JUSTUS-LIEBIG-UNIVERSITÄT GIESSEN

Doctoral Thesis

Cognitive Traits and Entrepreneurial Pursuits in the Digital Age: A Multi-Layered Perspective

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List of Abbreviations

AI	Artificial intelligence
AIC	Akaike's information criterion
ALE	Accumulated local effects
ANN	Artificial neural network
APS	Adult population survey
AUC	Area under the receiver operating characteristic curve
AutoML	Automated machine learning
BoW	Bag-of-words
CATA	Computer-aided text analysis
CE	Corporate entrepreneurship
CEO	Chief executive officer
CI	Confidence intervals
CRE	Correlated random effects
CTA	Company primary technology application
CVC	Corporate venture capital
DT	Decision tree
EE	External enabler
FE	Fixed effects
FN	False negative
FP	False positive
GEM	Global entrepreneurship monitor
GCV	Global corporate venturing
ICC	Intra-class correlation coefficients
ITU	International telecommunication union
IML	Interpretable machine learning
kNN	*k*-nearest neighbor
LIME	Local interpretable model-agnostic explanation
LIWC	Linguistic inquiry word count
LPM	Linear probability model
LR	Logistic regression
LTS	Letter to shareholders
MCC	Mathews correlation coefficient
ML	Machine learning
NB	Naïve bayes

NME	Necessity-motivated entrepreneurial activity
OME	Opportunity-motivated entrepreneurial activity
RE	Random effects
RF	Random forest
PE	Private equity
R&D	Research and development
ROC	Receiver operating characteristic curve
SCT	Social cognitive theory
SIC	Standard industry classification
SMOTE	Synthetic minority over-sampling technique
TN	True negative
TP	True positive
VC	Venture capital
VIF	Variance inflation factors
VPC	Variance partitioning coefficients
WVS	World values survey
XAI	Explainable artificial intelligence
XGBoost	Extreme gradient boosting tree ensemble

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Chapter 1

1. General Introduction

The overarching aim of this cumulative dissertation is to shed light and advance our understanding of the nexus between cognitive traits and entrepreneurial pursuits in the digital age. To achieve this goal, we take a multi-layered perspective throughout the course of three separate studies. To this end, we take into account the individual, firm, industry and country levels as units of analysis across the studies conducted. A multi-layered perspective—i.e., looking at the different hierarchical levels—is of particular importance because it enables the elucidation of mechanisms that explain why effects or relationships within and between the levels occur. Moreover, since the phenomenon of "digitalization" can be characterized by various aspects, this doctoral thesis considers "digital" in different ways throughout the studies, viz. *digital technology, digital infrastructure,* and *digital transformation*. Therewith, this dissertation does not only provide a multi-layered perspective in terms of the hierarchical levels considered—i.e., depth—but also regarding the breadth of domains that digitalization comprises. The structure of the dissertation is presented in Figure 1.

In Study 1 (see Chapter 2), we use *digital technology*, i.e., machine learning (ML), a subfield of artificial intelligence (AI), that marks the very center of the so-called digital era. Specifically, we apply ML algorithms and pursue a data-driven approach to unravel important agent-centric features for entrepreneurial pursuits. This way, ML enables us to investigate to what extent entrepreneurial activity is predictable, and more importantly, which features best explain the prediction. To this purpose, we apply various supervised machine-learning techniques—decision tree, random forest, extreme gradient boosting tree ensemble, *k*-nearest neighbor, artificial neural network, and naïve Bayes—as well as perform classical multiple logistic regression to the most comprehensive existing data set in the field of entrepreneurship. This approach enables us to engage in abductive reasoning and estimate the relative performance of the respective ML algorithm in predicting entrepreneurial activity. The benchmarking of the ML techniques reveals that the extreme gradient boosting tree ensemble is the best-performing ML technique in predicting both necessity and opportunity-motivated entrepreneurial activity with the highest overall accuracy and area under the receiver operating characteristic curve. The feature importance rankings suggest that despite psychological self-regulation mechanisms such as cognitions and personal traits (i.e., socio-cognitive traits), macro country-level factors external to the respective individual at the micro level may also play a pivotal role in the engagement in entrepreneurial pursuits.

In Study 2 (see Chapter 3), we engage in a hypothetico-deductive reasoning approach. Specifically, this study examines how the level of *digital infrastructure* of a country shapes the relationships between socio-cognitive traits and entrepreneurial action—so-called action-formation mechanisms. For our hypothetico-deductive approach, we combine the agent-centric social cognitive theory (SCT) (Bandura, 1986; Sherman et al., 2015; Wood & Bandura, 1989) with the external enabler (EE) framework (Davidsson et al., 2020). Given that SCT is rather coarse-grained and lacks a theoretical explanation of how contextual factors shape entrepreneurial action-formation at the micro-level, we augment SCT with the EE framework and engage in EE mechanism-based theorizing, which allows to reason on how a specific contextual factor, in terms of EE, develops through specific (situational) mechanisms. To investigate the triadic reciprocal relationship system between action-formation at the micro-level and digital infrastructure at the macro-level, we apply multilevel modeling. In line with the SCT, our analysis shows that the socio-cognitive traits of entrepreneurial self-efficacy and opportunity recognition increase entrepreneurial action, while fear of failure reduces it. The results further indicate that a country's level of digital infrastructure is an EE that takes a shaping role in the relationships between socio-cognitive traits and entrepreneurial action. Consistent with our theorizing derived from the EE framework, the findings suggest that, in particular, the resource access and market access mechanisms of digital infrastructure explain the moderating effects.

Figure 1: Structure of the doctoral thesis

Structure of Doctoral Thesis

Chapter 1: General Introduction

	Chapter 2: Study 1	**Chapter 3: Study 2**	**Chapter 4: Study 3**
Title and co-authors	**Predicting Entrepreneurial Activity Using Machine Learning** *with Monika C. Schuhmacher*	**Digital Infrastructure and Entrepreneurial Action-Formation: A Multilevel Study** *with Monika C. Schuhmacher*	**Responding to the Situational Urgency of Digital Transformation: A Multilevel Analysis of CEO Humility and Corporate Venture Capital** *with Petrit Ademi, & Monika C. Schuhmacher*
Research question	To what extent is entrepreneurial activity predictable and what are the most important features?	How does a country's digital infrastructure shape the entrepreneurial action-formation of individuals?	How do humble CEOs influence CVC investment activity in the context of urgency for digital transformation?
Theory	Atheoretical	Social cognitive theory (Wood & Bandura, 1989) and external enabler framework (Davidsson et al., 2020)	Attention-based view (Ocasio, 1997)
Level	Individual (micro)	Individual (micro) and country (macro)	Individual (micro), firm (meso), and industry (macro)
Method	Abductive analysis of various machine learning algorithms based on 1,192,818 observations from 99 countries	Logistic multilevel modeling based on 344,265 individual-level observations from 46 countries	Longitudinal study based of 373 CEOs from 198 firms and 35 industries between 2010 and 2019 (6,908 CVC investments over 1,597 firm-years)
Status	Published in *Journal of Business Venturing Insights* (ABDC: A)	Published in *Journal of Business Venturing* (FT50, ABS: 4, ABDC: A*, VHB-Jourqual: A)	Revise & Resubmit in *Journal of Management Studies* (FT50, ABS: 4, ABDC: A*, VHB-Jourqual: A)

Chapter 5: Concluding Remarks

In Study 3 (see Chapter 4), we examine whether the findings from Study 1 and 2 are transferable to the corporate context. The underlying assumption is that incumbent firms are increasingly fostering corporate entrepreneurial (CE) actions as a means of addressing challenges arising from the ongoing *digital transformation* of society and business. Existing research in the management and entrepreneurship literature has considerably advanced our knowledge of firm and industry-specific drivers of corporate venture capital (CVC) investment activity. However, the influencing role of CEOs is largely unknown. In digital times, the purposeful instigation of CE actions requires the CEO—as the top decision-maker and head of the organization—to not only uphold the company's existing strengths but also to identify weaknesses, obtain accurate self-knowledge and promote self-improvement through continual learning (Ou et al., 2018). An auspicious basis for such contemporary executive leadership that gained momentum in the literature is a person-centered cognitive characteristic known as "humility". In the study, we distinguish between two forms of urgency for digital transformation: (i) emerging digital competition at the external industry-level, and (ii) business model dependence on information and knowledge at the internal firm-level. By reasoning upon the situational mechanism emanated by the internal and external urgency for digital transformation, we aim to provide an understanding of CVC investments as a CE action that humble CEOs at the individual-level foster in the digital era. Through the application of a bag-of-words (BoW) approach for text analysis and multilevel modeling, we provide evidence for CEO humility as an important, yet overlooked, action-formation mechanism for CVC investment activity. While the study finds support for the moderating role of emerging digital competition (i.e., external urgency), the findings suggest that internal urgency for digital transformation originating from the firm's business model dependence on information and knowledge positively moderates the action-formation mechanism of CEO humility primarily for CVC investment activity in related ventures.

Chapter 2

2. Study 1 – Predicting Entrepreneurial Activity Using Machine Learning

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Predicting Entrepreneurial Activity Using Machine Learning

Abstract

This study evaluates the predictability of entrepreneurial activity using machine learning. We compare different supervised machine learning techniques: decision tree, random forest, artificial neural network, *k*-nearest neighbor, extreme gradient boosting tree ensemble, and naïve Bayes, as well as run the traditional multiple logistic regression for obtaining a baseline and estimating their relative model prediction performance on a Global Entrepreneurship Monitor dataset of 1,192,818 individuals from 99 countries. By comparing different machine learning techniques, we predict out-of-sample opportunity-motivated entrepreneurial activity with an overall accuracy ranging from 70.1% to 91.2%. The results demonstrate that the extreme gradient boosting tree ensemble is superior in predicting opportunity-motivated entrepreneurial activity. Finally, a global surrogate model reveals that knowing an entrepreneur, entrepreneurial self-efficacy, and opportunity recognition are the three most important features for predicting opportunity-motivated entrepreneurial activity. For comparison purposes, we perform the same analyses for necessity-motivated entrepreneurial activity. The results reveal that the extreme gradient boosting tree ensemble is also the best-performing technique in predicting this form of entrepreneurial activity with a 96.5% accuracy.

JEL classification: C45, C53, C55, D91, L26

Keywords: Supervised machine learning, classification, prediction, entrepreneurial activity

2.1 Introduction

Over the last few decades, scholars have attempted to unravel the focal phenomenon of entrepreneurial activity from different perspectives and found that disentangling the entrepreneurial event is extremely complex. Against this background, entrepreneurship scholars have proposed the *ignoramus et ignorabimus*-like thesis in leading journals that it is highly improbable and doubtful whether research will ever be able to construct a mathematical model that can be used to predict the occurrence of the entrepreneurial event (e.g., Bruyat & Julien, 2001; Churchill & Bygrave, 1990). These scholars argue that if "we want to understand entrepreneurship, our research methodology must be able to handle nonlinear, unstable discontinuities" (Churchill & Bygrave, 1990, p. 28).

However, the advancements in the area of artificial intelligence (AI) and machine learning (ML) in recent years have provided researchers with new methodological potentials for constructing models for predicting various human behaviors and offering fine-grained insights into the actual predictability of entrepreneurial events. As such, ML enjoys the greatest popularity in the business world and is used for performing the most complex prediction tasks, especially supervised machine learning techniques, which were designed for this purpose (Obschonka & Audretsch, 2020). The main benefit of ML is its high predictive accuracy, a property that is crucial in many areas of business (van Witteloostuijn & Kolkman, 2019). However, although the disruptive potentials of AI and ML in analyzing (big) data with a large number of observations or high dimensionality have received increasing attention in a variety of research and application fields, they have not undergone much scrutiny in contemporary entrepreneurship research yet (Hastie et al., 2009; Obschonka & Audretsch, 2020; Schwab & Zhang, 2019; Shepherd & Majchrzak, 2022; van Witteloostuijn & Kolkman, 2019).

This fact is surprising because AI-based ML provides mathematical approaches that can be applied to mine and analyze the most comprehensive datasets such as the Global Entrepreneurship Monitor (GEM) (Gerasimovic & Bugaric, 2018; Lévesque et al., 2022) and, consequently, challenge long-held assumptions about the predictability of entrepreneurial activity. In particular, ML offers algorithmic approaches that "learn" incrementally from the inferred data to make predictions by accommodating complex and high-order interactions. This way, ML techniques can select the functional form that best predicts the target outcome, whereas in classic statistical methods the functional form must be specified a priori (Arin et al., 2022). Moreover, ML techniques allow for the investigation of the "nuts and bolts, cogs and wheels" (Elster, 1989, p. 3), i.e., mechanisms, that lead to entrepreneurial activity. Understanding these mechanisms resulting from entrepreneurial activity-related features is critical (Cowen et al., 2022; Hedström & Swedberg, 1998), as entrepreneurial activity plays an important role in the economic growth and prosperity of a nation (e.g., Schumpeter, 1934; Wennekers & Thurik, 1999). Therefore, the better scientists and policymakers understand the relevant features and underlying mechanisms of entrepreneurial activity, the better they can leverage these aspects through specific actions. However, this understanding calls for research into effectively predicting entrepreneurial activity.

To answer the long-standing research question of whether and to what extent entrepreneurial activity can be predicted, we apply and compare multiple state-of-the-art supervised machines and deep learning[1] techniques to a GEM dataset of 1,192,818 individuals from 99 countries. As no large-scale investigation using ML has been conducted to date, the aim of this research is primarily to evaluate whether ML improves the accuracy of entrepreneurial activity prediction. Since causal inferences are not possible due to the cross-sectional nature of the individual-level GEM data, we predominantly seek to determine which supervised ML technique is superior in terms of predictive accuracy and identify which features are the most relevant in predicting entrepreneurial activity. Typically, entrepreneurship research distinguishes entrepreneurship activity either as a necessity-motivated entrepreneurial activity (NME) or an opportunity-motivated entrepreneurial activity (OME) (Amorós et al., 2019). According to this push/pull

[1] Since deep learning techniques, such as artificial neural networks, are a special case of ML, we use the term "machine learning" throughout the paper for greater clarity.

framework (Storey, 2016), NME is linked to unemployment and economic recession (e.g., Amorós et al., 2019; Shane, 2009). Thus, entrepreneurship research is mostly interested in OME, wherein individuals start a new business venture in pursuit of profit, innovation, and growth (see e.g., Reynolds et al., 2005; Stenholm et al., 2013). Hence, we apply different ML techniques to OME.

2.2 Data and methodology

2.2.1 Data, feature selection, and data pre-processing

This study uses the data of six years from the Adult Population Survey by the GEM initiative. We built a comprehensive cross-sectional sample of 1,192,818 individuals from 99 countries by pooling the individual-level GEM data from 2012 to 2017, with different individuals being observed in each year (Verbeek, 2008). As the GEM data provides labeled observations, the dataset is suitable for conducting supervised analyses. The GEM initiative estimates the prevalence rate of entrepreneurial activity across the participating countries (Reynolds et al., 2005). The GEM data have been used in various previous studies examining entrepreneurial activity (e.g., Aidis et al., 2008; Fredström et al., 2020).

As we aim to predict OME, we relied on the individuals from the GEM project who provided their assessment of whether they engage in entrepreneurial activity to take advantage of a business opportunity (*TEAyyOPP*). The GEM specifies OME as a binary feature (1 = yes, 0 = no). To ensure that OME is not simply predicted by the inherently non-orthogonal manifestations of this feature (e.g., total early-stage entrepreneurial activity, total early-stage entrepreneurial activity based on new technology, self-employment, etc.), we have removed these manifestations from the GEM datasets.[2]

[2] For example, if an individual engages in OME (*TEAyyOPP)*, the same person also tends to pursue total early-stage entrepreneurial activity *(TEAyy)*. The ML techniques would, therefore, use *TEAyy* as the most important feature in predicting *TEAyyOPP*.

We selected and included all agent-centric features from the unaggregated Adult Population Survey that were reported by the GEM. Specifically, we included several human capital endowment features, such as educational and occupational attainments (see e.g., Davidsson & Honig, 2003); socio-demographic characteristics, such as gender, age, household size *(hhsize)*; and self-regulatory mechanisms such as cognitions and personal traits—entrepreneurial self-efficacy (*suskill*), fear of failure (*fearfail*), and opportunity recognition (*opport*) (e.g., Baron, 2004; Mitchell et al., 2002; Shaver & Scott, 1992). Overall, we included a total of 21 explanatory features. These features are queried in the GEM datasets, as entrepreneurship research has shown that these features are significantly associated with entrepreneurial activity[3]. Feature definitions are presented in Appendix A. From the initial dataset, observations with missing values and those which are string data (i.e., open-ended survey questions) were excluded from the analyses. Additional information on the incidence and patterns of missing data are provided in Appendix B and C. To account for potential survey effects and unobserved temporal heterogeneity, we also included respondent identifiers (*setid*), country identifiers (*country*), year of survey (*yrsurv*), and the developmental stage of countries (*CAT_GCR1*) in the analyses.

2.2.2 Methodology

To predict OME, we utilized various supervised ML techniques. Since the target class, OME, is binary (i.e., unordered discrete response), we applied the most commonly used ML techniques suitable for solving classification problems. Specifically, we applied the following ML techniques: decision tree (DT), random forest (RF), deep artificial neural network (ANN) in the form of a feedforward multilayer perceptron, *k*-nearest neighbor (kNN), extreme gradient boosting tree ensemble (XGBoost), and naïve Bayes (NB).[4] For comparison, we also ran the traditional multiple logistic regression (LR) as a baseline-benchmark model. All ML techniques

[3] Features queried as special topics in individual GEM rounds are not taken into consideration.

[4] For the sake of brevity, we do not describe the ML methods used in greater detail. For a more comprehensive overview into the individual methods of statistical learning, the reader can refer to Hastie et al. (2009).

were used with their default hyperparameter settings.[5] The use of default hyperparameter settings ensures *c.p.* direct comparability of different ML techniques without additional human intervention. Hyperparameter settings for the applied ML techniques are reported in Appendix G. To compare these ML techniques, we split the GEM dataset into a "training & validation" sample and an unseen "hold-out" test sample (Mullainathan & Spiess, 2017). For training and validating the ML models, we used 70% of the sample. For evaluating the final predictive out-of-sample performance of the ML techniques, we used the remaining 30% (see Choudhury et al., 2021).

In a balanced dataset, the probabilities of engaging and not engaging in OME are equal. However, since entrepreneurial activity is a rather rare event, the input data is unbalanced. In other words, there are fewer observations for engaging in OME (i.e., 1 = yes) than for not engaging in OME (i.e., 0 = no). This unbalanced data lead to the issue of ML techniques being dominated by the majority class. To address this issue, we resampled the dataset. Specifically, we performed the synthetic minority over-sampling technique (SMOTE) suggested by Chawla et al. (2002), where data in the minority class is generated through over-sampling. This minority over-sampling was achieved by creating synthetic rows in the dataset by extrapolating between a real object of a given class and one of its nearest neighbors. Thus, the SMOTE increased the number of minority class observations, thereby improving the generalizability of the ML techniques (Chawla et al., 2002; Fernandez et al., 2018).

Further, to ensure the reasonable predictive performance of different models in out-of-sample prediction, we employed the *k*-fold cross-validation technique (Geisser, 1975; Stone, 1974). Therewith, the training data were split randomly into *k* approximately equal-sized subsets of data. These k subsets were used separately as validation data, i.e., a pseudo-hold-out sample, for assessing the predictive ability of the ML model, whereas the other $k - 1$ subsets were used to train the ML model. Moreover, *k*-fold cross-validation provides a means to the (over)fitting

[5] We adjusted the default setting of parameters in case the default values prevented the ML technique from technical functioning (e.g., the DT with the minimum number records per node and the number of threads).

conundrum, as cross-validation makes model prediction performance less sensitive to idiosyncrasies in any of the *k* subsets (Choudhury et al., 2021; Shao, 1993). For our calculation, we used 10-fold cross-validation ($k = 10$), which is a common choice for *k* (Choudhury et al., 2021; Kohavi, 1995). Besides cross-validation, we followed the recommendation of Choudhury et al. (2021) and normalized the scale of features to obtain a unit variance of each feature after splitting the data into the "training & validation" sample and "hold-out" partitions by building *z*-scores.[6] With such feature scaling, we ensure that features with greater magnitude do not outweigh features with smaller magnitudes when they are weighted by an ML technique. This can be especially crucial when ML techniques backpropagate information to update weights, such as in ANNs.

2.2.3 Classifier performance evaluation

To evaluate the performance of the ML techniques, i.e., classifiers, we rely on different prominent classification performance scores that are calculated based on the confusion matrix. In Appendix D, we provide a Pearson cross-correlation heatmap for all features used in the main analyses. Specifically, we capture true positive (TP), false positive (FP), true negative (TN), and false negative (FN) scores. In this notation, TPs are positive instances correctly predicted by an ML technique as positive; FP is the number of negative cases that an ML technique predicted as positive; TNs are negative instances in which the classifier correctly predicted them to be negative; FNs are the number of positive cases that the classifier incorrectly predicted as negative. Therewith, this 2×2 confusion matrix is useful in understanding the balance between FNs and FPs predicted by a specific classifier (Choudhury et al., 2021).

Based on these metrics, we rely on the most widely used classifier performance indices—precision, recall/sensitivity, F_1-score, and accuracy—to evaluate the out-of-sample performance and compare the overall model prediction performance (Bergstra & Bengio, 2012; Choudhury et

[6] To prevent information leakage, *z*-score normalization and SMOTE were performed after splitting the sample.

al., 2021; Mullainathan & Spiess, 2017). Moreover, we use the receiver operating characteristic (ROC) and investigate the area under the curve (AUC) estimates in order to evaluate and compare the overall performance of the group of classifiers. The ROC plots the TP rate of the confusion matrix against the FP rate. The AUC metric reflects the predictability of an ML technique and can be used to compare the superiority of a model. In addition, based on recent publications, we report the Mathews correlation coefficient (MCC) as an additional informative and reliable statistical score for evaluating binary classification tasks (Boughorbel et al., 2017; Chicco & Jurman, 2020).

2.3 Results

2.3.1 Comparison of classifier performance

Appendix E (Panel A) represents the 2 × 2 confusion matrices for all fitted ML models. Based on the confusion matrices, the overall classification performance of the respective supervised ML techniques in predicting OME is depicted in Table 1. Table 1 summarizes the out-of-sample performance results achieved by each ML technique with regard to the different performance scores described in section 2.2.3. The results in this table reveal that the RF model obtained a maximum overall accuracy of 91.2% in predicting OME, which is followed closely by the XGBoost model with an accuracy of 91.1%. In comparison, the kNN and the NB classifiers underperformed with a total accuracy of 80.0% and 70.1%, respectively. If we compare the different ML techniques with respect to the AUC, a marginally different picture emerges—the XGBoost model with an AUC value of 0.850 is superior to the other classifiers. A comparison of the ROC curves across all ML techniques with the corresponding AUCs is shown in Figure 2 (AUC estimates are in parenthesis). When considering the MCC score, the kNN model performs the best in predicting OME with a value of 0.289.

A comparative look at the different performance scores reveals that employing ML techniques for predicting OME based on the comprehensive GEM data outperforms the baseline, multiple LR model, which shows the second lowest prediction accuracy (72.7%) and AUC (0.799) estimates. The NB technique performs the worst, with a prediction accuracy of 70.1% and an AUC estimate of 0.782.

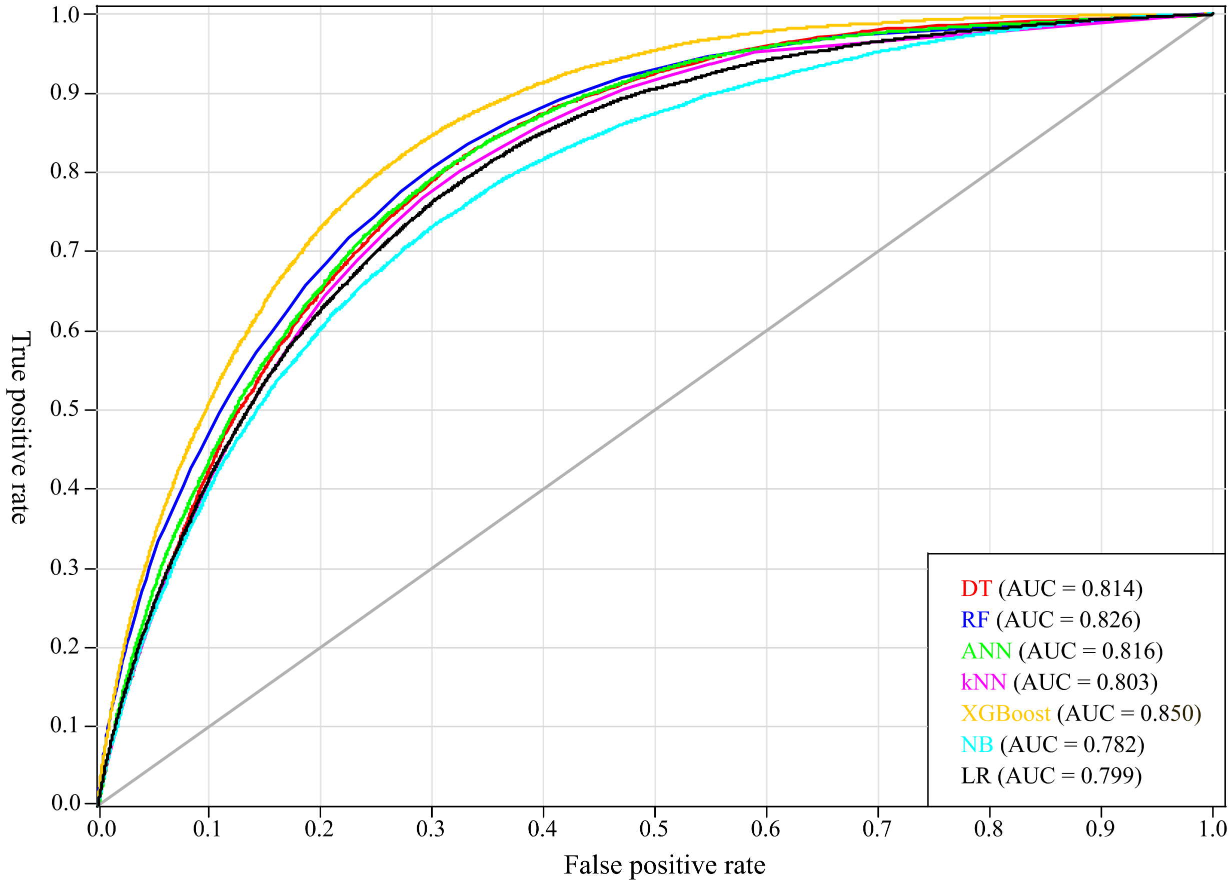
Furthermore, if we explicitly compare the difference between the best-performing ML model (i.e., XGBoost with an AUC of 0.850, accuracy = 0.911, and precision = 0.506) and the baseline LR (AUC = 0.799, accuracy = 0.727, and precision = 0.207), we can state that LR performs 18.4 percentage points (0.911− 0.727 = 0.184 × 100) worse at accurately predicting OME. Looking at the precision score as an estimate for how reliable a model can predict TP instances (i.e., class = 1) of OME—the proportion of relevant instances belonging to the positive class—we also see that LR correctly predicts an actual opportunity-motivated entrepreneur in only 20.7% of all cases. In comparison, the XGBoost model is 29.9 percentage points (0.506 − 0.207 = 0.299 × 100) better than LR in predicting OME; thus, it correctly predicts almost half of the actual OMEs. Given the fact, that LR primarily predicts non-OMEs precisely (class = 0), but fails in predicting positive data instances, the MCC for LR produces an overly optimistic, inflated score of 0.280.

