less on investments in technology and research and development (Eurofound, 2011). Despite knowing about the challenges when facing the ongoing digitalization (PricewaterhouseCoopers [PwC], 2016), the budget and willingness to invest in AI technology remain lower than in non-family firms.

*H4: Family firms spend significantly less money on AI than non-family firms.*

## 3. RESEARCH METHODOLOGY

### 3.1. Sample description

Data collection was conducted using a standardized online questionnaire containing open and closed questions. To check the questionnaire, a pre-test was first conducted with several subjects. Subsequently, the actual survey was conducted in the period from 22.10.2020 to 11.11.2020. For this purpose, e-mail addresses of German companies were randomly generated in advance using the Nexis database.

A total of 12,360 companies were contacted by e-mail, whereby 1,112 e-mails could not be delivered. Thus, 11,248 companies received the link to the online survey. The online questionnaire was accessed 283 times during the survey period, corresponding to a participation rate of 2.52%. A majority of respondents were business managers from the IT department of the respective companies. A non-response bias test was conducted to guarantee representativeness despite the small sample.

The data was analyzed using Microsoft Excel and Statistical Package for the Social Sciences (SPSS). The questionnaire contained 33 questions, which were divided into five sections. First, information about the company and the processor was requested, followed by a query about the general conditions and the relevance of AI in the company. The next section dealt with which technologies are used and which functional areas are particularly suitable, followed by an assessment of the importance of AI for the strategy and the impact on success.

### 3.2. Independent variables

The independent variable in the study is *family influence*. There are several operationalizations for this variable in the literature (Hiebl, 2015). Since the companies in the survey are primarily small and medium-sized enterprises and family businesses, which tend to answer less when questions are too complex, a single-item approach was chosen for the present study. To measure family influence, a 0/1 coded question "Is your company a family business" was used, which yields the variable *FAMILY*. 54 companies did not answer this question. Of the remaining 229 companies in the study, 95 are family enterprises and 134 are non-family enterprises.

### 3.3. Dependent variables

A different dependent variable was defined for each of the four hypotheses.

For *H1* the dependent variable is the subjective relevance of artificial intelligence for the company (*RELEVANCE*). The variable was measured using a five-point Likert scale from 1 = not very relevant to 5 = very relevant.

In the study, different AI technologies such as robotic process automation (RPA), deep learning, and machine learning were used in the questionnaire. Companies were asked whether they had implemented those technologies. For each technology, a utilization degree was asked using the values from 1 = low grade of utilization to 5 = high grade of utilization. For *H2*, we use the sum of the intensity of usage of implemented technologies (*TECHNOLOGY*) as a variable. Nine technologies were asked, so the variable can take the value from 9 (value 1 for all nine technologies) to 45 (value 5 for all nine technologies).

For *H3*, a question was asked: "How intensively is AI integrated into your corporate strategy?". The variable *INTEGRATION* can take the values from 1 = weak integration to 5 = very strong integration.

Budget spending on AI was operationalized by using the question "How much budget in the percentage of annual sales do you spend on AI?" with values 1 = less than 1 percent, 2 = between 1 and 4 percent, 3 = more than 4, and less than 10 percent, and 4 = more than 10 percent. Thus, the variable *BUDGET* is used as a linear variable for statistical analyses.

Unfortunately, the target group of family businesses tends to quickly abandon empirical surveys in the case of many multi-item scales or ordinal variables. Measuring several variables using binary constructs is, therefore, a painful but necessary compromise in questionnaire design and evaluation.

### 3.4. Control variables

As a control variable, the company size was chosen as a complexity-generating factor (Speckbacher & Wentges, 2012). The size of the enterprise — variable *SIZE* — was operationalized by the number of employees. 54 companies did not answer this question. The number of employees was surveyed in four classes:

- *SIZE_249*: enterprises with up to 249 employees (n = 113);
- *SIZE_250_499*: enterprises with between 250 and 499 employees (n = 33);
- *SIZE_500_2499*: companies with between 500 and 2,499 employees (n = 38);
- *SIZE_2500*: enterprises with 2,500 or more employees (n = 40).