Table 1: ML model performance on the OME "hold-out"- dataset

ML technique	Class	Recall	Precision	F_1-score	Accuracy	AUC	MCC
DT	0	0.969	0.922	0.945	-	-	-
	1	0.164	0.343	0.222	-	-	-
	Total	-	-	-	0.898	0.814	0.188
RF	0	0.993	0.917	0.954	-	-	-
	1	0.083	0.530	0.144	-	-	-
	Total	-	-	-	**0.912**	0.826	0.184
ANN	0	0.920	0.939	0.930	-	-	-
	1	0.388	0.322	0.352	-	-	-
	Total	-	-	-	0.873	0.816	0.284
kNN	0	0.819	0.955	0.882	-	-	-
	1	0.601	0.245	0.348	-	-	-
	Total	-	-	-	0.800	0.803	**0.289**
XGBoost	0	0.991	0.918	0.953	-	-	-
	1	0.095	0.506	0.160	-	-	-
	Total	-	-	-	0.911	**0.850**	0.191
NB	0	0.698	0.964	0.810	-	-	-
	1	0.734	0.191	0.304	-	-	-
	Total	-	-	-	0.701	0.782	0.259
LR - *baseline*	0	0.727	0.965	0.829	-	-	-
	1	0.729	0.207	0.322	-	-	-
	Total	-	-	-	0.727	0.799	0.280

However, if we consider the most precise ML models (i.e., XGBoost and RF), it must be noted that even these ML techniques are slightly better than a random draw at correctly predicting TPs of OME. The estimates of prediction error rates for each ML technique in the respective fold of the cross-validation can be inferred from Appendix F.

Figure 2: ROC curve comparison for OME

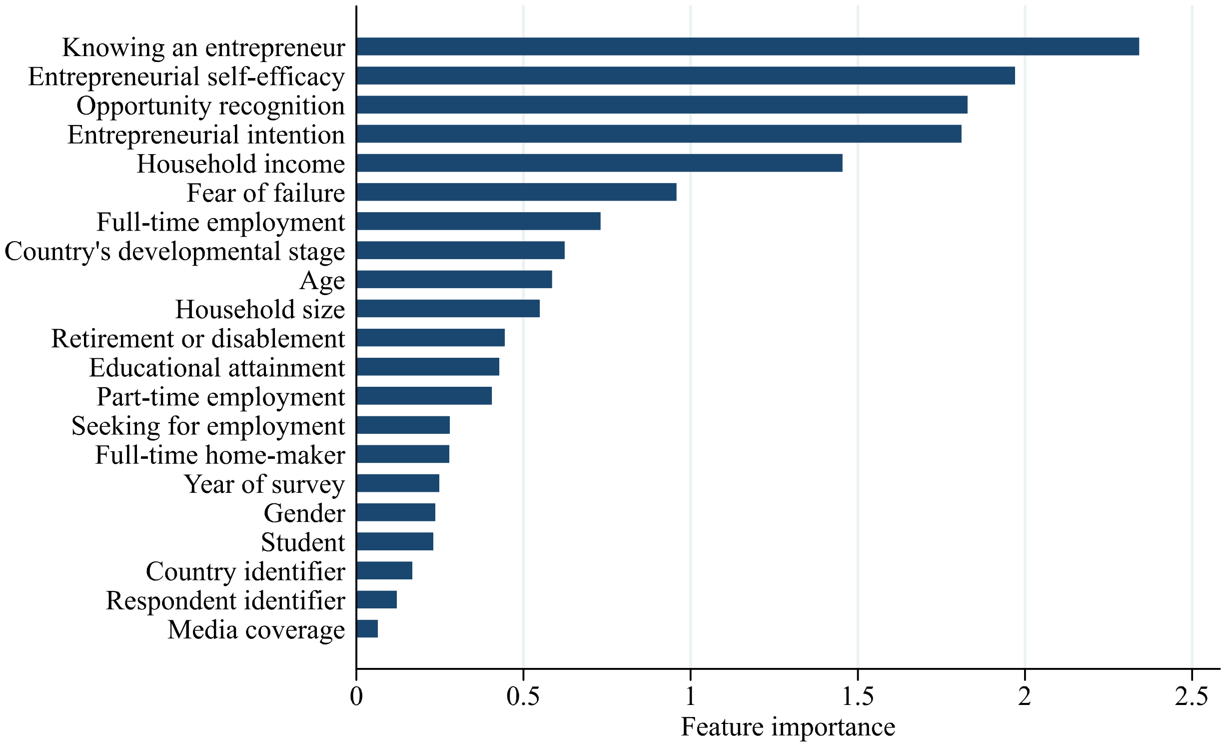


2.3.2 Global feature importance

To obtain a more detailed understanding of individual features in predicting entrepreneurial activity and enhance the interpretability of the outputs, we report on the global model-agnostic feature importance (Molnar et al., 2020). For this, we rank the importance of explanatory input features of the best-performing supervised ML technique in order to show how important each feature is on average in predicting OME. To estimate feature importance, we employ a global surrogate model method.

A surrogate model creates a model that is trained to mimic the behavior of the original model by finding an approximation function (Crombecq et al., 2011). In other words, the surrogate model can make the same predictions as the original model and, thus, can be used to understand how the different input features are related to the final prediction (Crombecq et al., 2011; Gorissen et al., 2009). Specifically, as the RF model performs best in true positively predicting OME (see precision score), we perform a surrogate RF model. Global feature importance is determined by counting how often a specific feature was selected for a split in the DTs and identifying the rank of a feature among all other available explanatory input features in the RF model trees. Figure 3 reports the global feature importance rank for predicting OME.[7]

Figure 3: Feature importance rank for predicting OME



This figure suggests that knowing an entrepreneur *(knowent)*, entrepreneurial self-efficacy *(suskill)*, and opportunity recognition *(opport)* are on average the three most important agent-centric features for predicting entrepreneurial activity. Furthermore, the rank of a country's developmental stage *(CAT_GCR1)* also indicates that a nation's business environment in which an individual is located plays a pivotal role in entrepreneurial activity prediction. On the other end of the continuum, we see that features such as gender and public media coverage of successful entrepreneurs *(nbmedia)* both play only a minor role in OME prediction.

[7] Features with higher values are more important for predicting the target feature (i.e., they have a larger effect on the model). The feature importance scale is relative.

2.3.3 Additional analysis and robustness check

To validate the predictive performance of the applied supervised ML techniques in predicting OME, we rerun all of the ML models using an automated ML technique (AutoML). Although we previously use the default parameter settings to better compare the used ML techniques, we now allow for hyperparameter optimization within the AutoML. Hyperparameters are a set of adjustable parameters that are unique to each ML technique. These parameters are assigned and tuned manually by the researcher to prevent overfitting or underfitting (i.e., stopping rules for rule-based DTs or the choice of a regularization term added to the loss function to penalize growing model complexity) and to further improve the out-of-sample predictive performance of the ML techniques (Choudhury et al., 2021; Mullainathan & Spiess, 2017). In the AutoML, the hyperparameters are automatically selected and tuned, which reduces the necessity for human interventions and, thus, increases overall comparability (Prüfer & Prüfer, 2020). The AutoML uses a Python-based library to find optimal values for regularization and other hyperparameters. As in the previous ML models, in the AutoML, we also implement 10-fold cross-validation. According to overall prediction accuracy and compared with the AUC values depicted in Figure 2, the results of the AutoML technique are identical to our main findings that XGBoost (AUC = 0.949) and DT (AUC = 0.936) are the best-performing ML techniques, followed by RF (AUC = 0.911). Since we allow for optimal parameterization in the AutoML technique, the OME prediction performance of all the applied ML techniques is higher compared to their performance according to the results in our main analysis.

Until now, we have used ML techniques to predict OME. However, according to the push/pull framework (Storey, 2016), entrepreneurial activity can also occur in the form of NME (*TEAyyNEC*). To account for this distinction and to compare OME vis-à-vis NME, we rerun our entire analyses for NME.[8] Appendix E (Panel B) presents the confusion matrix for the fitted ML models on NME. In Appendix H, we list the detailed results of the ML model performance

[8] For the prediction of NME, the same default parameter settings were used as for the prediction of OME (see Appendix G).

measures for predicting NME. Appendix I depicts the ROC curve comparison for NME. The results unveil that the XGBoost model again obtained a maximum overall accuracy of 96.5% in predicting NME, as well as the highest precision score (0.491) and AUC (0.824). The feature importance rank in Appendix J illustrates that the developmental stage of a country *(CAT_GCR1)*, the country identifier *(country)*, and household size *(hhsize)* are the most important features in predicting NME.

2.4 Discussion and conclusion

In this atheoretical study, we attempt to investigate the comparative performance of multiple supervised ML techniques in predicting OME (and NME). The findings of our utilized ML techniques reveal that entrepreneurial activity can be predicted with a maximum out-of-bag overall accuracy of 91.2% for OME (and 96.5% for NME), without hyperparameter optimization. Therewith, ML techniques outperform the traditional multiple LR. When we strive for optimal hyperparameter values, the predictive accuracy of entrepreneurial activity can be increased. However, concerning the precision, our results also provide suggestive evidence that even the best-performing ML techniques—XGBoost and RF—are still modest at correctly predicting entrepreneurship activity for the hold-out sample. One possible reason for this is that most of the individual-level GEM features are dichotomous. Nevertheless, these findings still provide clear evidence that, contrary to earlier assumptions of scholars, it is possible to construct mathematical models related to entrepreneurship that can correctly distinguish between entrepreneurs and non-entrepreneurs, even with limited information. The surrogate model in this study suggests that knowing an entrepreneur is the most important feature in predicting the occurrence of OME, followed by different self-regulation mechanisms such as cognitions and personal traits. These findings are in line with existing literature, highlighting the paramount importance of social capital and psychological characteristics of individuals as antecedents of entrepreneurial pursuits (e.g., Chen et al., 1998; Liñán & Santos, 2007).

The results of the ML techniques reveal that the XGBoost estimator is superior in predicting both OME and NME. Intuitively, this could be because ML techniques such as XGBoost and RF are ensemble methods that are developed primarily to perform two-class prediction tasks (i.e., coded 0 and 1) with structured data, such as the GEM. Since both techniques are tree-based, they could also benefit from the many binary features in the data, when splitting into branches. In addition, XGBoost uses a method known as "boosting" in which predictors are trained sequentially so that each model in the ensemble strives to minimize the errors of its predecessor. However, if we look at the precision estimates for NME prediction and compare them with the precision values for predicting OME, we can conclude that all ML techniques perform rather poorly at reliably predicting true positives for NME. These results provide suggestive evidence, that the features queried in the GEM are in favor of understanding OME instead of NME, and that crucial concepts predicting NME are presumably missing in the GEM data. Moreover, while we see that agent-centric features are of importance in predicting OME, geospatial factors and national entrepreneurial ecosystems in which individuals are embedded play a superordinate role in predicting NME.

Our study mainly contributes to the embryonic yet burgeoning body of ML-based entrepreneurship literature (e.g., Antretter et al., 2019; Prüfer & Prüfer, 2020; Tan & Koh, 1996) that is focused on analyzing and deciphering the complex phenomenon of entrepreneurial activity using ML methods that can effectively model highly non-linear processes. Due to the comparative nature of our study and by highlighting the predictive performance superiority of XGBoost, we provide an initial benchmark for future ML-based studies that seek to further improve the reliable predictability of entrepreneurial activity. As ML has only recently emerged as a tool for econometricians and entrepreneurship researchers, we consider this study as the first of a series of further studies exploring the predictability of different types of entrepreneurship activities, including digital entrepreneurship, female entrepreneurship, social entrepreneurship, corporate entrepreneurial activity, etc., to address research questions such as the following: Which ML technique is superior in predicting other forms of entrepreneurial activity? Which are the most important features in specific forms of entrepreneurial activity? However, research questions are not limited to positive outcomes. Of particular interest might also be investigations into the predictability of different kinds of business failures.

Nonetheless, our study has several limitations. First, it is tempting to draw causal conclusions from the findings. However, with utmost clarity, we emphasize that due to the cross-sectional nature of the individual-level GEM data, direct causal inferences and conclusions require extremely careful scrutiny. Despite that, even correlations and non-linear associations can reveal useful underlying structures and mechanisms in the data. Second, although the GEM is currently one of the most comprehensive datasets on individual entrepreneurial activity, a substantial part of the features is binary, which reduces the possibility of performing more in-depth analyses. To draw even more detailed conclusions about the hidden patterns, most frequent interactions, and underlying relationships between the target and a feature, the use of input features at a higher scale level (i.e., continuous or Likert-based scale) would be beneficial. A higher data quality would also allow for providing various partial dependence plots (PDPs), disaggregated individual conditional expectation curves (ICEs), or Friedman's H-statistic (Friedman & Popescu, 2008) on selected feature pairs to illustrate specific feature effects (Goldstein et al., 2015). These plots help to effectively visualize how a change in a single explanatory input feature changes the outcome prediction, i.e., (conditional) marginal feature effects and higher-order interactions (Friedman, 2001; Zhao & Hastie, 2021). Third, since we use a complete-case analysis approach, the prediction performance indices may be biased toward either over- or underestimation. However, this is only the case if the missing values are not missing completely at random (MCAR). Lastly, since our analyses only use the GEM data, our analyses may suffer from an omitted variable bias.

Our findings and limitations also provide directions for future research. First, since we find that the developmental stage of a country (*CAT_GCR1*) is the 8^{th} most important feature for predicting OME and the most important for NME prediction, country-specific factors seem to play a significant role in entrepreneurial activity. To this end, future research can draw on different theories that take into account country-level factors that were unraveled through a contextual view of entrepreneurship (Welter, 2011), the institutional theory (North, 1990; Williamson, 2000), or the external enabler framework (Davidsson et al., 2020). These contextual factors are proven to be relevant contingencies, as they influence, for instance, human capital or cognitions and their effects on entrepreneurial pursuits (e.g., Autio & Acs, 2010; Boudreaux et al., 2019). These factors provide specific (situational) mechanisms that shape the entrepreneurial action-formation of individuals (Schade & Schuhmacher, 2022). In doing so, even high-dimensional non-linear relationships between contextual factors could be identified. The first vivid example of this fruitful path is provided by Jabeur et al. (2022), who forecasted and examined macro-level determinants of entrepreneurial opportunities. Second, while our study focuses on the comparison of an array of implemented ML techniques, we aim to inspire future research to dive deeper into and engage in the so-called "interpretable machine learning" (IML) or "explainable AI" (XAI) by using various model-agnostic explanation methods such as PDPs/ICEs, accumulated local effects (ALE) plots, local interpretable model-agnostic explanation (LIME) models or SHAPley values to unravel how models arrived at specific decisions and explain hidden, robust, and even anomalous patterns in the data (Choudhury et al., 2021; Molnar et al., 2020; Shepherd & Majchrzak, 2022). With these post hoc methods and higher data quality, future research can effectively infer and understand relationships between different features and their interactions on different target outcomes. This also allows future research to conduct meta-analytic reviews on independent ML studies that focused on similar prediction tasks with different data. Treating a validated ML prediction model as a stylized fact also opens avenues for theory development. Specifically, to explain and theoretically explicate patterns detected in the data, scholars can either use appropriate existing theories or engage in algorithm-supported induction for building entirely new theoretical approaches (Shrestha et al., 2021). Theoretical approaches that attempt to account for the uncovered patterns in the data can be used for classical hypothetico-deductive theory testing.

Lastly, since entrepreneurship research is constantly in flux, bringing to light new insights into the entrepreneurial phenomenon, we encourage future scholars to replicate our analysis for even more fine-grained data using sophisticated AI techniques.

Declaration of competing interests

The authors declare no conflicts of interest with respect to research, authorship, and publication of this article.

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Chapter 3

3. Study 2 – Digital Infrastructure and Entrepreneurial Action-Formation: A Multilevel Study

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Digital Infrastructure and Entrepreneurial Action-Formation:
A Multilevel Study

Abstract

This study investigates how country-level digital infrastructure shapes the relationships between the action-formation mechanisms of socio-cognitive traits, i.e., entrepreneurial self-efficacy, fear of failure, and opportunity recognition, and entrepreneurial action. We amalgamate the agent-centric social cognitive theory with the external enabler framework and apply mechanism-based theorizing to explain how access-related mechanisms provided by digital infrastructure influence entrepreneurial action-formation. Based on a multilevel analysis of 344,265 individual-level observations from 46 countries and an additional robustness analysis of 391,119 individuals from 53 countries, we find that an individual's proclivity to starting a new venture is contingent upon the level of the digital infrastructure of a country. The empirical results show that a country's digital infrastructure is an external enabler that moderates the relationship between socio-cognitive traits and entrepreneurial action.

JEL classification: L26, D91

Keywords: Entrepreneurial action, digital infrastructure, social cognitive theory, external enabler framework, mechanism-based theorizing, multilevel analysis

3.1 Introduction

The World Economic Forum (2014) considers digital infrastructure as the backbone of digitalization and a prerequisite for venture creation and economic growth. Digital infrastructure refers to an unbounded, open, and evolving socio-technical system that includes technological and human components, networks, and systems (Hanseth & Lyytinen, 2010; Tilson et al., 2010). Hence, digital infrastructure refers to both applications of information and communication technologies and the associated infrastructure (Autio et al., 2018). Therefore, digital infrastructure is not limited to a distinct set of specific functions or restricted by strictly defined boundaries; rather, it is relational in nature (Tilson et al., 2010). In view of this relational property of digital infrastructure, we argue that digital infrastructure functions as a macro-level external enabler (EE) that provides specific mechanisms that shape individuals' entrepreneurial action-formation (Davidsson et al., 2020; von Briel, Davidsson, & Recker, 2018).

However, although public opinion and policies exalt digital infrastructure as a panacea for paving the way toward a digitally transformed economy and scholars stress its overriding relevance, there is a dearth of empirical research on whether and how a country's digital infrastructure shapes individuals' entrepreneurial action-formation as an EE. To shed light on entrepreneurship in the digital age, scholars adorn potentially effective theoretical lenses, such as the notion of digital affordances (Autio et al., 2018; Nambisan, 2017), the EE framework (Davidsson et al., 2020; von Briel, Davidsson, & Recker, 2018), or the digital entrepreneurial ecosystem perspective (Sussan & Acs, 2017). Although some of the concepts are *qua* design predominantly venture-level theoretical frameworks, they also allow for theorizing the enabling role of digital infrastructure in individual entrepreneurial action-formation.

Extant research on individual entrepreneurship provides ample empirical evidence that socio-cognitive traits, namely, entrepreneurial self-efficacy, fear of failure, and opportunity recognition, are essential mechanisms of entrepreneurial action (e.g., Busenitz & Barney, 1997; Shane & Venkataraman, 2000; Zhao et al., 2005). However, several researchers demonstrate that entrepreneurial action-formation also depends on the proximate and distal macro contexts in which individuals at the micro-level operate. These contexts are external to the respective focal phenomenon (i.e., entrepreneurial action) and enable or hinder entrepreneurship (Jack & Anderson, 2002; Spigel, 2017; Welter, 2011). Country-level contexts that have so far been investigated as moderators for the relationship between individual-level socio-cognitive traits and various entrepreneurial pursuits are social (Schmutzler et al., 2018), institutional, economic, and political (e.g., Autio & Acs, 2010; Boudreaux et al., 2019), or cultural (Stephan & Pathak, 2016; Wennberg et al., 2013) conditions, situations, circumstances, and environments. Although such research provides considerable information about traditional macro-level factors, limited effort has been made in theorizing the role of contemporary factors, such as digital technologies and infrastructure, in shaping entrepreneurial action (Nambisan, 2017).

This prevalent line of contextual thinking is consistent with the EE framework proposed by Davidsson (2015) and refined by Davidsson et al. (2020). In this framework, an EE refers to the aggregate macro-level circumstance that can shape individual entrepreneurial action-formation and plays a significant role in eliciting or enabling entrepreneurial endeavors. Thus, the framework also considers the crucial role of the individual (Kimjeon & Davidsson, 2021). Furthermore, the EE framework provides mechanisms that specify the benefits derived from external contexts, which can be strategically used for personal purposes regarding entrepreneurship (Davidsson et al., 2020; Kimjeon & Davidsson, 2021). Thus far, the EE framework has primarily been applied to different factors outside the scope of action by individuals, for example, the high-speed railway expansion in China (Chen et al., 2020), investments in physical infrastructure in the United States (Bennett, 2019), blockchain in the global music industry (Chalmers et al., 2021), and digital technologies in the IT sector (von Briel, Davidsson, & Recker, 2018), among others (e.g., Browder et al., 2019; Davidsson et al., 2021; Frederiks et al., 2019). We propose that digital infrastructure serves as an EE to support entrepreneurial action-formation (Davidsson, 2015; Nambisan, 2017). Hence, we theorize that digital infrastructure provides mechanisms that shape the impact of individual socio-cognitive traits on entrepreneurial action. On this basis, the overarching research question is as follows: *How does a country's digital infrastructure shape the entrepreneurial action-formation of individuals?* To answer this question, we used a large-scale, cross-sectional dataset comprising 344,265 individual-level observations from 46 countries—and for robustness analysis, a dataset of 391,119 individuals from 53 countries—and employed logistic multilevel modeling.

Overall, our study contributes to knowledge accumulation in the following ways. First, our study represents the first empirical investigation on whether and how a country's digital infrastructure fosters individual entrepreneurial action-formation, thereby responding to numerous calls in the literature to examine entrepreneurship as a multilevel phenomenon (e.g., Busenitz et al., 2003; Terjesen et al., 2016).

Second, our study contributes to the contextual entrepreneurship literature. Specifically, as we consider how digital infrastructure—a hitherto unconsidered technological contextual factor—shapes entrepreneurial action-formation, we add a novel *technological* dimension to the existing classification of contexts proposed by (Welter, 2011).

Third, we combine the agent-centric social cognitive theory (SCT) (Bandura, 1986; Sherman et al., 2015; Wood & Bandura, 1989) with the EE framework (Davidsson et al., 2020). Because SCT is rather unrefined and lacks a theoretical explanation of *how* contextual factors shape entrepreneurial action-formation at the micro-level, we augment SCT with the EE framework, which allows us to reason on *how* a specific contextual factor, in terms of EE, develops through specific mechanisms. With this theoretical approach, which allows for *mechanism-based theorizing*, we demonstrate the theoretical usefulness of the EE framework in elaborating on an existing agent-centric theory, thereby responding to calls from entrepreneurship scholars to merge the EE framework with agent-based theories (Davidsson et al., 2020; Kimjeon & Davidsson, 2021). Our results show that variations in country-level digital infrastructure play a significant role in the relationship between agential cognitions and entrepreneurial action at the individual level and, thus, provide an empirically substantiated theoretical elaboration of the emergent EE theory (Fisher & Aguinis, 2017). Specifically, we are the first to show that the EE framework is not only of paramount importance for theorizing at the venture level (Davidsson et al., 2020; von Briel, Davidsson, & Recker, 2018) but also an appropriate theoretical basis for explaining the role of EEs in the individual-level entrepreneurial phenomenon.

3.2 Theoretical framework

3.2.1 Social cognitive theory

According to SCT, the effects of an individual's predispositions, such as cognitions, emotions, etc., are *determined* and *shaped* by both individual-level characteristics and the external environment in which individuals find themselves (Bandura, 2015; Mischel, 2004; Wood & Bandura, 1989). Grounded in an agentic perspective, SCT states that environmental and socio-structural factors operate through psychological or self-regulatory mechanisms of the self-system to produce behavioral outcomes (Bandura, 2001). Moreover, according to Lent et al. (1994), external contexts exert either direct or indirect influence by moderating the individuals' socio-cognitive traits–behavior relationship. Thus, SCT clarifies the basic mechanisms of agency that govern individuals' behavior and provides a useful framework to understand underlying mechanisms through which individual dispositions lead to behavioral activity (Hmieleski & Baron, 2009; Ng & Lucianetti, 2016).

As SCT is centered on the agentic individual's embeddedness in their environment, the theory also considers the multilevel perspective necessary to understand complex behavioral processes (Hitt et al., 2007). In fact, Jack and Anderson (2002) and (Welter, 2011) demand that research takes into consideration the individual's external context at a higher macro-level to improve the understanding of the entrepreneurship phenomenon at a lower level of analysis. Therefore, we focus on how the external environment at the macro-level—digital infrastructure, in this case—indirectly influences the socio-cognitive traits–entrepreneurial activity relationship at the micro-level.

3.2.2 External enabler framework and venture creation

According to the EE framework, an EE is an aggregate macro-level circumstance that can shape the venture creation process and play a significant role in enabling entrepreneurial endeavors. The EE framework classifies different types of EEs that are external to the focal entrepreneurial phenomenon, based on their origins, such as technological, socio-cultural, macroeconomic, regulatory, demographic, and political factors, and the natural environment (Davidsson, 2015; Davidsson et al., 2020; Mair & Marti, 2009).

In understanding the EE framework, a mechanism is a relational construct that establishes a link between the external environment and the entrepreneurial agent (Davidsson et al., 2020). Hence, EE mechanisms provide a theoretical means of explaining in detail *how* external macro-level circumstances and the micro-level entrepreneurial phenomenon are connected. However, whether an EE provides particular mechanisms depends on both the properties of the enabler and the entrepreneurial agent (Davidsson et al., 2020). As SCT lacks specific theoretical explanations on *how* external factors shape entrepreneurial action-formation, we combine SCT with the EE framework and reason about the underlying mechanisms provided by the EE—here, digital infrastructure—to deduce our hypotheses and further motivate our multilevel approach.

3.3 Mechanism-based theorizing: Hypotheses development

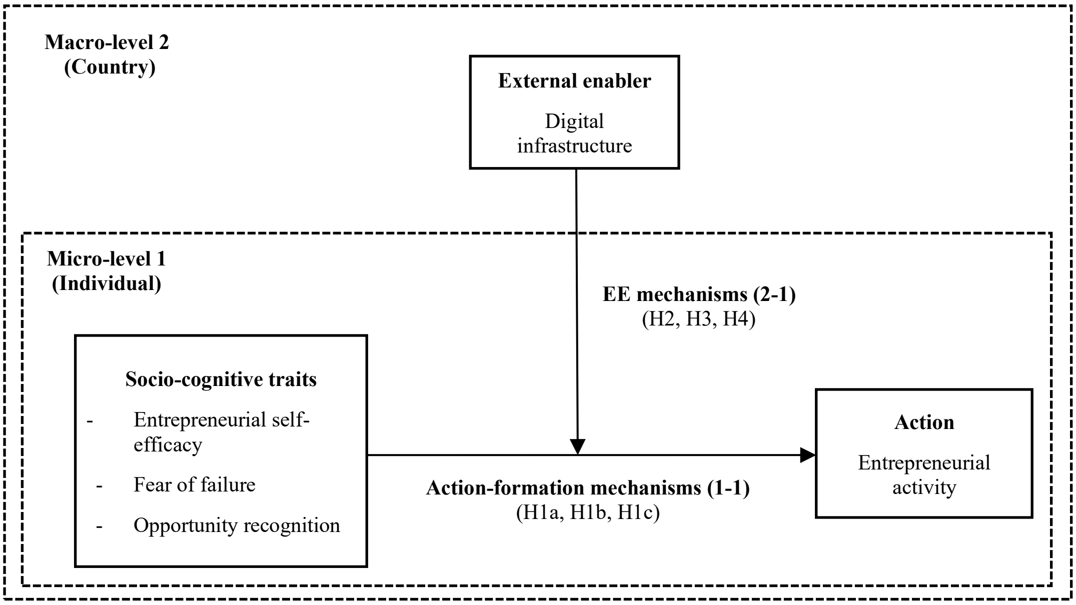
Based on the perspective of critical realism, mechanisms are causal structures that generate observable effects and events (Bhaskar, 1997; Henfridsson & Bygstad, 2013; Merton, 1968), by shaping relationships in a given set of elements (Tilly, 2001). Researchers categorize mechanisms as "situational, action-formation, or transformational mechanisms" depending on the level at which the mechanisms function (Hedström & Swedberg, 1998, pp. 22–23; Kim et al., 2016). First, action-formation mechanisms exclusively operate at the micro-to-micro-level (1-1). At this solely individual-centric micro-level, a plurality of psychological and socio-psychological mechanisms operate and provide a rationale for how agential cognitions, personal traits, beliefs, and motivations generate actions (Hedström & Swedberg, 1998). The action-formation mechanism perspective follows the psychological notion of human agency in SCT; it suggests that human action-formation arises from psychological or self-regulatory mechanisms. These self-regulatory mechanisms, in turn, emerge from lower-order cognitive mechanisms, specifically socio-cognitive traits (Bandura, 1989).

Second, transformational mechanisms influence or generate macro-level outcomes bottom-up from the micro-level to the macro-level (1-2) (Hedström & Swedberg, 1998; Kim et al., 2016).

Third, situational mechanisms cover contextual factors such as technological, political, socio-cultural, and environmental factors that occur top-down and rest at the interacting imbrication between the macro- and micro-levels (2-1). These situational mechanisms determine and shape existing socio-cognitive traits of individual actors at the micro-level (Coleman, 1986, 1994; Hedström & Ylikoski, 2010; Kim et al., 2016; Sarason et al., 2006). Hence, situational mechanisms are a set of plausible hypotheses that can be explanations of some phenomena, whereby the explanation takes the form of interactions between individuals at the micro-level and a circumstance at the macro-level (Coleman, 1994; Schelling, 1998).

We assert that the impact of digital infrastructure on entrepreneurial action-formation refers to such situational mechanisms. The understanding of situational mechanisms fully aligns with the notion of the underlying mechanisms of the EE framework, describing "*the higher-level relationship between the emergence of new digital technologies as external enablers (i.e. cause) and venture creation activity in a sector (i.e. the effect*)" (von Briel, Davidsson, & Recker, 2018, p. 51). Furthermore, this view of situational mechanisms is particularly emphasized in innovation research (Hedström & Wennberg, 2017) and entrepreneurship research concerning entrepreneurial action-formation (Johnson & Schaltegger, 2020; Kim et al., 2016; von Briel, Davidsson, & Recker, 2018). Since the understanding of situational and EE mechanisms are identical, we will refer to both in our theorizing as EE mechanisms. Figure 4 summarizes the theoretical model that we will hypothesize in the following subsections.

Figure 4: Theoretical model



3.3.1 Action-formation mechanisms at the individual level and baseline hypotheses

According to SCT (e.g., Bandura, 1986; Wood & Bandura, 1989), self-regulation explains how humans feel, think, and behave. Since both entrepreneurial activity and individuals' socio-cognitive traits are complex phenomena, we adopt the "cognitive approach to entrepreneurship" (Baron, 2004; Mitchell et al., 2002; Shaver & Scott, 1992). Specifically, we focus on the most prevalent goal-directed entrepreneurial socio-cognitive traits at the individual micro-to-micro-level (1-1) that are representations of the external environment captured through individuals' mental processes (Krueger, 2003) and are generative mechanisms for entrepreneurial action-formation (see e.g., Baron, 1998), namely, entrepreneurial self-efficacy (e.g., Bandura, 1982; McGee et al., 2009), fear of failure (e.g., Caliendo et al., 2009; Langowitz & Minniti, 2007), and opportunity recognition (e.g., Ardichvili et al., 2003; Baron, 2006).

An individual's perceived self-efficacy refers to the self-assessment of one's capabilities and skills (reflecting the innermost thoughts) to create and run a new business venture (McGee et al., 2009; Zhao et al., 2005). Previous studies provide empirical evidence that (entrepreneurial) self-efficacy, as developed by Bandura (1982), is a precursor of intentions (e.g., Chen et al., 1998;

Zhao et al., 2005) and the best ex-ante predictor of behavior (Armitage & Conner, 2001; Bagozzi et al., 1989).

Aside from favorable traits, there are also socio-cognitive traits that can stifle entrepreneurial action-formation. Under SCT, this is the case when individuals surmise that an intended goal is difficult to achieve and the likelihood of failure is omnipresent (Wood & Bandura, 1989). Venture creation epitomizes a perilous endeavor associated with high uncertainty and risk-taking; as such, fear of failure plays a pivotal role in entrepreneurial action-formation (Caliendo et al., 2009). An amplification of fear of failure negatively affects the probability of individual entrepreneurial action (Arenius & Minniti, 2005; Langowitz & Minniti, 2007; Wagner, 2007).

SCT also highlights the human capacity for self-motivation and self-direction by creating goals that serve as motivators and guides for action (Bandura, 1988). In this regard, entrepreneurial scholars have identified opportunity recognition as one of the most fundamental and distinctive personal traits of entrepreneurial action-formation (Kirzner, 1979; Venkataraman, 1997). Individuals who possess traits of opportunity recognition can translate symbolic conceptions into an appropriate course of action (Wood & Bandura, 1989) and may make individuals better at overcoming the inherent opacity of EE mechanisms and foreseeing their benefits (Davidsson et al., 2020; Grégoire & Shepherd, 2012). This idiosyncratic personal trait is described as an entrepreneur's evolving vision that is malleable and becomes more concrete with the progress of entrepreneurial action-formation (Berglund et al., 2020; Davidsson, 2021). Therewith, entrepreneurial action originates from the subjective perception that the introduction of a new product or service is feasible and worth pursuing (Ardichvili et al., 2003; McMullen & Shepherd, 2006).

In summation, on an individual micro-to-micro-level (1-1), SCT suggests that the individual socio-cognitive traits, i.e., entrepreneurial self-efficacy, fear of failure, and opportunity recognition, are essential action-formation mechanisms. Hence, we propose the following baseline hypotheses:

Hypothesis 1a *(H1a): An individual's perception of entrepreneurial self-efficacy is positively associated with entrepreneurial activity.*

Hypothesis 1b *(H1b): An individual's fear of failure is negatively associated with entrepreneurial activity.*

Hypothesis 1c *(H1c): An individual's opportunity recognition is positively associated with entrepreneurial activity.*

3.3.2 EE mechanisms of digital infrastructure and moderation hypotheses

To understand the role of digital infrastructure in entrepreneurial action-formation, we identify specific EE mechanisms by drawing upon the ontological properties of digital technologies (von Briel, Davidsson, & Recker, 2018). According to von Briel, Davidsson, and Recker (2018), digital technologies can be divided into two ambivalent properties—specificity and relationality. Specificity refers to the set of possible actions and interactions that can be performed with a technology (DeSanctis & Poole, 1994; von Briel, Davidsson, & Recker, 2018). In contrast, relationality refers to the set of relationships with other actors or end-users that have access to the same technology (Kallinikos et al., 2013; von Briel, Davidsson, & Recker, 2018).

In light of this ontology, digital infrastructure is not characterized by specificity but is inherently relational and provides enhanced accessibility to different location-independent resources and markets through direct interactions with geographically dispersed audiences and end-users (Autio et al., 2018; Nambisan, 2017; Tilson et al., 2010; Wasko, 2005). Thus, we argue that digital infrastructure mainly facilitates *access*-related EE mechanisms (Bruton et al., 2015; Tilson et al., 2010). Drawing on the EE framework, we propose that digital infrastructure particularly provides *resource access* and *market access* mechanisms (Kimjeon & Davidsson, 2021; Majchrzak et al., 2013; Podolny, 2001; von Briel, Davidsson, & Recker, 2018). While resource access mechanisms reflect "improved access for the [individual] to a previously existing type of resource," market access mechanisms are defined as "improved access for the focal [individual] to a previously existing market" (Kimjeon & Davidsson, 2021, p. 4). These access-related EE mechanisms are especially beneficial to those entities that pursue a specific goal

(Davidsson et al., 2020). In other words, digital infrastructure enables access to pre-existing resources and markets, thereby facilitating entrepreneurial action-formation of individuals with similar socio-cognitive traits.

3.3.2.1 Moderation of the self-efficacy action-formation mechanism

SCT suggests that the extent to which entrepreneurial self-efficacy fosters entrepreneurial action-formation depends on external contexts (Bandura, 1986; Wood & Bandura, 1989). Based on SCT, we theorize that digital infrastructure, with the accompanying resource access and market access mechanisms, is an EE that moderates the effect of entrepreneurial self-efficacy on entrepreneurial action. Specifically, we argue that this positive relationship is stronger when countries have a higher level of digital infrastructure for several reasons.

First, countries with a high level of digital infrastructure provide individuals with a market access mechanism, which refers to improved access to existing markets (e.g., capital, product, labor, credit, customer, etc.) (von Briel, Davidsson, & Recker, 2018). Such market access enables individuals to exchange, buy, or sell services and goods with various customers and vendors (Shelton & Minniti, 2018). Therewith, a market access mechanism enables access to global markets and offers the potential to sell to lucrative international customers via easily accessible online marketplaces and platforms. Simultaneously, market access mechanisms reduce distance-related issues, allow leveraging economies of scale, and lower transaction costs. These benefits enhance the probability that personal effort will lead to successful entrepreneurial performance (Chen et al., 1998). As digital infrastructure, and the associated market access mechanism, is considered an institutional arrangement (Leendertse et al., 2021), it also determines the relative rewards and expected returns from engaging in entrepreneurial activity (Baumol, 1996). Therefore, individuals having similar entrepreneurial self-efficacy beliefs but lacking market access have fewer options to offer products or services in the market, thereby lowering expected returns and enhancing incentives to pursue alternative career options, rather than entrepreneurship (Baumol, 1996). In contrast, in countries that provide market access, i.e., where digital infrastructure is high, existing markets are easily accessible and individuals with similar entrepreneurial self-efficacy are likely to not discount the marginal value of future profits. This, in turn, enhances the impact of individuals prone to mobilizing motivation, abilities, and skills in their effort toward entrepreneurial action (Chen et al., 1998; Wood et al., 2016).

Second, entrepreneurial action as an act of innovation describes an entrepreneur as an individual that utilizes existing resources necessary to produce and offer a product or service that fills a market gap (Drucker, 1985; Leibenstein, 1968). Thus, resources refer to access to, the possession of, and usage of specific human, financial, and other resources and assets necessary for entrepreneurial action-formation (Bull & Willard, 1993; Mitchell et al., 2000). Thus, entrepreneurial action-formation is the result of self-assessment in which individuals evaluate the perceived availability of resources and the constraints to task performance. The consideration of perceived personal resources, such as capabilities and skills (Gist & Mitchell, 1992), the type and amount of specific resources (i.e., tangible and intangible resources), as well as perceptions of external resource availability required to complete different tasks has been shown to determine and shape entrepreneurial action-formation (Bandura, 1988; Gist & Mitchell, 1992; Krueger, 1993). In countries with a low level of digital infrastructure resources relevant to the entrepreneurial process are hardly accessible. This, in turn, reduces the effect of individuals mobilizing personal resources on entrepreneurial action, thereby lowering the likelihood of becoming entrepreneurially active. Thus, individuals with identical entrepreneurial self-efficacy beliefs will ultimately be less likely to engage in entrepreneurial action in countries without resource access mechanisms in place, i.e., where digital infrastructure is low. In contrast, when resource access is given, i.e., digital infrastructure is high, individuals' self-efficacy allows them to virtually access more resources to address deficiencies that prevent them from starting a new business venture.

In summation, we argue that a high (low) level of digital infrastructure, i.e., countries that (do not) provide resource access and market access mechanisms, reinforces (attenuates) the impact of entrepreneurial self-efficacy on entrepreneurial action. Thus, we propose the following hypothesis:

> ***Hypothesis 2*** *(H2): The positive relationship between entrepreneurial self-efficacy and entrepreneurial activity is moderated by digital infrastructure, such that this relationship will be stronger when digital infrastructure is high than when it is low.*

3.3.2.2 Moderation of the fear of failure as an action-formation mechanism

Within SCT, the fear of failure negatively affects the probability of individual entrepreneurial activity (Arenius & Minniti, 2005; Langowitz & Minniti, 2007; Wagner, 2007). We theorize that digital infrastructure weakens the negative effect of the fear of failure on entrepreneurial action for some reasons. First, different obstacles pose serious threats to individuals in the entrepreneurial action-formation process (Cacciotti et al., 2016). These obstacles amplify individuals' fear of failure, for instance, the perception of tangible and intangible resource availability (e.g., Krueger, 2000). The resource access mechanism provided by digital infrastructure offers improved access to existing resources such as human and social capital, which are important conduits of information and resources for resolving uncertainties (Birley, 1985; Engel et al., 2017). For example, individuals can engage in socially persuasive communication and draw on rich informational expertise from various actors and entrepreneurs that are not in close proximity (Kuhn & Galloway, 2015; Nambisan, 2017; Nambisan & Baron, 2007). Hence, we expect individuals with a similar fear of failure, which dissuades them from becoming entrepreneurially active, to virtually receive assistance on a global scale when digital infrastructure is high, thereby weakening the relationship between fear of failure and entrepreneurial activity.

Second, founders generally finance their initial entrepreneurial activities with their own money and "love money" from family and friends (e.g., Bygrave et al., 2003). People showing fear of failure will very likely turn away from making use of such financial resources, leading to fewer entrepreneurial actions. Market access allows for more external funding sources. The market access mechanism through digital infrastructure permits mobilizing external funding directly from demand-side backers through social online networks and crowd-funding platforms, without any distance-related friction (Bruton et al., 2015; Eiteneyer et al., 2019). Hence, the market access mechanism permits individuals with similar failure concerns to mitigate the influence of fears stemming from financial security or the lack of ability to finance an entrepreneurial venture (Cacciotti et al., 2016).

Third, entrepreneurs typically start with a niche strategy; competing at the fringe of the market always carries the risk that founders fear—that the target market is too small for entrepreneurial survival and success (Cacciotti et al., 2016). Digital infrastructure provides a market access mechanism and, therewith, direct access to different existing (over) regional, independent markets, and customers that go far beyond those facilitated by physical infrastructure (see e.g., Chen et al., 2020). Thus, in countries that provide a market access mechanism through a high-level digital infrastructure, the relation between fear of failure and entrepreneurial activity will be weaker compared to countries without such a market access mechanism (i.e., low-level digital infrastructure).

In summation, countries that provide both resource access and market access mechanisms (i.e. high in digital infrastructure) bequeath individuals a similar fear of failure such that the latter can benefit from the provided mechanisms and the negative effect of fear of failure, which prevents individuals from becoming entrepreneurially active, is weakened. Thus, we formulate the following hypothesis:

Hypothesis 3 *(H3): The negative relationship between fear of failure and entrepreneurial activity is moderated by digital infrastructure, such that this relationship will be weaker when digital infrastructure is high than when it is low.*

3.3.2.3 Moderation of the opportunity recognition action-formation mechanism

Possessing the socio-cognitive trait of opportunity recognition is an important antecedent that positively increases the likelihood of entrepreneurial action (e.g., Kirzner, 1979; Wood & Bandura, 1989). We theorize that digital infrastructure strengthens the positive effect of opportunity recognition on entrepreneurial action for the following reasons. First, in countries with a high level of digital infrastructure and, thus, market access mechanisms, individuals who possess the socio-cognitive trait of opportunity recognition are able to evaluate new products, services, and/or business model ideas and meet market needs, thereby enhancing the impact of opportunity recognition on entrepreneurial activity. For instance, individuals can access already existing markets, customers, and relevant competitors through digital forums, discussion boards, and other platforms, or (social) networks. With market access, individuals can contact and converse with customers—i.e., demand-side narratives (Nambisan and Zahra, 2016)—that serve as relevant sources in driving the process of evaluating and modifying potential manifestations of envisioned products and services, as well as assessing their demand and use (Davidsson, 2021). Thus, individuals who affirmatively indicate that they possess the socio-cognitive trait of opportunity recognition benefit from the market access mechanisms provided by digital infrastructure through the enhanced ability to determine the viability of a new venture and the value of entrepreneurial action, thereby increasing the likelihood of entrepreneurial activity.

Second, in transiting from the subjective perception of an idea to a viable, operational business, individuals who possess the socio-cognitive trait of opportunity recognition benefit from the resource access mechanism provided by digital infrastructure. In countries with a high level of digital infrastructure, the resource access mechanism enables individuals to identify and acquire relevant but missing tangible and intangible resources (Bhagavatula et al., 2010; Haynie et al., 2009; Nambisan & Zahra, 2016), which condition the feasibility and viability of the entrepreneurial endeavor. In contrast, in countries that have a low level of digital infrastructure and, thus, do not provide resource access mechanisms, individuals with a similar level of opportunity recognition have a less possibility of obtaining resources needed for the feasibility and viability of the envisioned venture, thereby lowering the likelihood of entrepreneurial activity.

Summarizing the arguments, in countries that provide both resource access and market access mechanisms (i.e., a high level of digital infrastructure), these mechanisms strengthen the positive effect of opportunity recognition on entrepreneurial activity. On this basis, we conjecture the following:

> ***Hypothesis** 4 (H4): The positive relationship between opportunity recognition and entrepreneurial activity is moderated by digital infrastructure, such that this relationship will be stronger when digital infrastructure is high than when it is low.*

3.4 Research methodology

3.4.1 Data

To test the above-mentioned hypotheses, we used three years of the Adult Population Survey (APS) of the Global Entrepreneurship Monitor (GEM) initiative to create a comprehensive sample of 344,265 individuals from 46 countries. By using global individual population samples, the GEM project estimates the prevalence rate of the socio-cognitive traits and entrepreneurial activity of individuals across the participating countries (Reynolds et al., 2005). The GEM data have been used in a vast array of research studies in the past (e.g., Aidis et al., 2008; Fredström et al., 2020). By pooling the data from 2015 to 2017, we obtained a large-scale, cross-sectional dataset in which different individuals were observed in each period (Verbeek, 2008). As Terjesen et al. (2016) had opined—comparative international entrepreneurship research fails to consider the *"ecological fallacy"* problem—by making statements about individual behavior based on aggregated data (Robinson, 1950), prospective contextual entrepreneurship research is encouraged to rely on unaggregated data (Wurth et al., 2021). Accordingly, we relied on unaggregated individual-level data instead of aggregated country-level data and operationalized entrepreneurial action with early-stage entrepreneurial activity.

To assess macro-level determinants, we also linked the obtained individual-level (i.e., micro-level) data on socio-cognitive traits and entrepreneurial activity with country-level (i.e., macro-level) data on digital infrastructure from the International Telecommunication Union (ITU) database, as well as other covariates from various reliable sources such as the World Bank, World Values Survey, and the Fraser Institute. We included several potential macroeconomic and individual-centric control variables to preclude alternative explanations that could influence individuals' cognition for engaging in entrepreneurial activity. To control for unobserved temporal heterogeneity and potential survey effects, we also included year dummies.

3.4.2 Variables and measures

3.4.2.1 Dependent variable

Entrepreneurial activity. To operationalize entrepreneurial action-formation, we used entrepreneurial activity as a dependent variable. For the GEM initiative, the participating individuals provided their assessment of whether they are involved in early-stage entrepreneurial activity (*TEAyy*). The GEM specifies an entrepreneurial activity as a dichotomous variable (1 = yes, 0 = no). The measurement of entrepreneurial activity by a single-item proxy is used in different research projects (e.g., Amorós et al., 2019; Wennberg et al., 2013). At this point, we explicitly emphasize our awareness of the possible limitations of single-item measurements. However, we have weighed these inherent limitations against the advantages of overcoming ecological fallacy (Robinson, 1950).

3.4.2.2 Key explanatory variables

Entrepreneurial self-efficacy. Taken from the GEM variable *suskill*, entrepreneurial *self-efficacy* is measured as a dummy-coded variable. The variable equals 1 if a respondent answered in the affirmative to the question of whether they think they possess the knowledge, skills, and experience required to start a new business; otherwise, 0 (e.g., Estrin et al., 2013; Schmutzler et al., 2018).

Fear of failure. From the GEM database, we used the existing variable *fearfail* to capture the aspect of fear of failure. Based on data availability, fear of failure is a single-item dummy variable (yes = 1, if individuals responded that the fear of failure prevents them from starting a business; otherwise = 0) (e.g., Wennberg et al., 2013).

Opportunity recognition. Further, we used the *opport* variable from the GEM dataset to account for opportunity recognition (Boudreaux et al., 2019). Here, individuals indicate whether they affirmatively perceive that, in the next six months there will be good opportunities for starting a business in the area where they live (yes = 1; otherwise = 0).

Digital infrastructure. Given the absence of a holistically established construct that adequately operationalizes the level of the digital infrastructure of a country, we applied the measurement construct proposed by Billon et al. (2010). By using several multivariate techniques, the authors developed an index for 116 countries. After principal component analysis, the so-called "digitalization" index captures the following indicators: (i) broadband subscribers per 100 people, (ii) internet users in percentage, (iii) mobile phone subscribers per 100 people, (iv) personal computers in households as a percentage, (v) international internet bandwidth in Mbits/s, and (vi) secure internet servers per one million people. These composite indicators serve as proxies for a country's level of digital infrastructure (Alderete, 2017; Billon et al., 2010; Evangelista et al., 2014). These proxies are also in agreement with the construct applied by Stanley et al. (2018). Moreover, the employed construct reflects the "Network Readiness Index" of the Global Information Technology Report published by the World Economic Forum (Baller et al., 2016). This index was also proposed by Sussan and Acs (2017) for assessing a country's digital infrastructure. We built our index by merging data on relevant indicators from the International Telecommunication Union database. We further followed Billon et al. (2010) by log-transforming the index.