## 4. EMPIRICAL RESULTS

### 4.1. Correlations

Various regression models were used to test the hypotheses depending on the scale level of the dependent variables. This subsection shows the correlations of the variables considered in the study.

Table 1 shows the correlations in the sample. It is already evident from this simple evaluation that family-owned businesses are likely to feel a low relevance for AI, use less technology, and integrate AI less strongly into their strategy. Smaller companies with fewer than 250 employees also show less relevance to AI, fewer technologies deployed, less integration, and less budget. Overall, it is interesting to note that family businesses in the sample are investing more than non-family businesses.

**Table 1.** Correlations

| *Variables* | *SIZE_249* | *SIZE_250_499* | *SIZE_500_2499* | *SIZE_2500* | *RELEVANCE* | *TECHNOLOGY* | *INTEGRATION* | *BUDGET* |
|---|---|---|---|---|---|---|---|---|
| *FAMILY* | 0.073 | -0.093 | 0.029 | 0.009 | -0.139 | -0.062 | -0.195* | 0.056 |
| *SIZE_249* | 1 | -0.405** | -0.440** | -0.454** | -0.183* | -0.279** | -0.178 | -0.149 |
| *SIZE_250_499* | | 1 | -0.183** | -0.189** | -0.006 | 0.012 | 0.049 | 0.097 |
| *SIZE_500_2499* | | | 1 | -0.205** | 0.027 | 0.090 | 0.101 | -0.024 |
| *SIZE_2500* | | | | 1 | 0.266** | 0.319** | 0.101 | 0.119 |
| *RELEVANCE* | | | | | 1 | 0.707** | 0.661** | 0.244* |
| *TECHNOLOGY* | | | | | | 1 | 0.548** | 0.229* |
| *INTEGRATION* | | | | | | | 1 | 0.160 |
| *BUDGET* | | | | | | | | 1 |

*Note: * significance at the 5% level and 1% level (Wald test).*

### 4.2. Test of Hypothesis 1 (*H1*)

*H1* was tested with linear regression due to the ordinal scale level. The results are shown in Table 2.

The evaluation shows that family businesses are significantly less likely to perceive a high relevance of AI. This may be because they have not yet recognized the relevance of the technology or its potential, or because they underestimate it. This is underpinned by the SEW. The model quality is acceptable with a corrected $R^2$ of 10.3 percent. *H1* is accepted.

**Table 2.** Test of *H1*

| *Model 1* | | | | |
|---|---|---|---|---|
| *Dependent variable: RELEVANCE* | | | | |
| *Independent variable* | *β-coef.* | *p-value* | *Tolerance* | *VIF* |
| *FAMILY* | -0.158 | 0.048 | 0.966 | 1.036 |
| *SIZE_249* | 0.631 | 0.027 | 0.076 | 13.075 |
| *SIZE_250_499* | 0.480 | 0.018 | 0.150 | 6.683 |
| *SIZE_500_2499* | 0.574 | 0.009 | 0.130 | 7.721 |
| *SIZE_2500* | 0.807 | 0.001 | 0.106 | 9.440 |
| *Model fit* | | | | |
| $R^2$ | 0.133 | | | |
| Adj. $R^2$ | 0.103 | | | |
| F (model, global) | 4.393 | | | |

## 4.3. Test of Hypothesis 2 (*H2*)

*H2* was tested with linear regression due to the ordinal scale level. The results are shown in Table 3.

**Table 3.** Test of *H2*

| *Model 2* | | | | |
|---|---|---|---|---|
| *Dependent variable: TECHNOLOGY* | | | | |
| *Independent variable* | *β-coef.* | *p-value* | *Tolerance* | *VIF* |
| *FAMILY* | -0.073 | 0.243 | 0.974 | 1.027 |
| *SIZE_249* | 0.325 | 0.133 | 0.082 | 12.170 |
| *SIZE_250_499* | 0.330 | 0.038 | 0.153 | 6.553 |
| *SIZE_500_2499* | 0.422 | 0.012 | 0.137 | 7.290 |
| *SIZE_2500* | 0.616 | 0.000 | 0.133 | 7.538 |
| *Model fit* | | | | |
| $R^2$ | 0.152 | | | |
| Adj. $R^2$ | 0.133 | | | |
| F (model, global) | 7.980 | | | |