3.4.2.3 Control variables

We included control variables on both layers of the proposed two-level model. As socio-demographic controls at the individual level, we included various variables provided by the GEM: *age*, *female*, *education*, *labor status*, and *household size*, following previous studies (e.g., Kwon & Arenius, 2010). Furthermore, we included the dichotomous covariate *know entrepreneur*. In line with previous research, this measure is a proxy for an individual's social network and entrepreneurial role models (Estrin et al., 2016; Schmutzler et al., 2018).

At the country level, we controlled for the country's *GDP per capita* at purchasing power parity (natural logarithm) to represent the overall economic status of development, as well as the *change in GDP* compared with that of the preceding year, to capture the speed of economic development. Both variables have been shown to play a role in the decision to engage in entrepreneurial activity (e.g., Amorós et al., 2019). Second, the variable *exports* measures the proportion of exports in the total GDP (e.g., Oviatt & McDougall, 2005). As recent research shows—exports are related to entrepreneurial activity—we also controlled for this macroeconomic factor (see Schmutzler et al., 2018). Third, we controlled for the log-transformed *population size* to proxy the size of the internal market and, subsequently, impinge on the entrepreneurial activity of a country, i.e., the *population growth* (Boudreaux et al., 2019). This variable has been shown to have negative effects on, for example, entrepreneurial intentions (Schmutzler et al., 2018). Fourth, as unemployment influences entrepreneurial activity (Amorós et al., 2019), we also controlled for the nation's *rate of unemployment.* Fifth, earlier findings demonstrate that the intellectual property rights protection (*IPP*) of a country constitutes a relevant contextual regulator of individual-level behavior (Autio & Acs, 2010); therefore, we accounted for *IPP* by collecting data from the World Bank. Moreover, based on the recent findings of Boudreaux et al. (2019), we also included the Economic Freedom Index (*EFI*) data from the Fraser Institute in our analyses to control for formal economic institutions. Lastly, since culture is an important reflection of a country's informal institutions (North, 1990), we incorporated Inglehart–Welzel's cultural dimensions of *authority* and *well-being*, obtained from the World Values Survey as country-level covariates, into our model (Inglehart & Welzel, 2005, 2010). Appendix K provides the description, type, level, and source of all variables used in this study.

3.4.2.4 Empirical multilevel model

We incorporated the broader context of countries in which individuals are embedded and measured the dependent variable on the basis of individual, non-aggregate observations. Accordingly, we bypassed the potential for *ecological fallacy* (Robinson, 1950) and the accompanying spurious estimates by applying multilevel modeling and allowed the effects to vary at the country level (Hox et al., 2018). In other words, individuals at the micro-level are nested within country-time at the macro-level. To account for the hierarchical nature of our pooled cross-sectional data, and considering that the key dependent variable of entrepreneurial activity is a binary variable, we used a mixed-effects generalized multilevel logit model (Rabe-Hesketh & Skrondal, 2012). For a better interpretation of the cross-level interaction coefficients, the predictors were mean-centered. Additionally, we used multilevel modeling to produce an estimate of the intra-class correlation by omitting all explanatory variables (Hox et al., 2018).

3.5 Results

3.5.1 Descriptive statistics

In Table 2, we report the pairwise correlation matrix for all upper country-level and lower individual-level predictors and controls. Moreover, since our model comprises a decent number of variables at both levels, we performed a multicollinearity diagnostic test. The variance inflation factors (VIFs) test for all variables indicates that collinearity is not an issue in the analysis, as the VIF values are not greater than 10. Appendix L provides a summary of descriptive statistics (Mean, Std. dev., Min., and Max.) for all variables, and Appendix M augments the number of observations per country included in the analysis, as well as the average digital infrastructure per country during the investigation period.

3.5.2 Multilevel logistic regression results

We conducted our estimates in three steps. First, we tested the “totally unconditional model” for our multilevel logistic regression. Although there is no specific threshold in the academic literature, similar studies and technical recommendations suggest an ICC of between 5% and 30% (Mathieu & Chen, 2011). The ICC, which refers to the proportion of the total variance explained by the upper nesting level (i.e., countries) in the population, is 13.04% for our model, indicating the superiority of a multilevel approach over a "plain vanilla" logistic regression model (Aguinis, Gottfredson, & Culpepper, 2013; Hox et al., 2018). Second, we added upper country-level and lower individual-level covariates to our models step by step (Models 2–3 in Table 3). Third, we integrated the hypothesized cross-level interaction terms (Model 4 in Table 3). The respective change in the related information criterion of each model can be inferred from the model fit section in Table 3.

For a clearer interpretation of cross-level interaction effects, we provide two different plots (Aguinis, Gottfredson, & Culpepper, 2013). We report predictive average marginal effects and their respective 95% confidence intervals (Figures 5–7 marked with "a"), as well as the conditional marginal effects of the respective socio-cognitive trait with 95% confidence intervals (Figures 5–7 marked with "b").

The variance of the random intercept in the unconditional model (Model 1) compared with the more comprehensive Model 3 declined from 0.4934 to 0.2598. This reduction indicates that the considered covariates and controls in our model from both country and individual levels statistically capture about 47.34% (([0.4934 – 0.2598]/ 0.4934) ×100) of the variance from the upper nesting level (i.e., between countries).

Although not hypothesized, Model 3 in Table 3 shows a statistically significant direct effect between country-level digital infrastructure and individual-level entrepreneurial activity (dy/dx = 0.0056, $p < 0.05$). However, when introducing the cross-level interactions in Model 4, this positive direct effect becomes non-significant.

Moreover, consistent with our axiomatic theoretical expectations (*H1a*–*H1c*), we observe that the socio-cognitive traits of entrepreneurial self-efficacy (dy/dx = 0.0809, $p < 0.01$) and opportunity recognition (dy/dx = 0.0341, $p < 0.01$) increase the probability of entrepreneurial

Table 2: Correlation matrix for country and individual level variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
(1) Entrepreneurial activity	1.00																													
(2) Entrepreneurial self-efficacy	.25*	1.00																												
(3) Fear of failure	-.09*	-.14*	1.00																											
(4) Opportunity recognition	.16*	.18*	-.08*	1.00																										
(5) Know entrepreneur	.20*	.23*	-.03*	.19*	1.00																									
(6) Age	-.08*	.00	-.04*	-.06*	-.11*	1.00																								
(7) Female	-.05*	-.11*	.06*	-.05*	-.06*	.02*	1.00																							
(8) Household size	.06*	.05*	-.00*	.04*	.07*	-.25*	.01*	1.00																						
(9) Labortstat1-full time	-.08*	-.02*	.05*	.01*	.02*	-.10*	-.14*	-.00*	1.00																					
(10) Labortstat2-part time	-.04*	-.05*	.03*	-.01*	-.01*	-.07*	.10*	.01*	-.29*	1.00																				
(11) Labortstat3-retired/disabled	-.10*	-.08*	-.04*	-.05*	-.11*	.48*	.02*	-.20*	-.30*	-.11*	1.00																			
(12) Labortstat4-homemaker	-.05*	-.06*	.02*	-.04*	-.04*	.03*	.20*	.07*	-.21*	-.08*	-.08*	1.00																		
(13) Labortstat5-student	-.05*	-.08*	.00	-.01*	-.02*	-.30*	-.00*	.07*	-.20*	-.07*	-.08*	-.05*	1.00																	
(14) Laborstat6-not working	-.05*	-.02*	.03*	-.04*	-.03*	-.12*	.02*	.04*	-.28*	-.10*	-.11*	-.08*	-.07*	1.00																
(15) Laborstat7-self-employed	.35*	.25*	-.09*	.10*	.15*	.04*	-.06*	.04*	-.36*	-.13*	-.14*	-.10*	-.09*	-.13*	1.00															
(16) Educ1	-.03*	-.07*	.02*	-.06*	-.06*	.07*	.01*	.05*	-.11*	.00*	.05*	.11*	-.03*	.06*	-.01*	1.00														
(17) Educ2	-.01*	-.03*	.01*	-.02*	-.01*	-.09*	-.02*	.04*	-.06*	.02*	-.03*	.02*	.09*	.04*	-.00	-.39*	1.00													
(18) Educ3	.03*	.06*	-.02*	.05*	.04*	.02*	.01*	-.05*	.12*	-.01*	-.01*	-.08*	-.05*	-.07*	.00	-.34*	-.60*	1.00												
(19) Educ4	.02*	.04*	-.01*	.03*	.03*	.04*	-.00	-.05*	.07*	-.02*	-.01*	-.04*	-.04*	-.03*	.01*	-.12*	-.20*	-.18*	1.00											
(20) Digital infrastructure (log)	-.10*	-.09*	.01*	-.05*	-.10*	.18*	.00*	-.26*	.09*	.04*	.11*	-.10*	-.04*	-.07*	-.10*	-.07*	-.13*	.13*	.13*	1.00										
(21) Population (log)	.00*	.02*	-.00	.03*	.04*	-.07*	-.00*	.08*	-.05*	.00	-.06*	.06*	.00	.01*	.06*	.09*	-.04*	-.01*	-.06*	-.06*	1.00									
(22) Population (Growth)[b]	.10*	.06*	-.08*	.15*	.06*	-.06*	.00	.12*	-.02*	.05*	-.20*	.02*	-.02*	-.07*	.05*	-.01*	-.01*	.04*	-.03*	-.14*	.02*	1.00								
(23) GDP (per capita)[a]	-.12*	-.17*	.02*	-.07*	-.11*	.19*	.00	-.28*	.09*	.06*	.11*	-.09*	-.03*	-.07*	-.13*	-.07*	-.10*	.11*	.12*	.81*	-.28*	-.14*	1.00							
(24) GDP (Growth)[b]	-.01*	-.01*	.01*	-.00	.03*	-.02*	-.00	.05*	.01*	-.00*	-.03*	.02*	-.00	-.00*	-.00	-.02*	.01*	.01*	-.00	-.13*	-.04*	-.04*	.05*	1.00						
(25) Unemployment[b]	-.09*	-.03*	.05*	-.13*	-.05*	.01*	-.00	-.05*	-.07*	-.04*	-.02*	.01*	.05*	.18*	-.03*	.07*	.03*	-.07*	-.04*	-.03*	.01*	-.47*	.01*	-.03*	1.00					
(26) Exports (per GDP)[b]	-.03*	-.06*	.03*	-.02*	-.03*	.04*	.00*	-.05*	.06*	.01*	.03*	-.03*	.00	-.05*	-.06*	-.03*	-.01*	-.01*	.09*	.20*	-.62*	.10*	.44*	.29*	-.13*	1.00				
(27) IPP	-.08*	-.09*	-.02*	.01*	-.07*	.16*	.01*	-.23*	.07*	.08*	.12*	-.08*	-.05*	-.09*	-.10*	-.07*	-.08*	.08*	.11*	.67*	-.16*	.27*	.71*	-.02*	-.24*	.28*	1.00			
(28) Authority	-.14*	-.12*	.05*	-.10*	-.08*	.18*	-.00*	-.29*	.06*	.03*	.09*	-.09*	-.01*	-.01*	-.10*	-.07*	-.03*	.07*	.04*	.53*	-.19*	-.43*	.63*	-.02*	.26*	.19*	.41*	1.00		
(29) Well-being	-.10*	-.09*	-.01*	-.03*	-.10*	.19*	.00	-.26*	.04*	.08*	.11*	-.08*	-.02*	-.05*	-.11*	-.03*	-.08*	.09*	.04*	.67*	-.08*	-.01*	.78*	-.05*	.06*	.12*	.67*	.55*	1.00	
(30) EFI	-.05*	-.03*	-.01*	-.01*	-.07*	.15*	.00	-.18*	.05*	.05*	.08*	-.05*	-.04*	-.06*	-.07*	-.09*	-.08*	.10*	.11*	.60*	-.18*	-.01*	.65*	.11*	-.10*	.15*	.57*	.39*	.54*	1.00

Notes: The matrix is calculated using the full sample of *N*=344,265 observations (46 countries).* $p < 0.05$. [a] Denoted in U.S. dollars. [b] Denoted in %. Variables (1)–(19) are individual-level variables and variables (20)–(30) are country-level variables.

Table 3: Mixed-effects multilevel logistic regression model

	Model 1		Model 2		Model 3		Model 4	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
Fixed part estimates								
Individual-level variables								
Self-efficacy			0.0907***	0.0101	0.0864***	0.0052	0.0809***	0.0051
Fear of failure			-0.0227***	0.0037	-0.0194***	0.0024	-0.0183***	0.0025
Opportunity recognition			0.0408***	0.0030	0.0350***	0.0025	0.0341***	0.0034
Know entrepreneur			0.0544***	0.0072	0.0552***	0.0046	0.0549***	0.0054
Age			-0.0019***	0.0001	-0.0017***	0.0002	-0.0017***	0.0001
Female			-0.0062***	0.0024	-0.0071***	0.0022	-0.0065***	0.0022
Household size			0.0037***	0.0008	0.0012**	0.0005	0.0011**	0.0005
Labortstat2 - part-time			-0.0086	0.0068	-0.0079	0.0059	-0.0072	0.0059
Labortstat3 - retired/disabled			-0.0739***	0.0120	-0.0753***	0.0076	-0.0751***	0.0075
Labortstat4 - homemaker			-0.0297**	0.0124	-0.0350***	0.0094	-0.0359***	0.0094
Labortstat5 - student			-0.0854***	0.0103	-0.0805***	0.0085	-0.0809***	0.0084
Laborstat6 - not working			-0.0183*	0.0096	-0.0125	0.0078	-0.0128	0.0079
Laborstat7 - self-employed			0.1276***	0.0043	0.1259***	0.0084	0.1252***	0.0084
Educ2 - some secondary			0.0027	0.0048	0.0012	0.0037	0.0014	0.0036
Educ3 - secondary			0.0151**	0.0068	0.0138***	0.0042	0.0128***	0.0041
Educ4 - post-secondary			0.0277***	0.0077	0.0292***	0.0051	0.0289***	0.0050
Country-level variables								
Digital infrastructure (log)					0.0056**	0.0023	0.0019	0.0024
Population (log)					-0.0143***	0.0032	-0.0143***	0.0032
Population (Growth)					0.0194***	0.0071	0.0196***	0.0072

(continued)

Table 3: Continued

	Model 1		Model 2		Model 3		Model 4	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
GDP per capita (log)					-0.0300	0.0238	-0.0307	0.0237
GDP (growth)					-0.0008	0.0013	-0.0008	0.0012
Unemployment (%)					-0.0017***	0.0006	-0.0016***	0.0005
Exports (per GDP)					-0.0001	0.0016	-0.0001	0.0001
IPP					-0.0145**	0.0070	-0.0142**	0.0069
Authority					-0.0091	0.0065	-0.0090	0.0064
Well-being					0.0016	0.0063	0.0018	0.0063
EFI					0.0004	0.0090	0.0007	0.0090
Interactions – Individual × Country level								
ESE × Digital infrastructure							0.0042***	0.0007
FOF × Digital infrastructure							-0.0007**	0.0004
OPPORT × Digital infrastructure							0.0009**	0.0003
Random part estimates								
Variance of random intercept	0.4934	0.2496	0.1674	0.0929	0.2564	0.1174	0.2598	0.1182
ICC (*ρ*)	0.1304		-		-		-	
Number of groups (countries)	46		46		46		46	
Number of observations (*N*)	344,265		344,265		344,265		344,265	
Year dummies included	Yes		Yes		Yes		Yes	
Model fit statistics								
Degrees of freedom	2		18		29		32	
Wald χ^2 (sig.)	3.20		4762.55***		6420.89***		20582.19***	
Log-pseudolikelihood	115,656.54		-86,844.21		-84,992.11		-84,876.66	
AIC	231321,1		173728,4		170046,2		169821,3	

Notes: The table reports unstandardized average marginal effects for the multilevel random-intercept logistic model. Education dummy "primary" serves as a reference group. The same applies to the labor status dummy (Ref. group: full-time). Variable definitions are presented in Appendix K. AIC means Akaike's information criterion = 2k – 2 * (log-likelihood), where k denotes the degrees of freedom (number of predictors in the model). Standard errors are cluster-robust. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

activity by an individual. Likewise, the findings further provide empirical evidence that individuals' perceived fear of failure hampers the likelihood of entrepreneurial activity by approximately 2 percentage points (dy/dx = -0.0183, $p < 0.01$; see Model 4, Table 3). Next, we turn to the proposed cross-level interaction effects (*H2–H4*).

First, we find that a country's digital infrastructure significantly moderates the effect of entrepreneurial self-efficacy on entrepreneurial activity (dy/dx = 0.0042, $p < 0.01$). Concerning the estimated coefficients, the entrepreneurial self-efficacy's marginal effect corresponds to a value of 0.0809 for countries with a mean degree of log digital infrastructure (see Model 4, Table 3). The relationship between entrepreneurial self-efficacy and entrepreneurial activity is strengthened by 0.42 percentage points for every unit increase in the digital infrastructure scale. These findings imply that an increase of, for example, 10 units in the digital infrastructure scale reinforces the effect of entrepreneurial self-efficacy on entrepreneurial activity by 4.2 percentage points. The cross-level interaction is graphically shown in Figure 5a. The plot separately depicts predictive margins of entrepreneurial activity for individuals that affirmatively indicated they have entrepreneurial self-efficacy and for those who denied it. We used the entire range of (log) digital infrastructure to plot the moderation as recommended by Aguinis, Gottfredson, and Culpepper (2013) and Hayes (2018, p. 244). We see here that individuals who possess entrepreneurial self-efficacy have a higher probability of entrepreneurial activity, especially when there is a high degree of country-level digital infrastructure (see Figure 5a). This cross-level interaction is statistically significant for all values on the digital infrastructure continuum greater than -10 since from this point onward, the confidence intervals do not cross the zero line (see Figure 5b), thereby supporting *H2*.

Second, we find that the socio-cognitive effect of fear of failure on entrepreneurial activity depends on the country's degree of digital infrastructure, as the interaction across levels is statistically significant with $p < 0.05$ (dy/dx = –0.0007), indicating a reduced effect of fear of failure with an increase in digital infrastructure.

Figure 5: Interaction plots – Entrepreneurial self-efficacy and digital infrastructure

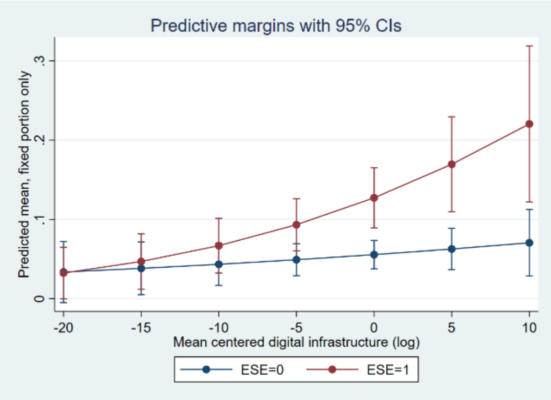


Figure 5a: Predictive margins of entrepreneurial self-efficacy (individual level) by digital infrastructure (country level) with a 95% confidence interval.

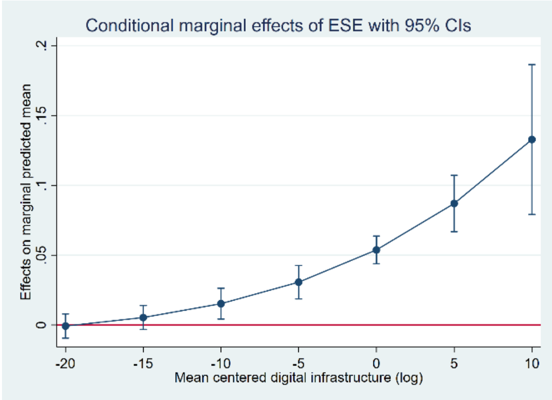


Figure 5b: Conditional marginal effects of entrepreneurial self-efficacy with 95% confidence intervals (CIs).

Figure 6: Interaction plots – Fear of failure and digital infrastructure

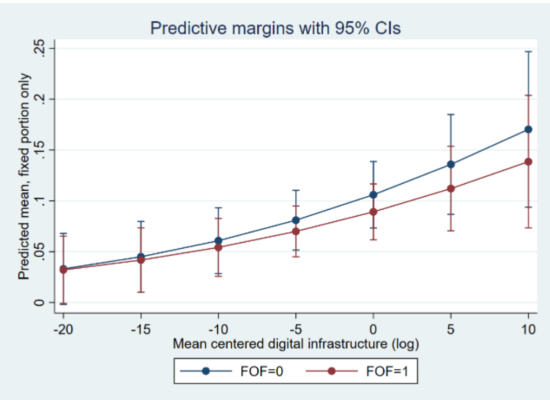


Figure 6a: Predictive margins of fear of failure (individual level) by digital infrastructure (country level) with a 95% confidence interval.

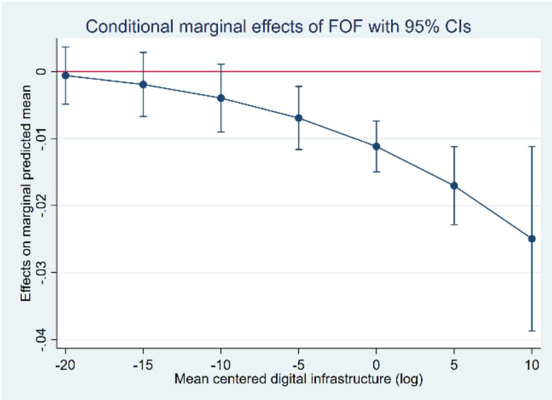


Figure 6b: Conditional marginal effects of fear of failure with 95% confidence intervals (CIs).

Figure 7: Interaction plots – Opportunity recognition and digital infrastructure

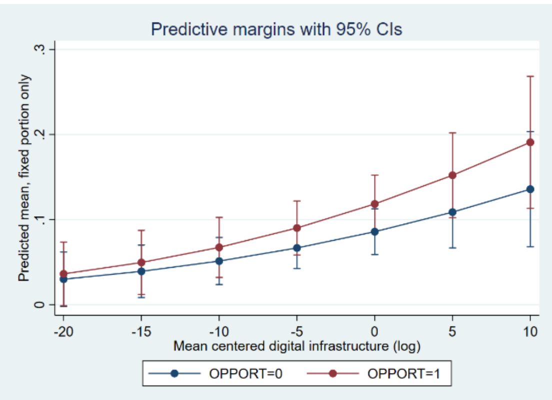


Figure 7a: Predictive margins of opportunity recognition (individual level) by digital infrastructure (country level) with a 95% confidence interval.

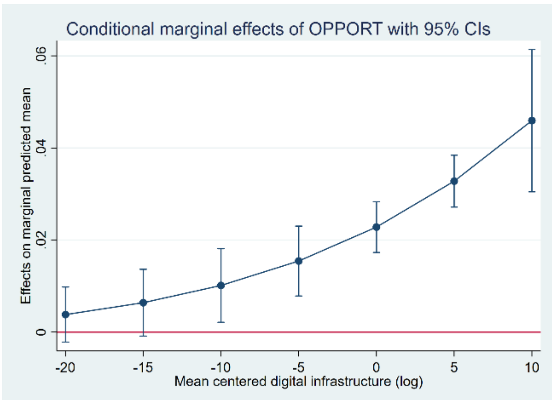


Figure 7b: Conditional marginal effects of opportunity recognition with 95% confidence intervals (CIs).

As the estimated coefficient reflects, the marginal effect of fear of failure decreases the likelihood of having an entrepreneurial activity by 1.83 percentage points (see Model 4) for countries with a mean level of digital infrastructure. However, this relation becomes weaker by 0.07 percentage points for a one-unit increase in log digital infrastructure. As we can see in Figure 6a, for the group of individuals who exhibit fear of failure, the slope is flatter than for those who do not. increase over the range of log digital infrastructure and are statistically significant for all values on the digital infrastructure continuum greater than -8. Thus, *H3* is supported. The conditional marginal effect of fear of failure (see Figure 6b) further supports our findings on the notion that the negative marginal effects.

Third, the effect of opportunity recognition on entrepreneurial activity is strengthened by the level of a country's digital infrastructure, as the cross-level interaction is statistically significant (dy/dx = 0.0009, $p < 0.05$; see Model 4). The marginal effect of opportunity recognition for countries with a mean level on the digital infrastructure scale increases the likelihood an individual has entrepreneurial activity by 0.09 percentage points for each log unit increase in a country's digital infrastructure. Figure 7a contains an illustration of the cross-level interaction. In the presence of a high degree of digital infrastructure, the slope for individuals who affirmatively stated that they perceive that, in the next six months, there will be a good opportunity for starting a new business is steeper compared with those who responded oppositely. Therefore, the impact of opportunity recognition on entrepreneurial activity is more pronounced in countries with a high degree of digital infrastructure. The conditional marginal effects in Figure 7b indicate that the marginal effects of opportunity recognition are statistically significant for all digital infrastructure values greater than -14. Thus, *H4* is supported.

3.5.3 Additional analyses and robustness checks

To evaluate the robustness of our findings and enhance quantitative theory-testing (Anderson et al., 2019), we conducted several supplementary analyses. First, we examined whether our reported results are affected by countries that deviate considerably in their number of observations from others (Aguinis, Gottfredson, & Joo, 2013). We identified Spain as a country with over-represented observations (see Appendix M) and excluded it from our analysis, meaning that only the main variables and interactions of interest were reported in the models. Overall, the results are consistent with the reported baseline findings (see Model 2, Appendix N).