Despite the acceptable model quality, the analysis shows no significant influence of family on technology adoption. This result can be seen as the antithesis of *H1*, so to speak. Even though family businesses consider AI less relevant than non-family businesses, they have not implemented the technology less in the business. Conversely, one could also say that non-family businesses do say that technology is more relevant to them. But they do not show higher levels of use. *H2* is rejected.

## 4.4. Test of Hypothesis 3 (*H3*)

*H3* was tested with linear regression due to the ordinal scale level. The results are shown in Table 4.

**Table 4.** Test of *H3*

| *Model 3* | | | | |
|---|---|---|---|---|
| *Dependent variable: INTEGRATION* | | | | |
| *Independent variable* | *β-coef.* | *p-value* | *Tolerance* | *VIF* |
| *FAMILY* | -0.211 | 0.027 | 0.971 | 1.030 |
| *SIZE_249* | 0.593 | 0.231 | 0.036 | 27.978 |
| *SIZE_250_499* | 0.491 | 0.148 | 0.076 | 13.147 |
| *SIZE_500_2499* | 0.652 | 0.101 | 0.055 | 18.021 |
| *SIZE_2500* | 0.665 | 0.124 | 0.047 | 21.278 |
| *Model fit* | | | | |
| $R^2$ | 0.093 | | | |
| Adj. $R^2$ | 0.050 | | | |
| F (model, global) | 2.150 | | | |

However, with insufficient model goodness of fit of 5 percent adjusted $R^2$, a significant negative impact of the family on the integration of AI into business strategy emerges. Here, we examined whether and to what extent AI is integrated into corporate strategy. On the strategic level, this seems to play less of a role so far than for non-family businesses. *H3* is thus accepted.

## 4.5. Test of Hypothesis 4 (*H4*)

*H4* was tested with linear regression due to the ordinal scale level. The results are shown in Table 5.

**Table 5.** Test of *H4*

| *Model 4* | | | | |
|---|---|---|---|---|
| *Dependent variable: BUDGET* | | | | |
| *Independent variable* | *β-coef.* | *p-value* | *Tolerance* | *VIF* |
| *FAMILY* | 0.070 | 0.487 | 0.974 | 1.026 |
| *SIZE_250_499* | 0.143 | 0.176 | 0.888 | 1.126 |
| *SIZE_500_2499* | 0.040 | 0.715 | 0.840 | 1.190 |
| *SIZE_2500* | 0.168 | 0.125 | 0.838 | 1.193 |
| *Model fit* | | | | |
| $R^2$ | 0.037 | | | |
| Adj. $R^2$ | -0.003 | | | |
| F (model, global) | 0.936 | | | |

The variable *SIZE_249* is not part of the final model. The model also does not provide a satisfactory explanation of the relationship between family and budget. Analogous to *H2*, non-family businesses are not spending more money on implementing AI technologies and strategies based on them, as expected. *H4* is therefore rejected.

## 5. DISCUSSION

This study has dealt with what we consider to be the still very new subject area of artificial intelligence in small and medium-sized enterprises as well as large companies, with a special focus on the size of family influence. At the outset, it was postulated that there are no specific studies to date on the perception and implementation of AI technologies in SMEs and family businesses. Theoretical models such as the technology acceptance model (TAM) by Davis (1989) can be used to explain the implementation of new technologies in business practice. However, such models have not yet been applied to our study object, at least empirically.

The study started with the premise based on SEW that the family in a family business is skeptical about AI, as AI may even be seen as a threat to the family's position in the business network. From an empirical perspective, the derived hypotheses can be partially maintained. From the sample's perspective, family businesses perceive AI as less relevant than non-family businesses. They also tend to use AI technologies less frequently and intensively, although this effect was not statistically significant.