Second, mechanisms are a relational construct situated at the imbrication of digital infrastructure at the macro-level and the individual at the micro-level who interacts with the infrastructure (Davidsson et al., 2020; Henfridsson & Bygstad, 2013; Leonardi, 2011). From this perspective, it can be argued that the technological components of digital infrastructure, in particular, enable resource access and market access mechanisms directly located at the intersection of an individual and the digital infrastructure. To verify this assumption, we built a new digital infrastructure construct based on indicators that are more related to the characteristics of interactions between individuals and the digital infrastructure. Specifically, we relied on application-specific indicators (i.e., broadband subscribers, internet users, and mobile phone subscribers) and re-estimated our analysis. Interestingly, the results in Model 3 of Appendix N show that when we solely use application-related indicators in our analysis, the effects of our main findings disappear. These non-significant results suggest that digital infrastructure is related to both applications of information and communication technologies and the associated infrastructure that provides resource access and market access mechanisms. These findings also corroborate the ontological view in the relevant literature (Autio et al., 2018; Hanseth & Lyytinen, 2010; Tilson et al., 2010).

Third, so far, we have investigated entrepreneurial activity in general. However, entrepreneurship research also decomposes entrepreneurship activity into necessity-motivated entrepreneurship (NME) and opportunity-motivated entrepreneurial (OME) activity (Amorós et al., 2019). While NME is linked to economic recession and unemployment (e.g., Amorós et al., 2019; Shane, 2009), entrepreneurship research is often interested in OME activity, which is associated with innovation and economic growth, as individuals start a venture in pursuit of profit, innovation, and growth (see Reynolds et al., 2005; Stenholm et al., 2013). To account for this distinction, we differentiated between OME (Model 4, Appendix N) and NME (Model 5, Appendix N) and analyzed each model separately. For the NME model, neither the marginal effects of the direct effects of fear of failure and opportunity recognition nor the interaction effects are significant (see Model 5, Appendix N). These findings are unsurprising since individuals are virtually "pushed" into NME by a lack of job opportunities (Shane, 2009). The findings from the OME analysis reveal that the cross-level interaction effects are even more strongly pronounced compared with our baseline findings (see Model 4, Appendix N). These findings suggest that OME activities benefit more from the mechanisms provided by digital infrastructure when individuals pursue their personal goals.

Fourth, for rigorous theory-testing, we conducted a scientific self-replication of our main analysis, as recommended by Anderson et al. (2019). To this end, we collected all the individual- and country-level variables of our main analysis for the period 2012–2014 and re-ran our calculations. We used identical methods, models, variables, and codes for this alternative random sample (Davidsson, 2016). The results from the data pertaining to 391,119 individuals from 53 countries confirm our baseline findings (see Model 6, Appendix N).

Fifth, although hierarchical modeling methods are superior to standard estimation techniques in the presence of nested and contextual data (Hox et al., 2018), multilevel modeling does not entirely rule out possible caveats due to omitted variable bias. To address potential issues arising from the selection of unobservables, we adopted the method provided by Altonji et al. (2005) and Oster (2019). The authors show that under the equal selection assumption, minor movements in the estimated coefficients of the key explanatory regressors indicate a limited omitted variable bias. Since we observe little shifts in the magnitude of the coefficients across the model specifications (see Models 2 to 4 in Table 3), we assume that our estimated parameters are robust to potential omitted variable concerns. Nevertheless, to validate further the sensitivity of our estimates, we re-estimated our comprehensive cross-level interaction model after excluding the highest non-orthogonal country-level variables and scrutinized the parameter stability for the direct and indirect effects of interest. The results confirm our initial assumption and baseline findings (see Appendix O).

Sixth, the assumption of the random effects (RE) model that the country-level error term is uncorrelated with level 1 regressors is often violated and not considered by researchers (Antonakis et al., 2021). To account for this potential caveat, we conducted a correlated random effects (CRE) model (Mundlak, 1978). To specify the CRE model and perform the maximum likelihood estimation for fixed effects (FE), we added the cluster means of level 1 regressors to our model (Allison, 2009; Schunck, 2013). Overall, the estimates shown in Appendix P, Model 1, reveal that the interaction effects are similar to our main analysis. It is only in the CRE model that do we not find a significant effect of the moderation between digital infrastructure and opportunity recognition. This could be due to the different stages of economic development of the investigated countries.

Lastly, to infer the within-effects of countries with different stages of economic development, we also estimated a linear probability model (LPM) with country-level FE, where individuals (level 1) are nested in country-years (level 2), which, in turn, are nested in countries (level 3). Thus, by applying an FE-LPM model, we obtained between-estimates at the individual level and within-estimates at the country level, as, in our cross-sectional data, only country-level covariates are time-variant. Model 2 in Appendix P reports the country FE for factor- and efficiency-driven economies. Model 3 shows country FE for innovation-driven countries. The results of the effects suggest that changes in digital infrastructure within countries are particularly important in innovation-driven countries.

3.6 Discussion

Our study is centered on whether a country's digital infrastructure is a vital, macro-level EE that provides specific EE mechanisms that impact relationships between individuals' socio-cognitive traits and entrepreneurial action at the micro-level. To this end, we blended the agent-centric SCT (Bandura, 1977; Wood & Bandura, 1989) with the EE framework (Davidsson et al., 2020; von Briel, Davidsson, & Recker, 2018) and engaged in mechanism-based reasoning to provide a theoretical framework for *how* the external macro-level digital infrastructure of a country moderates the relationships between individuals' socio-cognitive traits and entrepreneurial action. The cross-level moderation of our multi-level mixed-effects model provided empirical evidence that the extent of country-level digital infrastructure and the provided resource access mechanism and market access mechanism strengthens the positive effect of the socio-cognitive traits of entrepreneurial self-efficacy and opportunity recognition on entrepreneurial action. The findings also highlight that an increase in a country's digital infrastructure provides resource access and market access mechanisms that attenuate the effect of fear of failure on entrepreneurial action.

3.6.1 Contribution to the contextual entrepreneurship literature

Our study contributes to knowledge accumulation in the contextual entrepreneurship literature. A contextualized view of entrepreneurship was employed to explain that entrepreneurial activity at the micro-level also depends on the proximate and distal macro context in which individuals are embedded (Jack & Anderson, 2002; Zahra et al., 2014). Thus far, contexts are understood as social, political, economic, or cultural conditions, situations, circumstances, and environments that are external to the respective focal phenomenon and have the ability to enable or constrain the occurrence of entrepreneurship (Jack & Anderson, 2002; Spigel, 2017; Welter, 2011). Consequently, empirical research primarily investigated traditional contexts, such as institutions (e.g., Autio & Acs, 2010; Boudreaux et al., 2019), culture (Wennberg et al., 2013), and the societal environment, related to entrepreneurial intentions and activities (Meoli et al., 2020; Schmutzler et al., 2018). As we consider how digital infrastructure—a hitherto unconsidered technological contextual factor—shapes entrepreneurial action-formation, we add a novel *technological* dimension to the existing classification of contexts, as proposed by (Welter, 2011). Specifically, our findings suggest that through the ontological property of high relationality (Tilson et al., 2010;

von Briel, Davidsson, & Recker, 2018), country-level digital infrastructure provides resource access and market access mechanisms that shape individual-level entrepreneurial action-formation. In this regard, our cross-level analysis leads to a more nuanced understanding of *how* a contextual factor—here digital infrastructure—molds entrepreneurial action-formation in specific countries, as called for in recent entrepreneurship literature (e.g., Autio et al., 2018; Nambisan et al., 2019).

3.6.2 Contribution to the external enabler framework

Our study also makes significant contributions to the growing body of EE literature. First, we expand on the existing agent-centric SCT (Bandura, 1986; Wood & Bandura, 1989) by using the EE framework (Davidsson et al., 2020; von Briel, Davidsson, & Recker, 2018) to explain in detail the external role of digital infrastructure in entrepreneurship's core phenomenon—the process of individual entrepreneurial action-formation. Specifically, we disclose the theoretical limitations of SCT for theorizing how the EE mechanisms facilitated by digital infrastructure shape individual entrepreneurial action-formation across countries. In our case, the mechanisms derived from the EE framework, resource access and market access mechanisms, offer a basis to fill this gap (Davidsson et al., 2020; Kimjeon & Davidsson, 2021). Therewith, this study is the first to show the promise of theorizing based on EE mechanisms as explicit explanations for *how* external factors shape individual entrepreneurial action-formation (Hedström & Wennberg, 2017).

By setting mechanisms of the EE framework at the center of our theorizing, we managed to integrate knowledge from different research disciplines such as information systems, sociology, and psychology to simplify the understanding of the complex entrepreneurial phenomenon. With this form of analytic eclectism, our study not only highlights the shaping or modifying role of EE mechanisms in entrepreneurial action-formation but also proves that using the EE framework as a theoretical lens helps "improve the explanatory and predictive adequacy" of existing agent-centric theories (Fisher & Aguinis, 2017, p. 450). Hence, with our theoretical amalgamation, we extend the EE framework and answer recent calls to merge the EE framework with agent-centric theories (Davidsson et al., 2020; Kimjeon & Davidsson, 2021). Our study also strengthens the emphasis and knowledge on how EE mechanisms can be used strategically for personal purposes in the entrepreneurial action-formation process (Kimjeon & Davidsson, 2021).

Second, by combining an agent-centric theory with the EE framework, we also relaxed the underlying assumption of the EE framework being mainly relevant for theorizing on emerging ventures as the focal unit of analysis (Davidsson et al., 2020; von Briel, Davidsson, & Recker, 2018). Specifically, we show that variations in country-level digital infrastructure play a significant role in the variance among the relationships between agential cognitions and entrepreneurial action at the individual level. *Ipso facto,* our study facilitated an ontological shift by highlighting that the EE framework is not only of paramount importance for theorizing at the venture level (Davidsson et al., 2020; von Briel, Davidsson, & Recker, 2018) but also tailored as a fertile theoretical basis for explaining the role of an EE in the individual-level entrepreneurial phenomenon. Accordingly, as the EE framework is not yet a full-blown theory, our study provides an empirically substantiated theoretical elaboration on the emergent EE theory (Fisher & Aguinis, 2017).

3.6.3 Policy implications

Our results have important implications for public policymaking. Although policymakers regularly acknowledge the importance of expanding the national digital infrastructure for the future economy, until now, little was known about how a country's infrastructural developments influence individual entrepreneurial action-formation. Our study fills this gap by confirming the decisive and enabling role of digital infrastructure for prospective entrepreneurial action. As our results also underpin that digital infrastructure is related to both application of information and communication technologies and the associated infrastructure (Autio et al., 2018; Hanseth & Lyytinen, 2010; Tilson et al., 2010), we point to two distinct levers on the part of political decision-makers that provides reasonable mechanisms to foster entrepreneurial action.

On the institutional side, the government should do its best to provide the external resources necessary for digital infrastructure (i.e., international internet bandwidth expansion and the provision of secure internet servers) to set up a digital entrepreneurial ecosystem and provide people with the opportunity to benefit from the infrastructure. To achieve broadband network deployment, policymakers can promote frameworks and initiatives that foster investments through incentives, especially in countries with a low level of digital infrastructure (e.g., Guatemala, the Philippines, and South Africa). One example of a public funding initiative is the "Connecting Europe Broadband Fund" with a total investment volume of €1–1.7 billion for infrastructural development. Funding is provided for projects—whether fixed line or mobile—that make a significant contribution to achieving the "Digital Agenda for Europe." If not provided by the public sector, policymakers and regulators must reduce barriers to competition and evaluate unfavorable market concentrations. In countries with a higher level of digital infrastructure, policymakers should take an individual-oriented approach.

On the individual side, the benefits of digital infrastructure grow with each additional individual who uses digital devices to participate in the digital infrastructure (e.g., mobile phone). As a result, in order to unleash the beneficial mechanisms inherent in digital infrastructure, public policies must avoid impeding or even excluding certain groups of people from access via legal provisions and regulations that affect their contractual access rights (e.g., broadband and mobile phone subscription) and the application of these information and communication technologies. Policymakers can pave the way for a digitally transformed economy and create a national digital ecosystem for entrepreneurship and innovation by lowering the mentioned institutional- and individual-side boundaries of relationality.

Furthermore, as our findings highlight the importance of digital infrastructure in providing access-related mechanisms to facilitate entrepreneurial action-formation, we advise policymakers to continue investing in existing or new generations of digital infrastructure that have not yet been seen. Thus, public policy can ensure that beneficial mechanisms are also provided by digital infrastructure in the future.

3.6.4 Limitations and directions for future research

Since empirical models are mere attempts to reflect reality, our investigation, as any empirical study, is not without limitations. The first shortcoming is the use of binary measurement constructs within the GEM dataset. Instead of relying on a single item to measure entrepreneurial self-efficacy, fear of failure, opportunity recognition, and entrepreneurial activity in a dichotomous manner, a stronger inference could be achieved by using well-established or new, valid, and reliable psychometric Likert-based measurement scales, for example, to capture entrepreneurial self-efficacy and fear of failure (e.g., Cacciotti et al., 2020; McGee et al., 2009; Pushkarskaya et al., 2021). However, a single item measurement is more likely to dilute than exaggerate real effects (Lindell & Whitney, 2001).

Second, we used self-reported individual-level measures of socio-cognitive trait variables from cross-sectional GEM data, as previously done by several authors (e.g., Autio & Acs, 2010; Boudreaux et al., 2019; Schmutzler et al., 2018). These measures, however, are based on an individual's subjective and situational self-assessment. As a result, the direct effects on the individual level (H1a–H1c) may be affected by a "halo effect." The main concern here is endogeneity, which can be caused by a variety of factors such as reciprocal causality, common-method variance, measurement error, failure to account for clustered data, and so on (e.g., Greene, 2008; Kennedy, 2008). However, given that our study's overarching goal is to investigate cross-level interactions, endogeneity is unlikely to undermine our main findings (Podsakoff et al., 2012). Indeed, even if reported high entrepreneurial self-efficacy, low fear of failure, and high opportunity recognition are effects rather than causes of entrepreneurial activity, the beneficial EE mechanisms provided by digital infrastructure would continue to shape entrepreneurial activity. However, because we cannot completely rule out the possibility of endogeneity for individual-level main effects, we encourage future research to use experiments and panel studies to avoid the ecological fallacy (Terjesen et al., 2016). Furthermore, our additional analyses indicate that the results appear to hold up best in innovation-driven economies and for opportunity-driven entrepreneurship, whereas support is less certain in other contexts. Furthermore, we would like to emphasize that we cannot completely rule out the possibility that other country characteristics may also enable resource access, market access, or other EE mechanisms that would result in cross-level interactions.

Third, our findings show that digital infrastructure has a significant direct positive effect on entrepreneurial activity. The magnitude and significance of the effect, however, decrease when cross-level interaction terms are introduced. Thus, failing to account for the cross-level interaction effects leads to the conclusion that the positive attributes of digital infrastructure—increased market and resource access—apply to all entrepreneurs. However, we show that when interaction effects are taken into account, these positive attributes only shape the entrepreneurial activity of individuals with specific characteristics.

Fourth, conceptual work in information system research suggests that digital infrastructure may also provide mechanisms for directly influencing socio-cognitive traits (Henfridsson & Bygstad, 2013). This viewpoint does not contradict SCT or the EE frameworks, but rather agrees with Nambisan (2017), who believes that digital infrastructure may lead to various types of effective cognitions and behaviors and, therefore, can be broadly interpreted as an external trigger for new venture creation (von Briel, Davidsson, & Recker, 2018). As previously stated in the social sciences and entrepreneurship literature (e.g., Coleman, 1986; Hedström & Ylikoski, 2010; Kim et al., 2016), socio-cognitive traits may also function as individual-level mediators that traverse macro-level enablers and micro-level entrepreneurial action. To this end, examining chains of mechanisms, for example, through "2-1-1" multilevel mediation models, would be an excellent extension and would broaden our understanding of how mechanisms triggered by external factors and action-formation mechanisms are causally connected (Johnson & Schaltegger, 2020; Preacher et al., 2010). At this juncture, it is also worth noting that digital infrastructure is constantly changing. To that end, we advocate for comparable country-level data for the most recent sense of digital infrastructure (e.g., Blockchain, 5G, AI, 3D Printing, Cloud-Computing, IoT, etc.), as highlighted in recent research (Nambisan, 2017; Nambisan et al., 2019); this would be useful in revisiting our analysis.

Finally, when it comes to relationships, much of the existing entrepreneurship research takes a variable-centric approach. As a result, research leaves theoretical explanations between levels and variables as a black box. Scholars can reason about underlying mechanisms, i.e., "the nuts and bolts" (Elster, 1989, p. 1; Kim et al., 2016), through which, for example, contextual factors shape or trigger the entrepreneurial process and, thus, explain complex phenomena by adopting a mechanism-centric perspective. As a result, we encourage future research to take this mechanism-centric approach to reason and engage in *mechanism-based theorizing* about the role of other (external) factors and their effects on various entrepreneurial processes.

Declaration of competing interests

The authors declare no potential conflicts of interest with respect to research, authorship, and publication of this article.

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Chapter 4

4. Study 3 – Responding to the Situational Urgency of Digital Transformation: A Multilevel Analysis of CEO Humility and Corporate Venture Capital

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Responding to the Situational Urgency of Digital Transformation: A Multilevel Analysis of CEO Humility and Corporate Venture Capital

Abstract

While we see a rise of corporate entrepreneurial actions by incumbent firms as a response to the urgency for digital transformation, we lack an understanding of when CEOs as top decision-makers attend to these changing situational requirements. We propose a theoretical model that conceptualizes *situational urgency* for digital transformation as a mechanism influencing the allocation of top decision-managers' attention towards responsive strategic actions. We test our theorization by examining the relationship between CEO humility and corporate venture capital (CVC) investments as a strategic response to situational contexts of situational urgency for digital transformation. Testing a sample of 373 CEOs from 198 firms and 35 industries from 2010 to 2019 with multi-level analysis, we provide evidence for the relationship between CEO humility and CVC investments. In this regard, we find different moderating results for different types of situational urgency for digital transformation for the CEO humility-CVC relationship. Our study contributes to extant theory by showing that situational urgency influences top decision-makers' allocation of attention to responsive strategic actions.

JEL classification: L25, L26, M13, O33

Keywords: Attention-based view, CEO humility, corporate venture capital, digital transformation, situated attention

4.1 Introduction

The ongoing digital transformation of business and society is imperiling the sustained success of traditional business models and operational processes of incumbent firms (Amit & Han, 2017; Lanzolla et al., 2021; Menz et al., 2021). To ensure long-term survival and competitiveness in the rapidly changing digital era (Hanelt et al., 2021; Sebastian et al., 2017), firms are increasingly enacting corporate entrepreneurial (CE) actions that enable them to renew resources, capabilities, and routines digitally (Prügl & Spitzley, 2021). However, the productive facilitation of CE actions in the fast-paced digital world requires the CEO—as the head of the firm—to not only uphold the existing strengths of the firm, but also to recognize changing situational requirements and instigate responsive actions.

The understanding of how CEOs attend to changing situational requirements is grounded in the attention-based view of the firm (Ocasio, 1997, 2011). Specifically, according to the principle of situated attention that the attention-based view proposes, "individual decision-makers will vary their focus of attention depending on the situation" they find themselves in (Ocasio, 1997, p. 190). However, while literature has advanced our theoretical understanding of actions resulting from the allocation of attention (Yadav et al., 2007), we miss an understanding of what leads CEOs towards being more attentive to situational contexts. Extant studies examine the role of the CEO, presumably as "within any organization, the levers of power are uniquely concentrated in the hands of the CEO" (Nadler & Heilpern, 1998, p. 9). More specifically, the role of CEO characteristics for strategic actions and firm outcomes is well-established in management literature (Hambrick & Mason, 1984). However, a largely overlooked but relevant characteristic of CEOs that makes them sensitive to changing requirements arising from situational contexts is *humility*—"an individual's orientation toward obtaining accurate self-knowledge, appreciating others' strengths and contributions, and being open to self-improvement" (Ou et al., 2018, p. 1148). Humble leaders are well aware of the vulnerability of their firm and the resulting need for devoting their attention to situational contexts (Nielsen & Marrone, 2018; Zhang et al., 2017).

We argue that this awareness of humble CEOs makes them attentive to requirements arising from the digital transformation, which will lead to the expedient initiation of responsive CE actions.

We propose corporate venture capital (CVC) investments, which refers to minority equity investments in entrepreneurial ventures (Dushnitsky & Lenox, 2005; Sharma & Chrisman, 1999), as a prominent CE action that humble CEOs instigate in times of urgency for digital transformation. The establishment of CVC relations with entrepreneurial ventures is a promising instrument for tapping into the newest digital innovations (Huang et al., 2017). In fact, CVC investments serve as a “window on new technologies” (Benson & Ziedonis, 2009), providing innovation benefits for both incumbent firms (e.g., Dushnitsky & Lenox, 2005; Wadhwa & Kotha, 2006) and entrepreneurial ventures (e.g., Alvarez-Garrido & Dushnitsky, 2016; Park & Steensma, 2012; Uzuegbunam et al., 2019). Existing research has considerably advanced our understanding from a meta-perspective and unraveled the firm-level (e.g., Anokhin et al., 2016; Dushnitsky & Lavie, 2010) and industry-level drivers of CVC investment activity (Basu et al., 2011; Gaba & Meyer, 2008; Sahaym et al., 2010). However, while recent research examines the decision-making of individual CVC managers (Ademi et al., 2022), we surprisingly lack knowledge on the influencing role of the CEO as the top decision-maker. Yet, recent studies show that CEOs are part of the investment committee in approximately 39% of CVC investing firms (Strebulaev & Wang, 2021). Insights from qualitative studies provide further evidence for the involvement of the CEO in CVC investments (Basu et al., 2016; Souitaris & Zerbinati, 2014). Our study aims to overcome this shortcoming and advance our understanding of the mechanisms through which CEOs influence the CVC investment activity of their firm.

Building upon the principle of situated attention (Brielmaier & Friesl, 2022; Ocasio, 1997), we theorize upon the urgency for digital transformation to provide a contextual understanding of the relationship between CEO humility and CVC investments. Specifically, we distinguish between two contextual facets of the urgency for digital transformation (Firk et al., 2021): the emerging digital competition as an alarming signal that jeopardizes market positions (i.e., external at the macro-industry-level), and the business model dependence on information and knowledge as an indicator for substitutability by the newest digital technologies (i.e., internal at the meso-firm-level). In this vein, we reason upon the situational mechanism emanated by the external and internal urgency for digital transformation for CVC investments that humble CEOs foster (Sharma & Chrisman, 1999). We test our theoretical model with a sample of 373 CEOs from 198 CVC investing firms and 35 industries from 2010 to 2019 using multi-level analysis.

Overall, our study provides four main contributions. First, we advance theory on the principle of situated attention through our consideration of CEOs and situational urgency. Extant work on the attention-based view has advanced knowledge on the unfolding of the relationship between the allocation of attention and strategic behavior (Ocasio, 1997, 2011; Ocasio et al., 2018). However, we lack an understanding of the specific mechanisms through which the situated attention of top decision-makers is captured and distributed toward strategic actions (Brielmaier & Friesl, 2022). We develop and test a theoretical model proposing situational urgency as a mechanism that explains the enactment of actions in strategic settings requiring responsive behavior. Second, we contribute to extant CVC and leadership literature by identifying a previously unconsidered individual-level driver, namely humility, as a significant CEO characteristic that conveys a theoretical causation for CVC investments. Third, we identify the urgency for digital transformation—which originates from the internal business model dependence on information and knowledge and external emerging digital competition (Firk et al., 2021)—as an unconsidered but important situational factor that provides cross-level explanations for the pursuit of CE actions. In this regard, our theorization and operationalization of the urgency for digital transformation can provide promising research avenues for further understanding the role of decision-makers in today's times of digital change (Nauhaus et al., 2021; van Doorn et al., 2022). Fourth, our study contributes to a multi-level understanding of the attention-based view and CE actions. Existing research treats the allocation of attention and the enactment of strategic actions as the same unit of analysis (Klein et al., 1999). As we explicitly theorize across individual, firm, and industry levels (i.e., micro, meso, and macro) (Kim et al., 2016), our study contributes toward a more holistic theorizing and nuanced understanding of the cross-level nature of how strategic actions function.

4.2 Theoretical background

4.2.1 The attention-based view from the CEO perspective

The attention-based view of the firm regards firm behavior as a function of the attention that decision-makers allocate to strategic activities of the firm (Ocasio, 1997). Concretely, the attention-based view defines the strategy of a firm as a "pattern of organizational attention, the distinct focus of time and effort by the firm on a particular set of issues, problems, and opportunities, and threats, on a particular set of skills, routines, programs, projects, and procedures" (Ocasio, 1997, p. 188). In other words, the attention-based view adopts an information-processing perspective that is contingent upon the allocation of attention (Ocasio et al., 2018). Numerous studies have employed this theoretical lens to explain the role of CEO attention—particularly in interaction with the environmental context—for firm-level behavior and outcomes (e.g., Gamache et al., 2015; Gupta, 1984; Nadkarni & Chen, 2014).