From our point of view, the topic area of AI and strategy was also particularly interesting. As the results of the analysis show, family businesses are significantly less likely to incorporate AI into their strategic efforts. This could be a long-term sustainable competitive disadvantage. This seems all the more interesting because, according to the analysis, family businesses do not spend less on AI than non-family businesses, as expected, but tend to spend slightly more. A qualitative follow-up study would be necessary here to determine the extent to which family businesses invest in technologies that do not necessarily make sense for them in the specific situation. At this point, context variables such as the AI expertise of the employees, which were queried in our survey but not yet used for this paper, could also play a role. There is a presumption that employees in family businesses who are not so well trained in AI do not exploit the potential of these technologies 100 percent in the selection, implementation, and use of AI technologies in family businesses, and thus there is still room for improvement.

## 6. CONCLUSION

Ultimately, the study presented in this paper has some limitations: It is a quantitative-empirical study at a point in time with purely German companies. The results are thus only transferable to SMEs and family businesses in other countries to a limited extent. In addition, it is a single-informant study, as only one decision-maker per company was interviewed. In addition, a mixture of single-item and multi-item scales was used.

However, the analysis already shows that the topic of AI has high strategic relevance in SMEs and family businesses. This is all the truer as it is an uncertain but necessary investment in future technologies for the companies. Here, companies can afford a few missteps from a strategic perspective. In this respect, it is the task of research to derive explanatory and justification approaches for better perception and implementation of AI in corporate practice in in-depth studies to better exploit the potential benefits of these exciting technological developments.

## REFERENCES


1. Abbasi, W. A., Wang, Z., & Abbasi, D. A. (2018). Potential sources of financing for small and medium enterprises (SMEs) and role of government in supporting SMEs. *Journal of Small Business and Entrepreneurship Development, 5*(2), 39–47. https://doi.org/10.15640/jsbed.v5n2a4
2. Andersson, F. W., Johansson, D., Karlsson, J., Lodefalk, M., & Poldahl, A. (2018). The characteristics of family firms: Exploiting information on ownership, kinship, and governance using total population data. *Small Business Economics, 51*(3), 539–556. https://doi.org/10.1007/s11187-017-9947-6
3. Bahrammirzaee, A. (2010). A comparative survey of artificial intelligence applications in finance: Artificial neural networks, expert system and hybrid intelligent systems. *Neural Computing and Applications, 19*(8), 1165–1195. https://doi.org/10.1007/s00521-010-0362-z
4. Basly, S., & Bendaoud, H. B. (2020). Fall and revival of family businesses: An explanation based on socio-emotional wealth and owner-manager's entrepreneurial sins and cognitive emotions *Gestion 2000, 37*(4), 93–123. https://doi.org/10.3917/g2000.374.0093
5. Becker, W., Ulrich, P., Fibitz, A., Schuhknecht, F., & Reitelshöfer, E. (2019). *Digitale Arbeitswelten im Mittelstand: Veränderungen und Herausforderungen.* Springer Gabler. https://doi.org/10.1007/978-3-658-24372-2
6. Behringer, S., Ulrich, P., & Unruh, A. (2019). Compliance management in family firms: A systematic literature analysis. *Corporate Ownership & Control, 17*(1), 140–157. https://doi.org/10.22495/cocv17i1art13
7. Berrone, P., Cruz, C., & Gómez-Mejía, L. R. (2012). Socioemotional wealth in family firms: Theoretical dimensions, assessment approaches, and agenda for future research. *Family Business Review, 25*(3), 258–279. https://doi.org/10.1177/0894486511435355
8. Brock, J. K.-U., & Wangenheim, F. V. (2019). Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. *California Management Review, 61*(4), 110–134. https://doi.org/10.1177/1536504219865226
9. Bromiley, P., & Cummings, L. (1996). The organizational trust inventory (OTI): Development and validation. In R. Kramer & T. Tyler (Eds.), *Trust in organizations: Frontiers of theory and research* (pp. 302–330). SAGE Publications. https://doi.org/10.4135/9781452243610.n15
10. Brynjolfsson, E., & McAfee, A. (2017, July 18). The business of artificial intelligence: What it can — and cannot — do for your organization. *Harvard Business Review, 7*, 1–20. https://hbr.org/2017/07/the-business-of-artificial-intelligence
11. Buer, S.-V., Strandhagen, J. W., Semini, M., & Strandhagen, J. O. (2021). The digitalization of manufacturing: Investigating the impact of production environment and company size. *Journal of Manufacturing Technology Management, 32*(3), 621–645. https://doi.org/10.1108/JMTM-05-2019-0174
12. Cockburn, I. M., Henderson, R., & Stern, S. (2018). *The impact of artificial intelligence on innovation* (NBER Working Paper No. 24449). National Bureau of Economic Research. https://doi.org/10.3386/w24449
13. Commission of the European Community. (2003). Commission Recommendation 2003/361/EC of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises. *Official Journal of the European Union, L124*, 36–41. https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2003:124:0036:0041:en:PDF
14. Crew, B. (2020, July 13). *Google Scholar reveals its most influential papers for 2020.* Nature Index. https://www.natureindex.com/news-blog/google-scholar-reveals-most-influential-papers-research-citations-twenty-twenty
15. Davenport, T. D., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116. https://hbr.org/2018/01/artificial-intelligence-for-the-real-world
16. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008
17. Deloitte. (2019). *Family business survey 2019: Long-term goals, meet short-term drive.* https://www2.deloitte.com/content/dam/Deloitte/lu/Documents/strategy/lu-family-business-survey-2019.pdf?nc=1
18. Deloitte. (2020). *State of AI in the enterprise: Ergebnisse der befragung von 200 AI-experten zu künstlicher intelligenz in deutschen unternehmen* (3rd ed.). https://www2.deloitte.com/content/dam/Deloitte/de/Documents/technology-media-telecommunications/DELO-6418_State%20of%20AI%202020_KS4.pdf
19. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., . . . Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

20. El Kasmi, S., Morin, L., Abel-Koch, J., Topczewska, A., Acevedo, M. F., & Al Obaidi, L. (2019). *Going digital: The challenges facing European SMEs* [Paper presentation]. European SME Survey. https://www.kfw.de/PDF/Download-Center/Konzernthemen/Research/PDF-Dokumente-Studien-und-Materialien/PDF-Dateien-Paper-and-Proceedings-(EN)/European-SME-Survey-2019.pdf
21. Ernst & Young (EY). (2019). How the world's largest family businesses are responding to the transformative age. https://www.ey.com/en_gl/growth/how-the-world-s-largest-family-businesses-are-responding-to-the-transformative-age
22. European Commission. (2016). *Family business: Internal market, industry, entrepreneurship and SMEs*. https://ec.europa.eu/growth/smes/supporting-entrepreneurship/family-business_en
23. Eurofound. (2011). *Family businesses: Do they perform better? Literature review by London Economics*. https://londoneconomics.co.uk/wp-content/uploads/2011/09/101-Comparing-the-economic-performance-of-family-businesses-and-non-family-businesses.pdf
24. Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People — An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines, 28*(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5
25. Gómez-Mejía, L. R., Haynes, K. T., Núñez-Nickel, M., Jacobson, K. J. L., & Moyano-Fuentes, J. (2007). Socioemotional wealth and business risks in family-controlled firms: Evidence from Spanish olive oil mills. *Administrative Science Quarterly, 52*(1), 106–137. https://doi.org/10.2189/asqu.52.1.106
26. Gualdi, F., & Cordella, A. (2021, January 5). Artificial intelligence and decision-making: The question of accountability. In T. Bui (Ed.), *Proceedings of the 54th Hawaii International Conference on System Sciences* (pp. 2297–2306). Kauai, Hawaii, USA. https://doi.org/10.24251/HICSS.2021.281
27. Hahn, C., Traunecker, T., Niever, M., & Basedow, G. N. (2020, December 14–17). Exploring ai-driven business models: Conceptualization and expectations in the machinery industry. In *Proceedings of the 2020 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)* (pp. 567–570). Singapore. https://doi.org/10.1109/IEEM45057.2020.9309824
28. Hansen, E. B., & Bøgh, S. (2021). Artificial intelligence and internet of things in small and medium-sized enterprises: A survey. *Journal of Manufacturing Systems, 58*(B), 362–372. https://doi.org/10.1016/j.jmsy.2020.08.009
29. Hiebl, M. R. W. (2015). Family involvement and organizational ambidexterity in later-generation family businesses: A framework for further investigation. *Management Decision, 53*(5), 1061–1082. https://doi.org/10.1108/MD-04-2014-0191
30. Institut für Mittelstandsforschung (IfM) (2016). *KMU-definition*. https://www.ifm-bonn.org/definitionen-/kmu-definition-des-ifm-bonn
31. Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons, 63*(1), 37–50. https://doi.org/10.1016/j.bushor.2019.09.003
32. Kellermanns, F. W., Eddleston, K. A., & Zellweger, T. M. (2012). Article commentary: Extending the socioemotional wealth perspective: A look at the dark side. *Entrepreneurship Theory and Practice, 36*(6), 1175–1182. https://doi.org/10.1111/j.1540-6520.2012.00544.x