However, while this theoretical perspective has significantly contributed to our understanding of how the enactment of strategic actions unfolds (Brielmaier and Friesl, 2022), we lack a profound understanding of the mechanisms emanating from situational contexts in which top decision-makers operate. Employing this logic to our study, the situational contexts influencing the proclivity of CEOs toward CVC investments can be divided into an external and internal one (Zahra & Covin, 1995). The external situational context is defined by the industry in which the firm of the CEO operates (Ocasio, 1997). The examination of industrial factors in the context of the strategic actions of the firm is long-standing (Dess et al., 1990). CEOs observe industry-level changes to analyze competitors, assess the relative stance of their firm (Stephan et al., 2003), and make decisions about CVC investments as an instrument for strategic change. Additionally, CEOs are influenced by the internal situational context in their consideration of CVC investments. As the head of the firm, the CEO has a full overview of the business model of the firm (Bock et al., 2012). Thus, CEOs can assess the strength of the business model of their firm in the face of recent technological developments and make decisions on leveraging CVC investments to renew or modify firm capabilities.

4.2.2 CEO humility and CVC investments as a CE action

Originating from psychology literature, the concept of humility is increasingly finding application in leadership studies (Mao et al., 2019; Ou et al., 2018; Zhang et al., 2017). Ou et al. (2018) highlight three orientations that humble CEOs exhibit in the organizational context: (1) willingness to obtain accurate self-knowledge, (2) tendency to keep an open mind and continuously learn and improve, and (3) appreciation of the strengths and contributions of others. Extant studies have mostly elaborated on these three orientations to explain how humble CEOs deal with top management teams (e.g., Cortes-Mejia et al., 2021; Ou et al., 2014). Specifically, researchers find that humble CEOs influence the decentralization of top management teams (Cortes-Mejia et al., 2021). Further, there is a growing consensus that CEO humility positively influences firm performance (Ou et al., 2018) and market performance (Petrenko et al., 2019). However, beyond these general insights, our understanding of *how* and *when* CEO humility influences strategic actions at the firm-level is still scarce.

We examine CVC investments as an important *strategic action* that CEOs influence at the firm-level. CVC investments are strategic actions—or CE activities (Sharma & Chrisman, 1999)—that firms undertake to obtain financial (i.e., returns) and strategic value (i.e., access to the newest technological knowledge) through investment relations with entrepreneurial ventures (Dushnitsky & Lenox, 2005, 2006; Maula, 2007). Recent literature reviews highlight a range of industry-level and firm-level antecedents of CVC investment activity (Jeon & Maula, 2022; Röhm, 2018). However, extant research has largely neglected the role of the CEO as the key decision-maker for CVC investments. Yet, CVC investments impact stock prices (Mohamed &

Schwienbacher, 2016), innovation (e.g., Dushnitsky & Lenox, 2005; Wadhwa & Kotha, 2006), and firm value (Dushnitsky & Lenox, 2006)—outcomes that are of central interest to the CEO.

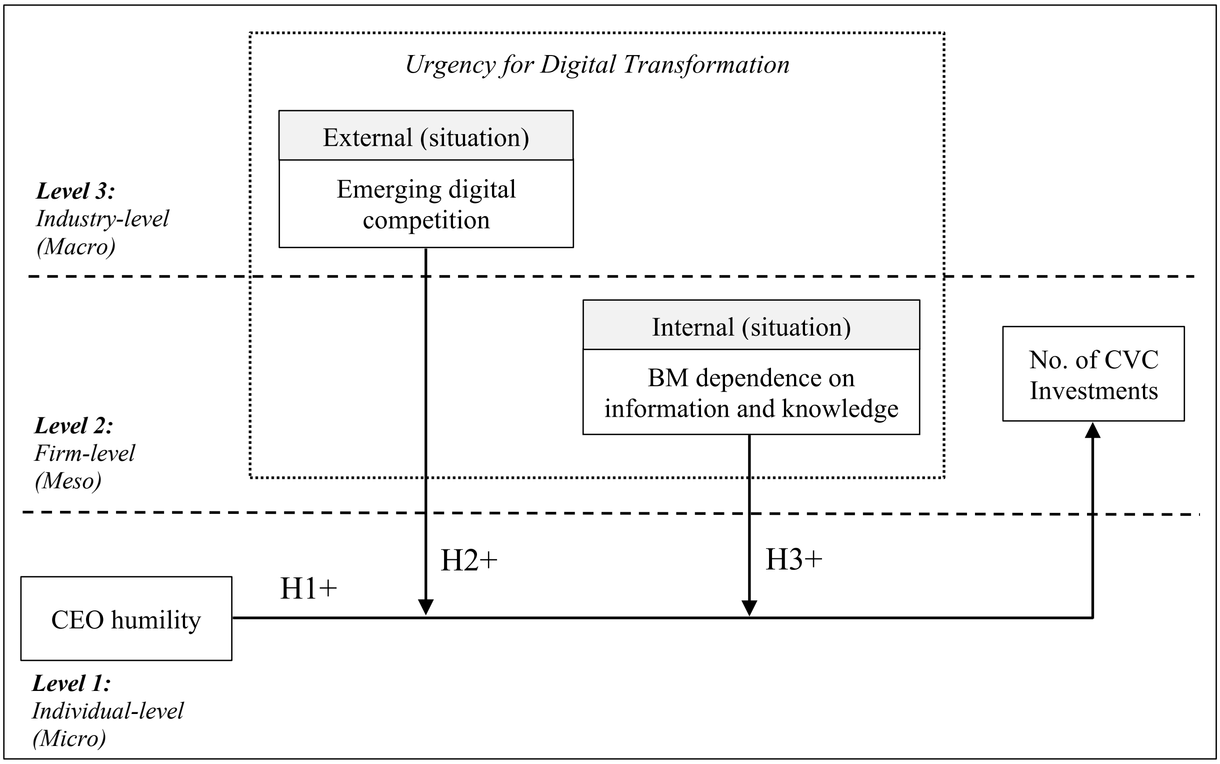
4.2.3 Digital transformation as a context of situational urgency

Digital transformation refers to the "organizational change that is triggered and shaped by the widespread diffusion of digital technologies" (Hanelt et al., 2021, p. 1160). Thus, digital transformation is a contemporary challenge that incumbent firms face to ensure their long-term competitiveness (Amit & Han, 2017; Sebastian et al., 2017). Firk et al. (2021) define the urgency for digital transformation along two dimensions: (1) emerging digital competition (i.e., external situation) and (2) business model dependence on information and knowledge (i.e., internal situation). Emerging digital competition refers to the entrance of digital technology ventures—that is, ventures that have a digital technology at their core (von Briel, Recker, & Davidsson, 2018)—into the industry of a focal incumbent firm. Since incumbent firms have built their competitive advantage on industrial-age innovations (i.e., innovations building upon a classical modular architecture), we argue that the entrance of ventures with novel digital technologies into the industry of a focal firm results in an external form of urgency for transformation at the macro-industry-level. That is, the pressure for embracing digital technologies that originates from outside the boundaries of the firm (i.e., competition).

The dependence of a business model on information and knowledge describes the intensity of a firm's reliance on intangible assets, including patents, copyrights, and trademarks (Firk et al., 2021). Case examples show that firms relying heavily on information and knowledge are greatly affected by ongoing digital transformation processes. For example, with the translation of analog information into digital forms (Tilson et al., 2010) and the proliferation of the Internet, individuals have shifted to mobile and online media consumption. This shift in consumer preferences has urged traditional publishers to digitalize their business models and operations. Similarly, knowledge-based business models are increasingly threatened by the newest digital technologies, as for instance artificial intelligence solutions that can substitute traditional knowledge-creation processes (Tschang & Almirall, 2021). Thus, the vulnerability of a firm toward digital transformation is particularly strong when its business model is easily replaced by digital substitutes. Consequently, in line with Firk et al. (2021), we argue that the dependence of a firm's business model on information and knowledge exhibits an internal form of urgency for digital transformation at the meso firm-level, that is, the necessity for adopting digital technologies that originates from within the boundaries of the firm (i.e., business model).

In sum, we reason that the urgency for digital transformation is a contextual situation that shapes the influence of mirco-level CEO humility on CVC investments. In this regard, we examine CVC investments as a CE response to the contextual situations of external and internal urgency for digital transformation, which allows investment firms to collaborate with entrepreneurial ventures, access the newest technologies, and add value to mainstream business units. Figure 8 depicts our conceptual framework.

Figure 8: Conceptual framework



4.3 Hypotheses development

4.3.1 CEO humility and CVC investments

We propose that CEO humility is positively associated with the number of CVC investments of a firm. Extant research finds that incumbent firms prefer CVC investments over acquisitions when payoffs are difficult to evaluate in advance (Tong & Li, 2011). Therefore, CVC investment activity has been conceptualized as an option-creating instrument (Basu & Wadhwa, 2013; Van de Vrande & Vanhaverbeke, 2013), which serves as a proven vehicle for absorbing external technological knowledge (Dushnitsky & Lenox, 2005). Therewith, researchers agree that CVC investments represent relatively low-risk investments in terms of size and commitment in comparison to other firm-level strategic actions, such as acquisitions (Tong & Li, 2011). There is ample evidence that overconfident CEOs spur the engagement of a firm in acquisitions (Malmendier & Tate, 2005) and even pay acquisition premiums (Hayward & Hambrick, 1997). Against this backdrop, we argue that a CEO exhibiting high levels of humility will increase the number of CVC investments.

This is because, first, with their willingness to obtain accurate self-knowledge (Ou et al., 2018), we expect that humble CEOs can recognize and acknowledge the limitations of the capabilities and resources of the firm. Resultantly, they proactively look for means to overcome these limitations. In this regard, humble CEOs recognize the importance of investing in various new ventures that can fill existing gaps in capabilities and resources (Chesbrough, 2002). Second, the open-mindedness and willingness to continuously learn and improve make humble CEOs more open to external digital innovations and their integration with existing products or services within the firm. In other words, we assume that humble CEOs do not suffer from the "not invented here syndrome" (Katz & Allen, 1982), and instigate additional investment activities. Notably, prior research has found that CVC investment relations often result in strategic alliances to facilitate inter-organizational knowledge transfer (Van de Vrande & Vanhaverbeke, 2013). Humble CEOs will acknowledge the opportunity of intensifying technological collaborations with investee ventures to drive innovation, and thus, they have a more positive mindset about the formation of CVC investment relations. Third, because they appreciate the strengths and contributions of others (Ou et al., 2018), humble CEOs will not underestimate the innovativeness and potential of entrepreneurial ventures to add value to well-established lines of business within their firm. Therefore, humble CEOs increase the usage of CVC as an existing innovation vehicle of the firm by initiating a higher number of CVC investments. We hypothesize that:

> ***Hypothesis 1*** *(H1): CEO humility is positively associated with the number of CVC investments.*

4.3.2 The influence of external situational urgency for digital transformation

Building upon the attention-based view of the firm, we propose that CEO humility will be more strongly associated with higher numbers of CVC investments in contexts with emerging digital competition. Such contexts are characterized by new ventures that are able to scale up digital technologies in a short period of time (Huang et al., 2017). These new and agile ventures increasingly enter existing competitive market structures (Skog et al., 2018), thereby competing with incumbent firms in their focus industries, which results in potential disruption for incumbents. These shifts in competitive structures provide a situational mechanism of urgency for digital transformation, which reduces the stability of the competitive advantage of a company (Firk et al., 2021; von Briel, Recker, & Davidsson, 2018).

Contexts characterized by a high level of emerging digital competition threaten the long-term survival of incumbents, urging them to take measures for overcoming organizational inertia. Here, humble CEOs focus their attention on the pressure and threats imposed by emerging digital competition as an externally grounded urgency for digital transformation situated in the industry. The urgency to act, exerted by digital entrants in the industry, strengthens the open-mindedness of humble CEOs about obtaining external digital innovations. To access external digital innovations and create conditions that facilitate inter-organizational learning, humble CEOs identify the existing CVC vehicle as a promising instrument that can be quickly leveraged through the equipment with necessary resources to increase investment activity. Paying attention to the changing structure of the industry reinforces the appreciation of humble CEOs for the digital capabilities and resources of emerging ventures, which increases their awareness that it is not purposeful to rely solely on the traditional sources of competitive advantage of the firm. As a result, humble CEOs channel their attention toward renewing organizational routines by leveraging CVC investments (Corbett et al., 2013; Ou et al., 2018; Simsek & Heavey, 2011). Emerging digital competition can fundamentally change industry structures, which will lead CEOs towards spurring investments into a multiplicity of ventures that create diverse development opportunities. Therefore, among CEOs possessing a similar level of humility, the ones facing higher industry-level urgency for digital transformation through emerging digital competition engage in the increase of CVC investments to form more and various technological collaborations with entrepreneurial ventures.

In industries with a low level of emerging digital competition, competitive structures change less rapidly and less uncertain. Therefore, paying timely attention to the digital capabilities and resources of various emerging ventures in the focal industry becomes less urgent. This leads humble CEOs to refrain from the continuous re-evaluation of the competitive advantage of their firm (McGrath, 2013). Rather, humble CEOs focus their attention on the self-improvement measures of their firm in response to well-established competitors. For this, they have a better understanding how to develop digitally. Therefore, we argue that—among CEOs possessing a similar level of humility—those who must cope with less industry-level urgency for digital transformation put less emphasis on acknowledging the limitations of the capabilities of the firm. Therefore, these CEOs would focus on a few, but very specific number of investments in entrepreneurial ventures. By doing so, they are less likely to proactively spur various CVC investments. On this basis, we conjecture that:

> ***Hypothesis 2*** *(H2): Emerging digital competition positively moderates the relationship between CEO humility and the number of CVC investments.*

4.3.3 The influence of internal situational urgency for digital transformation

In line with arguments from the attention-based view, we propose that humility will be strongly associated with high numbers of CVC investments when CEOs find themselves in firms with information and knowledge-based business models. Business models with high dependence on information and knowledge are easily replaced by digital substitutes, putting firms under pressure for renewal (Firk et al., 2021). This pressure reflects an internally grounded situational mechanism of urgency for the digital transformation, which likely enforces humble CEOs to leveraging existing CVC vehicles by instigating more CVC investments.

Humble CEOs have an increased awareness of the vulnerability of their firm to digital substitutes in firm contexts where the business model dependence on information and knowledge is high. Humble CEOs engage more thoroughly with business unit managers (Ou et al., 2014), which helps them identify the specific pain points in existing business models that require a digital overhaul. The awareness of the vulnerabilities of the business model enforces the attention of humble CEOs on activities that spur self-improvement and continuous learning. In this context, increasing the number of investments is promising to obtain access to various digital technologies that can spur the digital transformation of the business model of the firm. Entrepreneurial ventures are at the forefront of the development of the digital technologies (Huang et al., 2017), which is a strength that humble CEOs acknowledge.

In firm contexts where the dependence of a business model on information and knowledge is low, that is, in firms that rely heavily on tangible assets, such as large-scale production facilities or machinery, the urgency for digital transformation is not as pronounced as in firms with information and knowledge-based business models (Firk et al., 2021). In this case, the organizational self-knowledge of humble CEOs increases their awareness of the low urgency for digital transformation. Contrarily, humble CEOs are well aware that—while they need to be vigilant for developments in the digital technology sphere—their business model cannot be easily replaced by emerging digital technologies. Therefore, in these contexts, humble CEOs concentrate their continuous learning orientation on facilitating efficiency and incremental improvements to their existing business model, which translates into limited, but very specific CVC investment focus. As they perceive no necessity to radically innovate their business model, humble CEOs are less likely to focus their attention on equipping the existing CVC vehicle with a strong investing mandate. Accordingly, when CEOs exhibit similar levels of humility, the ones directing firms with high business model dependence on information and knowledge will direct their attention and action-formation strongly toward leveraging CVC investments. Thus, we hypothesize that:

> ***Hypothesis 3*** *(H3): Business model dependence on information and knowledge positively moderates the relationship between CEO humility and the number of CVC investments.*

4.4 Method

4.4.1 Data and measures

To test our hypotheses, we collected data for the time period from 2010 to 2019. All investment data were obtained from the "Private Equity Screener" of the Refinitiv Eikon database, and all other firm and industry variables were retrieved from S&P Capital IQ. To ensure the accuracy of our CVC investment data, we followed data cleaning suggestions by Röhm et al. (2020). Specifically, we dropped all undisclosed investors classified as CVCs. Additionally, we triangulated our data with information available in the S&P Capital IQ database and excluded all investors for which we could not identify a profile that matched with Refinitiv Eikon (i.e., unknown investors). Using the "corporate tree" function and business descriptions in S&P Capital IQ, we determined if the investor is truly a CVC. We removed all investors that were not considered "wholly-owned subsidiaries" or were falsely declared as CVCs, such as accelerators, business angels, incubators, independent VCs, and private equity investors. By applying this thorough data-cleaning procedure, our dataset follows a generic definition for a CVC unit and promotes coherence in CVC research (Röhm et al., 2020).

Relevant CEO-level variables and firm-level controls were collected through the S&P Capital IQ database. To measure the humility of CEOs, we collected annual reports from the corporate website of the respective company and extracted the letter to shareholders (LTS). For annual reports not found on the company websites, we used search engines to supplement our data. Overall, the sample of this study consists of 373 CEOs from 198 CVC investing firms and 35 industries. In total, the sample contains 1,597 firm-year observations and 6,907 CVC investments over the period considered. We present all variable descriptions in Appendix Q.

4.4.2 Dependent variable

Number of CVC investments. We relied on the data provided by the 'Private Equity Screener' of the Refinitiv Eikon database and collected information on all completed CVC investments over the period from 2011 to 2019. In unison with research on CVC activity, we measured the number of CVC investments by counting all minority equity investments of the incumbent firm in ventures in the given year t (see e.g., Keil et al., 2008). To enhance causal inference, we lagged the dependent variable by one year ($t + 1$). In line with our theorizing, we considered only the variance of investment activity between and within firms with established CVC units. Since we theorize upon increasing investment activity through an existent CVC unit and not the launch of a new CVC unit (Cabral et al., 2021), the consideration of firms that do not have any CVC unit at all would distort our theoretical and empirical model.

4.4.3 Independent variable

CEO humility. We capture CEO humility by conducting a dictionary-based and computer-aided text analysis (CATA) of annual LTS from 2010 to 2018. This bag-of-words (BoW) approach corresponds with existing research showing that the cognitive traits and orientations of CEOs determine the strategic actions of a corporation (Gamache & McNamara, 2019; Nadkarni & Chen, 2014; Shipp & Jansen, 2011). To linguistically inquire about CEO humility, we measured the reversed "clout score," a summary variable from the well-known Linguistic Inquiry Word Count (LIWC) Software (Pennebaker et al., 2015). High values of "clout" suggest "that the author is speaking from the perspective of high expertise and is confident," whereas low values suggest "a more tentative, humble, even anxious style" (Pennebaker et al., 2015, p. 22). In other words, CEOs with a high level of humility exhibit low “clout” in their language[1]. The “clout” score was derived from the project on the use of pronouns by Kacewicz et al. (2014) and is increasingly finding application in management research (e.g., Zyung & Shi, 2021). As such, the “clout” score is directly incorporated in the LIWC software and serves as a concrete indicator of how humble individuals express themselves.

4.4.4 Moderator variables

To operationalize urgency for digital transformation, we adapted the measure provided by Firk et al. (2021), consisting of emerging digital competition (i.e., external urgency) and business model dependence on information and knowledge (i.e., internal urgency).

External urgency for digital transformation. The first moderator is emerging digital competition and captures the external industry-level situation. To measure emerging industry-level digital competition, we counted the number of digital ventures that received a VC investment in the same industry as the focal CVC investing firm (i.e., 2-digit-SIC overlap) and year t, divided by the number of non-digital ventures that received a VC investment in the same year and industry. To classify ventures as digital or not, we relied on the Refinitiv Eikon’s classification of the “company primary technology application (CTA),” which categorizes the technology of a venture specifically. We considered ventures as “digital” if their primary technology is classified within one of the following categories in the Refinitiv Eikon database: “Internet/Online Related,” “Content or Services via the Internet/Online,” “E-commerce via the Internet/Online,” “Communications/Infrastructure,” “Internet/Online Hardware Technology,” “Software or Tools for the Internet/Online,” or “Services for the Internet.” With this measure, we can distinguish the technological classification of the venture (i.e., digital or not) from the primary industry it operates in. For example, the venture “AutoTrader” runs an online marketplace that brings together car dealers, manufacturers, and individuals to facilitate sales processes. The CTA filter in Refinitiv Eikon considers the primary technology of AutoTrader as “E-commerce via the Internet/Online,” while the standard industrial classification (SIC) of the venture is 5012 (Automobiles and other vehicles). Thus, while the venture is considered digital, it will likely compete with firms operating in the Automobile industry. Additionally, we considered only VC-backed ventures to control for quality and ensure visibility in the industry.

Internal urgency for digital transformation. The second moderator is business model dependence on information and knowledge. Similar to Firk et al. (2021), to capture firm-level urgency for digital transformation, we calculated the total intangible assets of a firm subtracted by the amount of goodwill, divided by the total assets of a firm (Antia et al., 2010). A high value suggests that the business model of the firm exhibits high dependence on information- and knowledge-based assets (e.g., patents, copyrights, and trademarks). A low value indicates that the business model of the firm relies more heavily on tangible assets, such as machinery or production equipment.

4.4.5 Control variables

We include several potential control variables to empirically test the deduced hypotheses and preclude alternative explanations that could influence the proclivity of a CEO to increase CVC investment activity. At the individual CEO-level, we controlled for age, change, digital orientation, education, gender, and tenure. Extant research has spawned empirical evidence that young CEOs are highly incentivized to engage in acquisition activities (Yim, 2013). Further, we controlled for CEO age because young CEOs may be considerably eager to engage in CVC activities. We control for CEO change since a replacement of the CEO likely leads to the heterogeneity of humility. In addition, we also controlled for CEO tenure (Nadkarni & Chen, 2014). To ensure that the number of CVC investments is not solely driven by a CEO's digital orientation, but by humility, we controlled for the verbiage-based digital orientation of a CEO by applying the construct of Kindermann et al. (2021). The construct is manifested in four dimensions, i.e., (i) digital technology scope, (ii) digital capabilities, (iii) digital ecosystem coordination, and (iv) digital architecture configuration, which we obtained through CATA. Further, we controlled for the educational attainment of the CEO by adapting the classification proposed by Datta and Rajagopalan (1998). We assessed the level of CEO education by differentiating between undergraduate degree, master's degree, and doctorate. Further, we included CEO gender as a socio-demographic covariate.

In addition to the CEO-level controls, we account for general firm-level contingencies to diminish the possibility of drawing misleading conclusions about the hypothesized effect of CEO humility. To control for the strong reliance on advertising expenditures as the strategy of a firm to achieve market penetration (Covin et al., 1994), we controlled for log-transformed advertising expenditures in millions of USD. We controlled for a firm's age by counting the years since its founding. This is because young firms may face a higher likelihood to exploit new domains of competencies than old firms, which exhibit high inertia to innovate (Basu et al., 2011; Sørensen & Stuart, 2000). We controlled for a firm's available slack, captured as total current assets to total liabilities, as it has been shown to affect general investment proclivity, e.g., in the form of acquisitions (Nohria & Gulati, 1996). Additionally and consistent with previous research, we controlled for log-transformed R&D expenditures to proxy a firm's technological capabilities and reflect the overall strategy of a company (Dushnitsky & Lenox, 2006; Seo et al., 2015). In case R&D expenditures data were not reported, we used mean-replacement. This procedure has been carried out in previous analyses on various variables for calculating diversification, the value of acquisitions, and firm investment horizon (Gamache & McNamara, 2019; Gamache et al., 2015). Lastly, considering the findings of Singh (1986) that large firms possess greater resources to make uncertain and discretionary investments in new ventures, we controlled for firm size using the log-transformed number of total employees.

At the industry-level, we included log-transformed covariates for industry R&D expenditures (in millions of USD) and industry size measured in the total revenue of the 2-digit SIC. Further, since the number of CVC investments may vary over time, we controlled for systematic period effects using year-dummy variables for the sample period and included industry dummies to account for unobserved industry effects.

4.5 Analysis and results

4.5.1 Analysis

Our sample consisted of 373 CEO observations over time (level 1; micro), nested within 198 CVC investing firms (level 2; meso), and 35 industries (level 3; macro). To statistically reflect the hierarchical nature of the data, we used a three-level hierarchical modeling technique (Rabe-Hesketh & Skrondal, 2012). Since the dependent variable—the number of CVC investments—is a count-based variable, which can only take values that are integer and non-negative, we applied a nonlinear regression approach (Hausman et al., 1984). More specifically, we employed multi-level negative binomial regression to model our data. To test our cross-level moderation hypotheses, we followed best practices and mean-centered the predictors (Aguinis, Gottfredson, & Culpepper, 2013). Additionally, by excluding all explanatory covariates in our multi-level model (Hox et al., 2018), we calculated the variance partitioning coefficients (VPCs), which is analogous to the intra-class correlation coefficients (ICCs) for continuous responses (Leckie et al., 2020). As we aim to understand how the relationship between CEO humility and the number of CVC investments varies in interaction with urgency for digital transformation situated at the firm-level and industry-level, we allowed the intercept and slope to vary (Aguinis, Gottfredson, & Culpepper, 2013; Preacher et al., 2006). Consistent with previous research and to enhance causal inference, we lagged our dependent variable by one year (t_{+1}) for all analyses performed (e.g., Gamache & McNamara, 2019; Nadkarni & Chen, 2014).

We calculated the estimates in three steps (see Table 5). First, we estimated the "fully unconditional model" to calculate the VPCs for our multi-level negative binomial regression model. Second, we added individual-, firm-, and industry-level controls (Model 1). Third, we integrated the individual-level main effect of CEO humility (Model 2). Fourth, we added the cross-level interactions (Model 3).