33. Koeberle-Schmid, A. (2008). Das system der family business governance. *Zeitschrift für Corporate Governance, 4*. https://doi.org/10.37307/j.1868-7792.2008.04.04
34. Koppe, T., & Schatz, J. (2021). Cloud-based ML technologies for visual inspection: A case study in manufacturing. In T. Bui (Ed.), *Proceedings of the 54th Hawaii International Conference on System Sciences* (pp. 1020–1029). Kauai, Hawaii, USA. https://doi.org/10.24251/HICSS.2021.124
35. Kotlar, J., De Massis, A., Frattini, F., Bianchi, M., & Fang, H. (2013). Technology acquisition in family and nonfamily firms: A longitudinal analysis of Spanish manufacturing firms. *Journal of Product Innovation Management, 30*(6), 1073–1088. https://doi.org/10.1111/jpim.12046
36. Kraus, S., Pohjola, M., & Koponen, A. (2012). Innovation in family firms: an empirical analysis linking organizational and managerial innovation to corporate success. *Review of Managerial Science, 6*(3), 265–286. https://doi.org/10.1007/s11846-011-0065-6
37. Kruse, L., Wunderlich, N., & Beck, R. (2019, January 8–11). Artificial intelligence for the financial services industry: What challenges organizations to succeed. In T. Bui (Ed.), *Proceedings of the 52nd Hawaii International Conference on System Sciences* (pp. 6408–6417). Maui, Hawaii, USA. https://doi.org/10.24251/HICSS.2019.770
38. Kwon, O., Bae, S., & Shin, B. (2020, January 7–10). Understanding the adoption intention of ai through the ethics lens. In T. Bui (Ed.), *Proceedings of the 53rd Hawaii International Conference on System Sciences* (pp. 4972–4981). Maui, Hawaii, USA. https://doi.org/10.24251/HICSS.2020.611
39. Law, R., Sun, S., & Chan, I. C. C. (2019). Hotel technology: A perspective article. *Tourism Review, 75*(1), 286–289. https://doi.org/10.1108/TR-05-2019-0150
40. Le Breton-Miller, I., & Miller, D. (2006). Why do some family businesses out-compete? Governance, long-term orientations, and sustainable capability. *Entrepreneurship Theory and Practice, 30*(6), 731–746. https://doi.org/10.1111/j.1540-6520.2006.00147.x
41. Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging technology and business model innovation: The case of artificial intelligence. *Journal of Open Innovation: Technology, Market, and Complexity, 5*(3), Article 44. https://doi.org/10.3390/joitmc5030044
42. Loecher, U. (2000). Small and medium-sized enterprises — Delimitation and the European definition in the area of industrial business. *European Business Review, 12*(5), 261–264. https://doi.org/10.1108/09555340010373537
43. McKinsey & Company. (2020). *Global survey: The state of AI in 2020*. https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/McKinsey%20Analytics/Our%20Insights/Global%20survey%20The%20state%20of%20AI%20in%202020/Global-survey-The-state-of-AI-in-2020.pdf
44. Michiels, A., & Molly, V. (2017). Financing decisions in family businesses: A review and suggestions for developing the field. *Family Business Review, 30*(4), 369–399. https://doi.org/10.1177/0894486517736958
45. Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management, 53*, Article 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