4.5.2 Results

Table 4 displays the descriptive statistics and correlation matrix for all industry-level and firm-level variables, as well as individual CEO-level predictors, and covariates for the final sample. Results from the performed variance inflation factors (VIFs) test show that we can exclude multicollinearity in our data (VIFs < 5).

To decompose the proportion of the variance in the number of CVC investments, as explained by the specific nesting levels (i.e., individuals, firms, industries), we calculated the VPCs. Overall, 41.27% of the variance was explained by individual CEO-level, 54.28% by the firm-level, and the remaining 4.45% by the industry-level. Since VPC calculation is a new methodological approach for decomposing variance structures in count-based multi-level models, there are no existing "thresholds" that would indicate the appropriateness of multi-level modeling. However, extant research recommends multi-level modeling for cases where the ICC takes a value greater than 5% (Mathieu & Chen, 2011). Given the VPC results, we conclude that multi-level modeling is advantageous over the conventional (non-hierarchical) negative binomial regression (Aguinis, Gottfredson, & Culpepper, 2013; Georgakakis & Ruigrok, 2017; Hox et al., 2018). In Table 5 we report the results of the multi-level negative binomial regression.

Table 4: Descriptive statistics and correlation matrix for CEO-, firm- and industry-level variables

Variables	Mean	Std. dev.	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	VIF
(1) CEO humility	12.01	7.71	1	45.93	1.00																	1.06
(2) CEO age	55.04	6.46	32	80	0.10	1.00																1.28
(3) CEO change	0.13	0.34	0	1	-0.02	-0.14	1.00															1.18
(4) CEO digital orientation	0.88	1.06	0	5.76	-0.03	-0.20	-0.04	1.00														1.46
(5) CEO education	2.75	0.71	1	4.00	-0.01	-0.04	-0.01	-0.08	1.00													1.05
(6) CEO gender	0.04	0.19	0	1	0.04	-0.06	0.00	0.08	0.06	1.00												1.04
(7) CEO tenure	6.53	5.61	0	35	0.05	0.20	-0.37	0.15	-0.02	-0.01	1.00											1.37
(8) Number of CVC investments	3.81	9.27	0	101	-0.00	-0.07	0.06	0.20	-0.00	-0.03	-0.01	1.00										1.18
(9) Firm advertising exp. (ln)	1.81	2.93	-1.35	9.38	-0.06	0.05	0.00	0.16	-0.06	-0.00	-0.06	0.14	1.00									1.17
(10) Firm age (ln)	4.07	0.90	0	6.48	-0.02	0.19	0.02	-0.32	0.04	-0.01	-0.16	-0.05	-0.03	1.00								1.41
(11) Firm available slack	1.60	1.05	0.22	11.18	-0.01	-0.10	0.02	0.05	0.02	-0.00	-0.01	0.14	0.04	-0.20	1.00							1.33
(12) Firm R&D exp. (ln)	2.99	3.66	0	10.27	-0.09	0.04	0.02	0.00	0.11	-0.03	-0.05	0.24	0.18	0.00	0.30	1.00						1.74
(13) Firm size (ln)	10.40	1.37	5.04	13.38	-0.11	0.20	0.02	-0.03	0.04	-0.10	-0.16	0.18	0.26	0.38	-0.20	0.16	1.00					1.55
(14) BM dependence on I. & K	0.10	0.11	0	0.58	-0.14	-0.00	-0.04	0.02	0.01	0.04	0.01	0.06	0.09	-0.06	-0.16	0.08	-0.07	1.00				1.10
(15) Emerging digital competition	4.15	6.52	0	48	0.01	-0.28	0.01	0.46	-0.14	0.01	0.12	0.07	0.06	-0.30	0.01	-0.19	-0.15	0.04	1.00			1.52
(16) Industry R&D expenditures (ln)	8.74	3.73	-6.91	12.27	0.01	0.01	0.02	0.09	0.02	0.08	0.01	0.13	0.15	-0.15	0.27	0.52	-0.07	0.09	0.07	1.00		1.59
(17) Industry size (ln)	14.88	0.74	11.30	15.76	-0.00	0.03	0.04	0.00	-0.06	0.04	-0.15	0.08	-0.01	0.05	-0.06	0.04	-0.04	-0.00	0.06	0.17	1.00	1.12

Notes: N = 1,597 years by 373 CEOs (level 1) from 198 firms (level 2) and 35 industries (level 3). CEO: chief executive officer. Distribution of industry groups by SIC: Manufacturing (46.40%), Transport & Public Utilities (17.91%), Services (17.41%), Finance, Insurance, & Real Estate (8.39%), Wholesale Trade (4.32%), Retail Trade (2.88%), Mining (1.88%), and Construction (0.81%). Correlations greater than 0.05 or less than -0.06 are significant at $p < 0.05$.

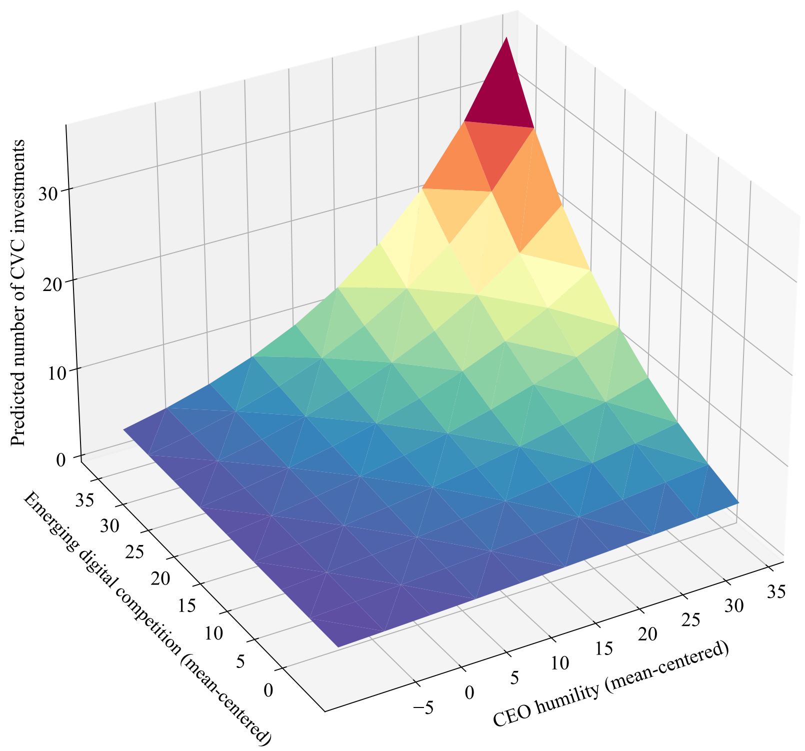
Table 5: Multilevel negative binomial regression

	Model 1			Model 2			Model 3		
DV: No. of CVC investments (t+1)	Coef.	p-value	Sig.	Coef.	p-value	Sig.	Coef.	p-value	Sig.
CEO variables (level 1)									
CEO age	-0.038 (0.023)	0.100		-0.039 (0.023)	0.096	*	-0.038 (0.023)	0.096	*
CEO change	0.168 (0.113)	0.137		0.162 (0.113)	0.151		0.166 (0.113)	0.140	
CEO digital orientation	0.143 (0.056)	0.011	**	0.141 (0.059)	0.017	**	0.144 (0.060)	0.018	**
CEO education	-0.023 (0.089)	0.790		-0.027 (0.088)	0.755		-0.030 (0.087)	0.732	
CEO gender (female = 1, male = 0)	-0.193 (0.251)	0.440		-0.231 (0.253)	0.361		-0.203 (0.249)	0.415	
CEO tenure	0.026 (0.014)	0.062	*	0.025 (0.014)	0.078	*	0.026 (0.014)	0.077	*
Firm variables (level 2)									
Firm advertising exp. (ln)	0.027 (0.012)	0.027	**	0.029 (0.011)	0.014	**	0.028 (0.012)	0.019	**
Firm age (ln)	0.083 (0.122)	0.083		0.079 (0.126)	0.528		0.079 (0.129)	0.540	
Firm available slack	0.010 (0.039)	0.800		0.012 (0.039)	0.762		0.010 (0.039)	0.800	
Firm R&D exp. (ln)	0.098 (0.021)	0.000	***	0.099 (0.022)	0.000	***	0.098 (0.022)	0.000	***
Firm size (ln)	0.268 (0.049)	0.000	***	0.272 (0.052)	0.000	***	0.270 (0.054)	0.000	***
BM dependence on I. & K	0.153 (0.712)	0.830		0.196 (0.691)	0.777		0.333 (0.673)	0.621	
Industry variables (level 3)									
Emerging digital competition	0.012 (0.013)	0.343		0.013 (0.013)	0.309		0.014 (0.013)	0.287	
Industry R&D expenditures (ln)	-0.073 (0.114)	0.522		-0.073 (0.114)	0.523		-0.071 (0.112)	0.524	
Industry size (ln)	0.306 (0.215)	0.156		0.313 (0.214)	0.144		0.308 (0.213)	0.147	
Main effect									
CEO humility				0.014 (0.006)	0.020	**	0.012 (0.005)	0.010	**
Cross-level interaction effects									
CEO humility × Emerging digital competition							0.001 (0.001)	0.019	**
CEO humility × BM dependence on I. & K.							0.054 (0.050)	0.275	
Additional information									
Degrees of freedom	31			32			34		
Wald χ2 (sig.)	10500.68***			53703.03***			1.26e+06***		
Log-pseudolikelihood	-3172.64			-3168.77			-3166.96		
AIC	6413.28			6405.54			6401.93		

Notes: N = 1,597 years by 373 CEOs (level 1) from 198 firms (level 2) and 35 industries (level 3). AIC refers to Akaike's information criterion. Cluster robust standard errors in parentheses. Year-fixed and industry-fixed effects included. Two-tailed tests with *** p<0.01, ** p<0.05, * p<0.1.

Consistent with Hypothesis 1, the results presented in the comprehensive Model 3 (see Table 5) show that CEO humility is significantly and positively associated with the number of CVC investments ($\beta = .012$, $p < .05$). Further, in line with Hypothesis 2, we observe that the urgency for digital transformation, which is manifested via emerging digital competition situated at the external industry-level context, positively moderates the effect of CEO humility on the number of CVC investments ($\beta = .001$, $p < .05$) (see Model 3, Table 5). Figure 9 shows the moderation in the form of a 3D surface plot. Lastly, the cross-level interaction between CEO humility and business model dependence on information and knowledge, as the internal manifestation of the urgency of a firm for digital transformation, is not statistically significant. Thus, we find no support for Hypothesis 3 (see Model 3, Table 5).

Figure 9: Number of CVC investments as predicted by CEO humility and emerging digital competition – 3D surface plot



4.5.3 Additional analyses and robustness checks

Drawing upon organizational learning theory (Cohen & Levinthal, 1990), prior studies highlighted the importance of relatedness between the investing firm and the investee venture for both the formation (Colombo & Shafi, 2016; Dushnitsky & Shaver, 2009) and the outcomes of CVC investment relations (Keil et al., 2008; Van de Vrande & Vanhaverbeke, 2013; Wadhwa & Kotha, 2006). Thus, we conducted an additional analysis by splitting our dependent variable (i.e., number of CVC investments) into related and unrelated CVC investments. To capture the venture relatedness, we conducted SIC code matching between the venture and focal investing firm (e.g., Haleblian & Finkelstein, 1999; Villalonga & McGahan, 2005). Specifically, we classified the CVC investment as "related" if the first two digits of the SIC codes between the investing firm and the investee venture were identical; otherwise, the CVC investments were designated as "unrelated" (Bryce & Winter, 2009). The results reported in Table 6 (Models 1 and 2) confirm that our main findings depicted in Table 5 (Model 3) are robust for both types of investments. However, Model 2 (see Table 6) reveals that the cross-level interaction effect between business model dependence on information and knowledge and CEO humility becomes significant for related investments ($\beta = .081$, $p < .1$). This significant finding indicates that humble CEOs foster the number of related investments to enforce the business model when it is vulnerable to digitalization.

Further, clustered data can arise in two different ways. When there is a hierarchy of data, where CEOs are nested in firms, which, in turn, are nested in industries. In such a case, multi-level modeling is used to account for the nesting structure of the data. Conversely, clustered data can also originate from repeated observations of the same units (i.e., panel data) (Rabe-Hesketh & Skrondal, 2012). Additonally, as our data can also be considered as a panel structure with 1,597 firm-year observations, and to check for the robustness of our results, we conducted negative binomial regressions with both firm fixed-effects and firm random-effects (Greene, 1997). Overall, the results reported in Appendix R and S are robust and almost identical to the reported baseline findings (Model 3, Table 5).

Table 6: Related vs. unrelated CVC investments – Multilevel analysis

	Model 1 Unrelated CVC Investments			Model 2 Related CVC Investments		
DV: No. of CVC investments (t+1)	Coef.	p-value	Sig.	Coef.	p-value	Sig.
CEO variables (level 1)						
CEO age	-0.036 (0.018)	0.053	*	-0.047 (0.029)	0.115	
CEO change	0.149 (0.120)	0.213		0.229 (0.100)	0.022	**
CEO digital orientation	0.128 (0.073)	0.079	*	0.104 (0.040)	0.009	***
CEO education	-0.001 (0.089)	0.991		-0.238 (0.080)	0.003	***
CEO gender (female = 1, male = 0)	-0.104 (0.234)	0.656		-0.208 (0.389)	0.593	
CEO tenure	0.031 (0.018)	0.090	*	0.019 (0.014)	0.177	
Firm variables (level 2)						
Firm advertising exp. (ln)	0.035 (0.013)	0.011	**	0.012 (0.015)	0.435	
Firm age (ln)	0.094 (0.135)	0.485		-0.088 (0.184)	0.630	
Firm available slack	0.008 (0.059)	0.892		0.017 (0.021)	0.402	
Firm R&D exp. (ln)	0.103 (0.025)	0.000	***	0.071 (0.038)	0.064	*
Firm size (ln)	0.260 (0.057)	0.000	***	0.436 (0.099)	0.000	***
BM dependence on I. & K	0.616 (0.730)	0.399		-0.524 (0.531)	0.324	
Industry variables (level 3)						
Emerging digital competition	0.007 (0.015)	0.617		0.006 (0.014)	0.680	
Industry R&D expenditures (ln)	-0.124 (0.106)	0.242		0.223 (0.149)	0.135	
Industry size (ln)	0.337 (0.262)	0.198		0.619 (0.448)	0.167	
Main effect						
CEO humility	0.012 (0.004)	0.013	**	0.015 (0.006)	0.031	**
Cross-level interaction effects						
CEO humility × Emerging digital competition	0.001 (0.001)	0.037	**	0.001 (0.001)	0.008	***
CEO humility × BM dependence on I. & K.	0.047 (0.058)	0.413		0.081 (0.049)	0.096	*
Additional information						
Degrees of freedom	34			34		
Wald χ2 (sig.)	61905.34***			8.96e+11***		
Log-pseudolikelihood	-2742.87			-1310.86		
AIC	5553.74			2687.72		

Notes: N = 1,597 years by 373 CEOs (level 1) from 198 firms (level 2) and 35 industries (level 3). Relatedness is measured by SIC code matching between CVC investing firm and investee venture (1 if the first two SIC-digits are identical, 0 if not). In total, 1,808 CVC investments (26%) were related, and 5,099 CVC investments were unrelated (74%). Year-fixed and industry-fixed effects included. AIC refers to Akaike's information criterion. Cluster robust standard errors in parentheses. Two-tailed tests with *** p<0.01, ** p<0.05, * p<0.1.

Lastly, to investigate the potential value-creating effect of CVC investments, we performed a lagged fixed-effects panel regression with the number of CVC investments (t_0) as the independent variable and Tobin's q as the dependent variable ($t_{+1} - t_{+4}$). Tobin's q captures firm value (Chung & Pruitt, 1994), and has been used by prior CVC studies (e.g., Dushnitsky & Lenox, 2006; Titus & Anderson, 2018). Our sample comprises 1,544 firm-years from 196 firms for the time frame of 2010–2019. Table 7 provides evidence for the relationship between the number of CVC investments and Tobin's q for the periods t_{+1}, t_{+2}, and t_{+3} after the investment. In year t_{+4} after the CVC investment, the significant effect vanished.

Table 7: Firm value effect of CVC investments – Lagged fixed-effects panel analysis

DV: Tobin's q (t_n)	Tobin's q (t_{+1})	Tobin's q (t_{+2})	Tobin's q (t_{+3})	Tobin's q (t_{+4})
Control variables				
Advertising exp. (log)	-0.003 (0.002)	-0.003 (0.002)	-0.004* (0.002)	-0.003 (0.266)
Available slack	0.049*** (0.005)	0.017 (0.005)	0.006 (0.006)	-0.010 (0.151)
Capital exp. (log)	-0.018** (0.008)	-0.022** (0.009)	-0.001 (0.010)	0.004 (0.011)
Firm age	0.065** (0.030)	0.040 (0.035)	0.025 (0.042)	0.053 (0.051)
Firm size (log)	0.046*** (0.016)	0.051 (0.018)	0.033 (0.022)	0.042* (0.024)
R&D exp.	-0.009** (0.004)	-0.001 (0.004)	0.006 (0.005)	0.004 (0.005)
Return on assets	0.004*** (0.001)	0.003*** (0.001)	0.001 (0.001)	0.001 (0.001)
Total revenue (log)	-0.071*** (0.016)	-0.065*** (0.018)	-0.050** (0.021)	-0.047* (0.024)
Industry revenue	-0.016 (0.026)	0.013 (0.288)	0.035 (0.031)	0.001 (0.034)
Industry R&D exp.	-0.004 (0.003)	0.002 (0.004)	-0.002 (0.005)	-0.008 (0.008)
Main effect				
No. of CVC investments (t_0)	0.0015*** (0.0005)	0.0017*** (0.0006)	0.0014** (0.0007)	0.0004 (0.0008)
Additional information				
Year-fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Firm-fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Observations (firm-years)	1,554	1,393	1,228	1,058
Groups	196	191	189	182
R^2	0.163	0.076	0.058	0.061
F-Test (sig.)	12.45***	5.15***	3.52***	3.31***

Notes: Two-tailed tests with *** p<0.01, ** p<0.05, * p<0.1.

4.6 Discussion

Our study aimed to theoretically develop and empirically test the role of situational urgency for the enactment of strategic actions by top decision-makers. To do so, we investigated the role of CEO humility for CVC investments in the context of the external and internal urgency for digital transformation. We find empirical support for the direct CEO humility–CVC investments relationship, and our findings show that emerging digital competition (i.e., external situational context) positively moderates this relationship. While we do not find support for the moderating role of business model dependence on innovation and knowledge (i.e., internal situational context) for CVC investments, our findings suggest that the situational urgency arising from the firm-level context moderates the relationship between CEO humility and CVC investments for investments in related ventures.

4.6.1 Theoretical contributions

Our theorization and findings point to four important contributions to extant theory and literature. First, we develop a theoretical model of situational urgency that provides a nuanced understanding of how strategic actions emerge from top decision-makers' allocation of attention to responsive strategic actions. Concretely, with theoretical development and empirical analysis, we theorize that strategic actions are contingent on both the "meso-level" and "macro-level" context of the CEO as the firm's key individual decision-maker (Jack & Anderson, 2002; Zahra & Covin, 1995). Through our empirical context, we advance the attention-based view to explain the externally and internally situated role of urgency for digital transformation in the unfolding of CE actions. In particular, our theoretical model extends the principle of situated attention—which echoes the tenets of contingency leadership by stating that CEOs vary their allocation of attention contingent upon the contextual situation (Brielmaier & Friesl, 2022; Ocasio, 1997)—to situational urgency as an action-oriented context that influences how humble decision-makers allocate their selective attention to instigate strategic behavior of the firm. Thus, we show that contextual considerations are important for theorizing corporate entrepreneurial pursuits (Jack & Anderson, 2002; Zahra, 2007; Zahra et al., 2014).

Second, as our analysis sheds initial light on CEO humility as a significant antecedent cognition for CVC investment activity, we introduce CEO humility as a previously unrecognized but relevant driver for CE actions. In other words, the cognitive mechanism of humility serves as an important lever that generates observable CE activities (Bhaskar, 1997). Although CVC research has examined a range of firm and industry-level drivers of CVC investment activity (Jeon & Maula, 2022; Röhm, 2018), it has largely overlooked the role of the CEO as the top decision-maker. By evidencing the relationship between humility—as a less egocentric and more outward-looking characteristic of CEOs—and CVC investment activity, we overcome this research gap and contribute toward the individual-based view on CVC. Investigating the role of CEO humility for strategic actions is important since it can help to uncover the mechanisms through which humble CEOs drive innovation and firm performance.

Third, in the attention-based view of the firm, environmental change is a crucial situation for top decision-makers. Employing the attention-based view to study CVC dynamics as an indicator for CE actions, we introduce a hitherto omitted factor, namely urgency for digital transformation (Firk et al., 2021), that emanates from internally (i.e., business model dependence on information and knowledge) and externally (i.e., emerging digital competition) grounded situations that CEOs devote their selective attention to. This contribution can provide an intriguing angle and empirical operationalization for the nuanced examination of the emergence of both internal and external corporate venturing activity in general, and ultimately, firm performance outcomes in the digital era.

Fourth, given the complexity of factors potentially affecting CE actions in the digital era, we propose a theoretical model along three distinct levels of analysis that assumes that CVC investments—as a form of CE—are determined by the interaction of the individual-level, firm-level, and industry-level. In comparison to our approach, extant research treats the relationship between CEO characteristics and strategic actions as well as performance outcomes of the firm at the same level of analysis (Klein et al., 1999). CE has predominantly been studied from a purely single level or pseudo-multi-level angle by not considering nesting structures (e.g., CEOs nested in firms, nested in industries). By explicitly theorizing across multiple levels, our work promotes a more comprehensive and cross-level theorizing of entrepreneurial phenomena (Schade & Schuhmacher, 2022). In this way, our multi-level model is an improvement over alternative single-layer approaches as it includes cross-level explanations that are important for understanding CE actions.

4.6.2 Practical implications

Our findings provide important practical implications. Supervisory boards that are interested in opening up the organizational boundaries of the incumbent firm for driving innovation through

CVC investment activity may use our findings to select CEOs. Specifically, our findings suggest that supervisory boards should draw their attention to humility when hiring CEOs for fostering CE in times of urgency for digital transformation. The willingness of humble CEOs to obtain accurate self-knowledge, their openness for continuous learning and improvement, and their appreciation of the strengths and contributions of others (Ou et al., 2018) lead them toward positively assessing the potential value that entrepreneurial ventures can yield in the realm of CVC investment relationships. Given our evidence for the innovation and firm performance benefits of CVC investments, hiring humble CEOs should increase innovation and performance. Drawing upon these findings, we encourage incumbent firms to further pursue CVC investments as an important vehicle for innovation and firm performance in the digital age. Further, our results highlight the importance of the urgency for digital transformation as a contextual moderating factor of the CEO–CVC investment activity relationship. Thus, our results suggest that humble CEOs are sensitive to the context of urgency for digital transformation, which provides support for the importance of the humility trait to cope with new challenges arising from the digital transformation process.

4.6.3 Limitations and future research

As other empirical studies, our research also has limitations. First, we limit our theoretical scope to the examination of CEO humility as an important characteristic that is gaining increasing academic attention (Ou et al., 2018). However, other CEO characteristics could also play an important role in spurring or inhibiting CVC investment activity, and in fact, CVC literature has largely overlooked this perspective. Future studies should dive further into this theoretical lens and examine CEO characteristics that have been found to influence strategic actions, such as the big five personality traits, temporal focus (Nadkarni & Chen, 2014), regulatory focus (Gamache et al., 2015), or digital orientation (Kindermann et al., 2021). In this regard, while we control for digital orientation and find a significant relationship with CVC investment activity, future studies can theorize upon this construct to examine the CVC investment process in more detail (e.g., regarding the composition of CVC investment portfolios). In this regard, the development of dictionary-based measures that are currently missing—such as for the big five personality traits—would help to advance longitudinal inquiries on the CEO role.

Second, although the examination of CEO humility through CATA allows the avoidance of retrospective reporting biases inherent to common survey-based measures (e.g., Ou et al., 2014), we are well aware of the common limitations of using LTS. However, we weighed these limitations against the benefits of obtaining a longitudinally comparable data basis for length, scope, and audience across the different firm, industry, and geographical contexts (Gamache & McNamara, 2019). Importantly, prior studies showed that CEOs—as the head of firms and the ones bearing responsibility for shareholder value—are intensively involved in the formulation of annual LTS, which they ultimately sign personally (Duriau et al., 2007). In addition, there has been recent evidence for the significant correlation between cognitive constructs retrieved through the content analysis of LTS and those obtained through the analysis of transcribed texts from video interviews of CEOs, which further confirms validity (Back et al., 2020). This is in line with earlier studies, which found that CEOs are consistent in their use of language across different public formats (Nadkarni & Chen, 2014).

Third, while we took great care to construct a hand-collected and unique dataset, we do acknowledge the common limitations of secondary data. Future research could employ scenario-based experiments with CEOs to provide detailed insights into their cognitive processes and decision-making, albeit obtaining access to such data is a great challenge.

4.7 Conclusion

CVC investment activity is increasingly establishing itself as an instrument to spur digital transformation. Our findings unravel the role of CEO humility for CVC investments and shed light on the urgency for digital transformation as an important contextual factor that emanates a situational mechanism to strengthen the CEO humility–CVC investments relationship. In this vein, our study contributes to the attention-based view by developing a model that conceptualizes situational urgency as a theoretical mechanism explaining the allocation of attention towards the enactment of strategic actions. We hope that future research will build upon our work to examine the role of the CEO and other top decision-makers to shed light on CE pursuits for addressing challenges imposed by the context of digital transformation.