46. O'Boyle, E. H., Jr., Rutherford, M. W., & Pollack, J. M. (2010). Examining the relation between ethical focus and financial performance in family firms: An exploratory study. *Family Business Review, 23*(4), 310–326. https://doi.org/10.1177/0894486510375412
47. Organisation for Economic Co-operation and Development (OECD). (2017). *Key Issues for digital transformation in the G20.* https://www.oecd.org/g20/key-issues-for-digital-transformation-in-the-g20.pdf
48. Organisation for Economic Co-operation and Development (OECD). (2019). *OECD SME and entrepreneurship outlook.* OECD Publishing. https://doi.org/10.1787/34907e9c-en
49. Philbeck, T. D., & Davis, N. R. (2018). The fourth industrial revolution: Shaping a new era. *Journal of International Affairs, 72,* 17–22. https://jia.sipa.columbia.edu/fourth-industrial-revolution-shaping-new-era
50. PricewaterhouseCoopers (PwC). (2016). *The 'missing middle': Bridging the strategy gap in family firms.* https://www.pwc.de/de/mittelstand/assets/family-business-survey-2016.pdf
51. Samala, N., Katkam, B. S., Bellamkonda, R. S., & Rodriguez, R. V. (2020). Impact of AI and robotics in the tourism sector: A critical insight. *Journal of Tourism Futures, 8*(1), 73–87. https://doi.org/10.1108/JTF-07-2019-0065
52. Schepers, J., Voordeckers, W., Steijvers, T., & Laveren, E. (2014). The entrepreneurial orientation-performance relationship in private family firms: The moderating role of socioemotional wealth. *Small Business Economics, 43*(1), 39–55. https://doi.org/10.1007/s11187-013-9533-5
53. Sluhan, A. (2018). *Non-financial dimensions of family firm ownership: How Socioemotional wealth and familiness Influence Internationalization* (PhD Series, No. 17.2018). Copenhagen Business School (CBS). https://research.cbs.dk/en/publications/non-financial-dimensions-of-family-firm-ownership-how-socioemotio
54. Soluk, J., Kammerlander, N., & Zöller, M. (2020). *Digitale transformation im mittelstand und in familienunternehmen: Eine explorative studie zur digitalisierung von prozessen, produkten, dienstleistungen und geschäftsmodellen in deutschen mittelstands- und familienunternehmen.* Institut für Familienunternehmen. https://docplayer.org/178473121-Digitale-transformation-im-mittelstand-und-in-familienunternehmen.html
55. Speckbacher, G., & Wentges, P. (2012). The impact of family control on the use of performance measures in strategic target setting and incentive compensation: A research note. *Management Accounting Research, 23*(1), 34–46. https://doi.org/10.1016/j.mar.2011.06.002
56. Strebel, P. (1996). Why do employees resist change? *Harvard Business Review, 74,* 86–92. https://hbr.org/1996/05/why-do-employees-resist-change
57. Ward, J. L. (2004). *Perpetuating the family business: 50 lessons learned from long-lasting, successful families in business.* Palgrave Macmillan.
58. Weber, F. D., & Schütte, R. (2019). State-of-the-art and adoption of artificial intelligence in retailing. *Digital Policy, Regulation and Governance, 21*(3), 264–279. https://doi.org/10.1108/DPRG-09-2018-0050
59. Wiseman, R. M., & Gómez-Mejía, L. R. (1998). A behavioral agency model of managerial risk taking. *The Academy of Management Review, 23*(1), 133–153. https://doi.org/10.5465/amr.1998.192967
60. Žigienė, G., Rybakovas, E., & Alzbutas, R. (2019). Artificial intelligence based commercial risk management framework for SMEs. Sustainability, 11(16), Article 4501. https://doi.org/10.3390/su11164501