Declaration of competing interests

The authors declare no conflicts of interest with respect to research, authorship, and publication of this article.

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5. Concluding Remarks

The overarching aim of this doctoral thesis was to investigate the nexus between cognitive traits and entrepreneurial pursuits in the digital age. To achieve that goal and in an attempt to advance the literature on entrepreneurship, this doctoral thesis has taken a multi-layered perspective to examine different manifestations of digitization along different levels of analyses—i.e., individual (Study 1 from Chapter 2), individual and country (Study 2 from Chapter 3), and individual, firm, as well as industry (Study 3 from Chapter 4). The incorporation of different hierarchical levels across the analyses permits hypotheses to be made about the unobservable mechanisms situated within and between the levels considered—i.e., about horizontal action-formation mechanisms, and top-down vertical situational mechanisms—that can explain the relationships between cause and effects (Hedström & Swedberg, 1998). By focussing on mechanisms that have not yet been considered relevant in the existing literature or have only been considered vital in a different context, this doctoral thesis aims to make theoretical contributions by examining "why" the relationships or effects proposed by a certain theory occur (Makadok et al., 2018). Scholars can build upon the findings of this thesis to further contribute to the advancement of theory and practice in different research fields outside the realm of digitalization.

First, while Study 1 (see Chapter 2) provides important insights about agent-centric features to predict different entrepreneurial pursuits, future research could examine the role of various environmental features and changes in an individual's context (e.g., crisis, technological changes, socio-cultural shifts, natural environments, etc.). The application of prediction models allows scholars to let data speak freely about important features, without a priori theoretical assumptions (see Schade & Schuhmacher, 2023). Such an "empirics-first" approach is beneficial, as it allows researchers to engage in algorithm-supported induction for building theory (Golder et al., 2023; Shrestha et al., 2021). The theoretical frameworks constructed in this way can afterward be falsified using classical hypothesis testing. Furthermore, the prediction of various events that are critical for the economy and the prosperity of societies provides insights into important drivers and helps to decipher the complex phenomenon of entrepreneurial pursuits. However, future scholars should be aware to not get trapped in a strange loop of epistemology when iteratively applying abduction and algorithm-induced deduction.

Second, while this work provides important insights on the contingent role of contextual factors on the action-formation of individual and corporate-level entrepreneurial pursuits, this thesis largely leaves out the backend of the equation—i.e., how action influenced by the context influences the context in turn—which would allow scholars to come full circle. This neglection of how lower-level actions constitute aggregate outcomes seems to be a lacuna in current research. However, understanding bottom-up transformational processes is vivid as, when considered collectively—i.e., situational, action-formation, and transformational—they allow researchers to draw a comprehensive model to explain how phenomena on higher hierarchical levels emerge (Coleman, 1994; Cowen et al., 2022; Kim et al., 2016), which offers promising avenues for new theorizing. Such a holistic view would also help to consider changes in the context of entities not to be viewed as "exogenous" but rather as "endogenous" processes. To illustrate this, consider for example Study 2 (see Chapter 3). Here, digital infrastructure is considered an aggregate-level EE for the new venture creation process by providing specific EE mechanisms (Schade & Schuhmacher, 2022). However, such emerging ventures that are triggered, shaped, or whose outcome is enhanced by EEs in turn trigger disequilibrating changes in existing markets. Such new disequilibrating changes in the markets can, in turn, represent new aggregate-level EEs, for other entities. This cascading notion or looping enablement—i.e., the realization of a serial-connected array of enablement—could be continued, accordingly. Thereby, dissolving the exogeneity assumption of the underlying theory towards a form of "endogenous enablement". This notion can also be applied to Study 3 (see Chapter 4).

Third, however, instead of aiming to broaden the scope of understanding by drawing a holistic picture of the relationship of context-entrepreneurship-context, it can also be particularly insightful for future research to, figuratively speaking, turn the magnifying glass on e.g., situational mechanisms to understand how they materialize. In particular, it might be interesting to combine the concept of affordances (Autio et al., 2018; Gibson, 1979; Leonardi, 2011; Volkoff & Strong, 2013) with the mechanisms provided within the EE framework (Davidsson et al., 2020). Although both theoretical notions are described to convey a similar logic (Davidsson et al., 2020, p. 320), and currently exist as two separate streams in the literature, both perspectives have distinct theoretical properties. While the notion of affordances assumes an *ex-ante* actualization view of action-potentials, the concept of EE mechanisms takes an *ex-post* actualization perspective. Thus, by actualizing affordances, agents materialize the enabling EE mechanism(s) afforded by external circumstances and objects. Such a complementary understanding would also allow EE mechanisms to be identified through the lens of affordances (Bygstad et al., 2016). In addition, the reconciliation of both mid-range theories would be beneficial, as it could provide guidance for design science in entrepreneurship (Seckler et al., 2021).

Overall, the trifecta of the presented studies in this cumulative doctoral thesis contributes towards a multi-layered perspective on the intersection of cognitive traits and entrepreneurial pursuits in the digital age. As this thesis opens up promising avenues for future research, I hope this work provides a fertile ground for other scholars to further theoretically advance this captivating line of research.

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Appendices

Appendix A: Feature definitions

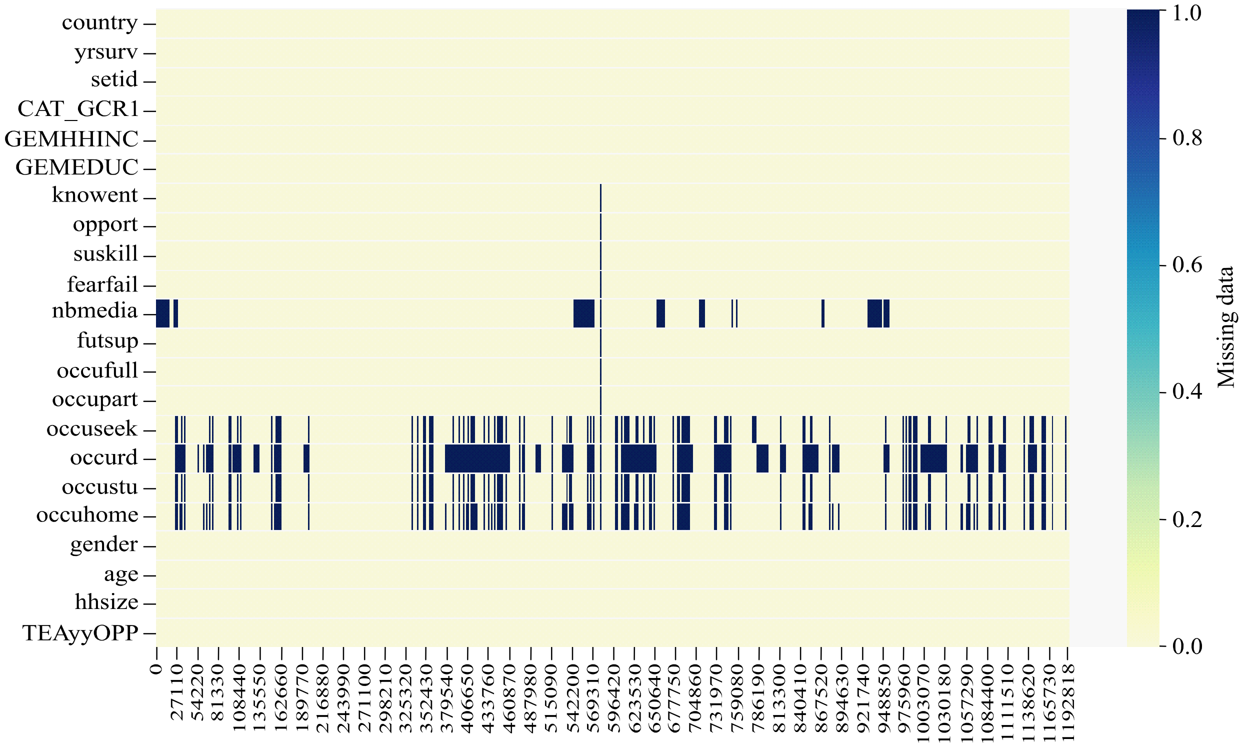
Feature *(Abbreviation)*	Description	Type
Target		
Opportunity-motivated entrepreneurial activity *(TEAyyOPP)*	Coded 1 if the individual is involved in opportunity early-stage entrepreneurial activity (*1=yes; 0=no*)	Binary
Explanatory		
Country identifier *(country)*	Country identifier	Continuous
Year of survey *(yrsurv)*	Year survey was administered	Continuous
Respondent identifier *(setid)*	Harmonized respondent identifier	Continuous
Country's developmental stage *(CAT_GCR1)*	Country group GCR report - 5 categories: *(1=stage 1: factor driven; 2=transition between stage 1 (factor) and stage 2 (efficiency); 3=stage 2: efficiency driven; 4=transition between stage 2 (efficiency) and stage 3 (innovation); 5=stage 3: innovation driven)*	Categorical
Household income *(GEMHHINC)*	GEM harmonized household income categories *(1=lower 33%tile; 2=middle 33%tile; 3=upper 33%tile)*	Categorical
Educational attainment *(GEMEDUC)*	GEM harmonized educational attainment categories: *(0=none; 1=some secondary; 2=secondary degree;3=post-secondary;4=graduate)*	Categorical
Knowing an entrepreneur *(knowent)*	Do you personally know someone who started a business in the past 2 years? *(1=yes; 0=no; −1= I don't know)*	Categorical
Opportunity recognition *(opport)*	In the next 6 months, there will be good opportunities for starting a business in the area where you live? *(1=yes; 0=no; −1= I don't know)*	Categorical
Entrepreneurial self-efficacy *(suskill)*	Do you think you possess the knowledge, skills and experience to start a new business? *(1=yes; 0=no; −1= I don't know)*	Categorical
Fear of failure *(fearfail)*	Fear of failure would prevent you from starting a new business? *(1=yes; 0=no; −1= I don't know)*	Categorical
Media coverage *(nbmedia)*	In my country, you will often see stories in the public media about successful new businesses? (*1=yes; 0=no; −1= I don't know*)	Categorical
Entrepreneurial intention *(futsup)*	Within the next 3 years, do you expect to start alone or with others a business, including any type of self-employment? *(1=yes; 0=no; −1= I don't know)*	Categorical
Full-time employment *(occufull*)	Respondent is employed by others in full-time work *(1=yes; 0=no; −1= I don't know)*	Categorical
Part-time employment *(occupart)*	Respondent is employed by others in part-time work *(1=yes; 0=no; −1= I don't know)*	Categorical
Seeking for employment *(occuseek)*	Respondent is seeking employment *(1=yes; 0=no; −1= I don't know)*	Categorical
Retirement or disabeld *(occurd)*	Respondent is not working because of retirement or disablement *(1=yes; 0=no; −1= I don't know)*	Categorical
Student *(occustu)*	Respondent is a student *(1=yes; 0=no; −1= I don't know)*	Categorical
Full-time home-maker *(occuhome)*	Respondent is full-time home-maker *(1=yes; 0=no; −1= I don't know)*	Categorical
Gender *(gender)*	Gender of the respondent (*1=male; 2=female*)	Binary
Age *(age)*	The age of the respondent at the time of GEM survey	Continuous
Household size *(hhsize)*	How many members make up your permanent household, including you?	Continuous

Notes: Source GEM 2012-2017. The abbreviations in parentheses correspond to the feature names used in the GEM datasets.

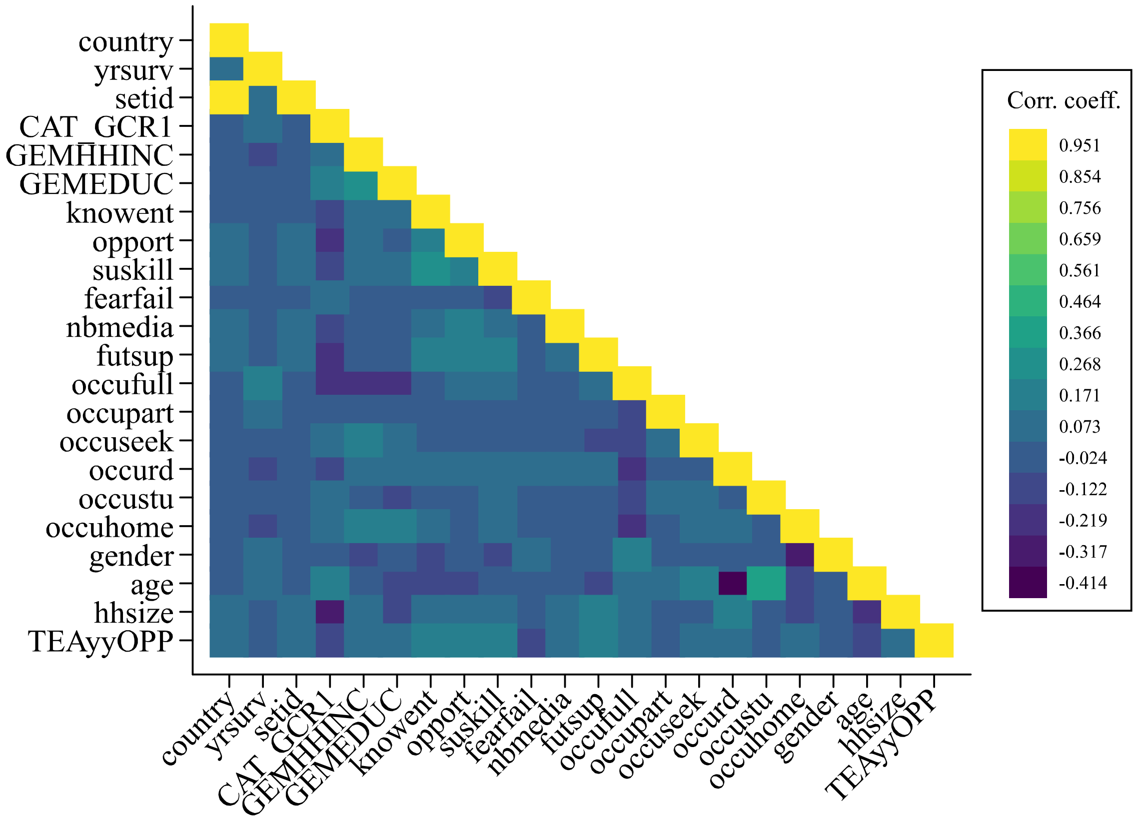
Appendix B: Incidence of missing values

Feature	Obs.	Missings	Freq. Missings (%)
country	1,192,818	0	0
yrsurv	1,192,818	0	0
setid	1,192,818	0	0
CAT_GCR1	1,192,818	4,084	0.342
GEMHHINC	1,192,818	0	0
GEMEDUC	1,192,818	0	0
knowent	1,192,818	73	0.006
opport	1,192,818	76	0.006
suskill	1,192,818	78	0.007
fearfail	1,192,818	78	0.007
nbmedia	1,192,818	105,639	8.860
futsup	1,192,818	89	0.008
occufull	1,192,818	79	0.007
occupart	1,192,818	79	0.007
occuseek	1,192,818	213,330	17.88
occurd	1,192,818	457,076	38.32
occustu	1,192,818	212,051	17.78
occuhome	1,192,818	267,042	22.39
gender	1,192,818	8	0.001
age	1,192,818	2,616	0.220
hhsize	1,192,818	303	0.025
TEAyyOPP	1,192,818	0	0

Appendix C: Patterns of missing values



Appendix D: Pearson cross-correlation heatmap



Appendix E: Confusion matrices

ML technique	Class	*Panel A:* OME TP	FP	TN	FN	*Panel B:* NME TP	FP	TN	FN
DT	0	134023	11275	2217	4250	144936	5091	288	1450
	1	2217	4250	134023	11275	288	1450	144936	5091
RF	0	137278	12371	1121	995	144941	4936	443	1445
	1	1121	995	137278	12371	443	1445	144941	4936
ANN	0	127259	8257	5235	11014	138445	4113	1266	7941
	1	5235	11014	127259	8257	1266	7941	138445	4113
kNN	0	113236	5385	8107	25037	120737	2681	2698	25649
	1	8107	25037	113236	5385	2698	25649	120737	2681
XGBoost	0	137020	12211	1281	1253	146331	5326	53	55
	1	1281	1253	137020	12211	53	55	146331	5326
NB	0	96473	3592	9900	41800	95214	1541	3838	51172
	1	9900	41800	96473	3592	3838	51172	95214	1541
LR - *baseline*	0	100560	3651	9841	37713	99637	1596	3783	46749
	1	9841	37713	100560	3651	3783	46749	99637	1596

Appendix F: Error rates of the *k*-fold cross-validation

		Error rates in %									
ML technique	Fold *k*	1	2	3	4	5	6	7	8	9	10
DT		6.036	6.070	6.062	6.152	6.256	6.145	6.104	5.949	5.703	5.581
RF		4.836	4.919	4.934	4.967	5.012	5.204	4.958	4.739	4.542	4.335
ANN		10.910	11.131	11.240	11.820	11.571	11.375	11.359	11.555	10.969	11.045
kNN		13.920	13.671	14.094	13.958	14.357	14.720	14.629	14.093	13.454	13.361
XGBoost		4.928	4.980	4.962	5.084	5.101	5.327	5.045	4.851	4.679	4.418
NB		22.137	22.132	22.614	22.603	22.919	23.088	22.808	22.276	21.674	21.291
LR - *baseline*		23.944	23.974	24.054	23.986	24.055	24.535	24.454	24.245	23.931	23.866

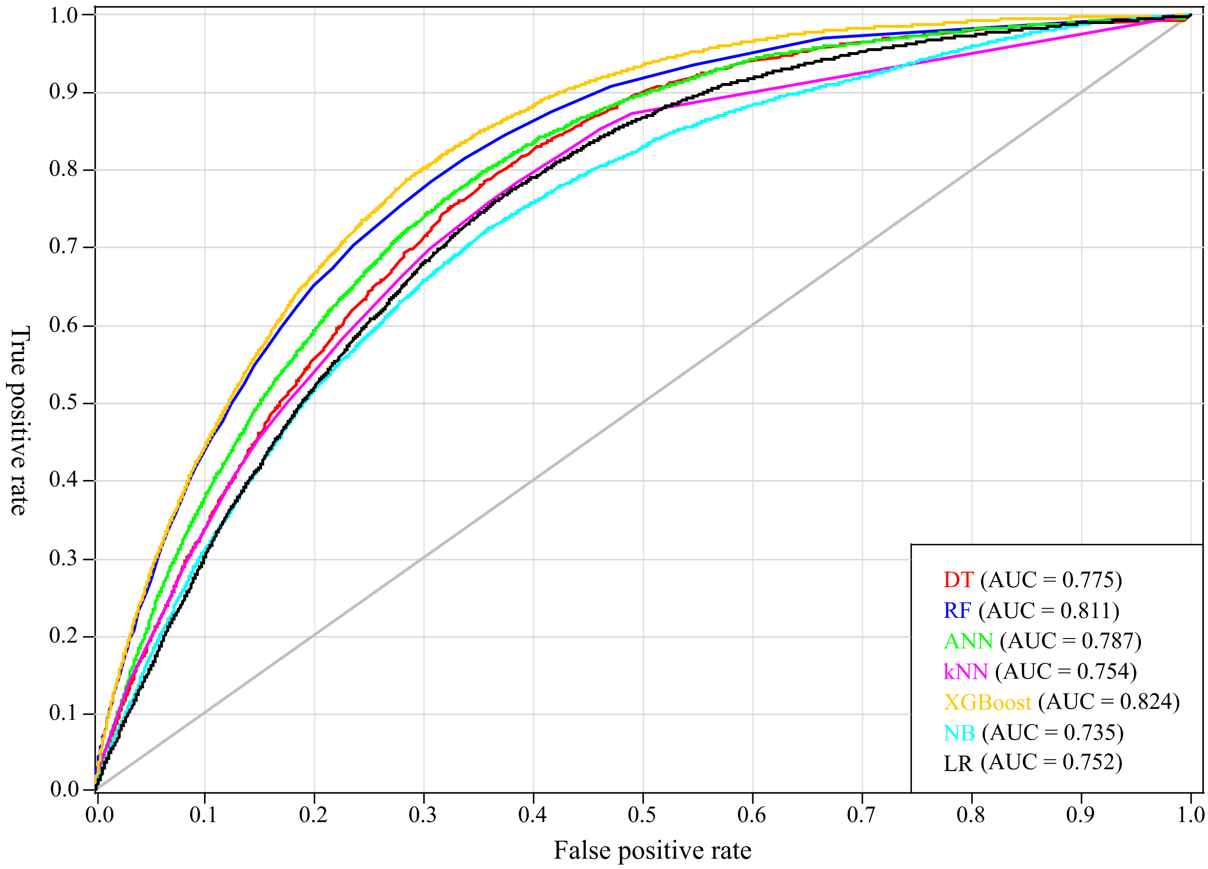
Appendix G: Default hyperparameter settings

DT	RF	ANN	kNN	XGBoost	NB	LR - *baseline*
Quality measure: Gini index; Pruning method: No pruning; Min. no. records per node: 18; No. of threads: 18	Split criterion: Information gain ratio; N estimators: 100 Voting: Hard voting	Max. no. of iterations: 100; Learning rate: 1e^{-2}; Etas: 0.5, 1.2; Step size: 1e^{-6}, 50; Algorithm: PROP; Number of hidden layers: 1; No. of hidden neurons per layer: 100	No. of neighbors (k) to consider: 24; Distance metric: Euclidian Distance weighting: No Output class probabilities: Yes	Learning rate: 0.3; N estimators: 100; Max. depth: 6; Lamda: 1; Alpha 1; Sketch epsilon: 0.003; Batch size: 1.000	Default probability: 0.0001; Min. S.D.: 0.0001; Threshold S.D.: 0.0; Max. no. of nominal values per attribute: 20	Solver: Stochastic avg. gradient; Max. no. epochs: 100; Epsilon: 1.0e^{-5}; Learning rate: Fixed (0.1); Regularization: L2

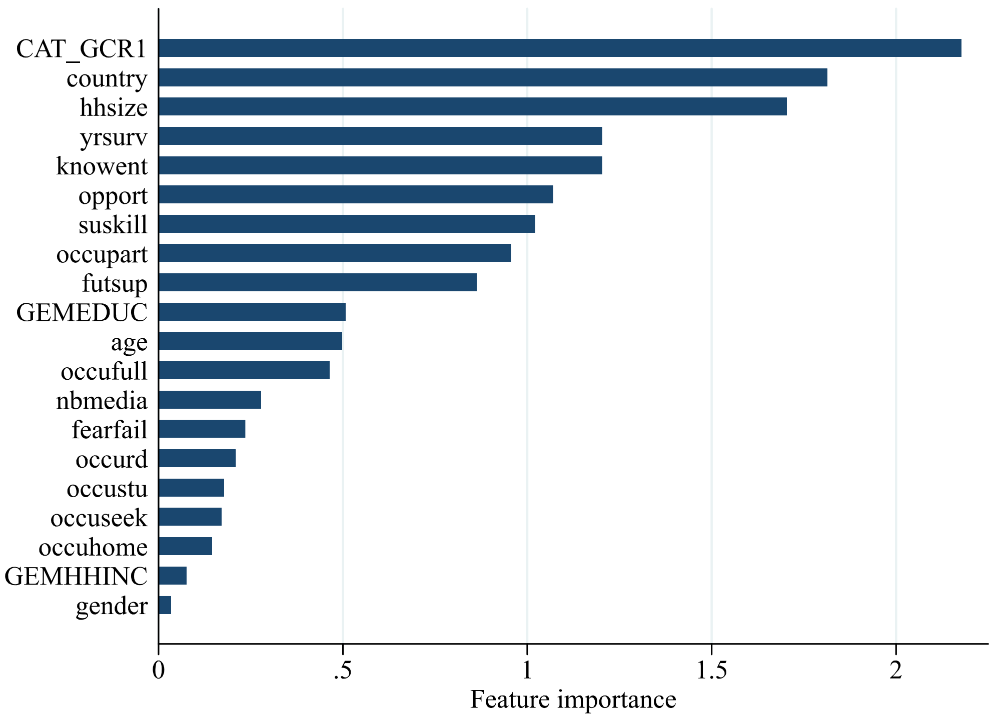
Appendix H: ML model performance on the NME "hold-out"- dataset

ML technique	Class	Recall	Precision	F_1-score	Accuracy	AUC	MCC
DT	0	0.990	0.966	0.978	-	-	-
	1	0.054	0.166	0.081	-	-	-
	Total	-	-	-	0.957	0.775	0.065
RF	0	0.990	0.967	0.978	-	-	-
	1	0.082	0.235	0.122	-	-	-
	Total	-	-	-	0.958	0.811	0.121
ANN	0	0.946	0.971	0.958	-	-	-
	1	0.235	0.138	0.174	-	-	-
	Total	-	-	-	0.921	0.787	0.140
kNN	0	0.825	0.978	0.895	-	-	-
	1	0.502	0.095	0.160	-	-	-
	Total	-	-	-	0.813	0.754	**0.155**
XGBoost	0	1.00	0.965	0.982	-	-	-
	1	0.01	0.491	0.019	-	-	-
	Total	-	-	-	**0.965**	**0.824**	0.066
NB	0	0.650	0.984	0.783	-	-	-
	1	0.714	0.070	0.127	-	-	-
	Total	-	-	-	0.653	0.735	0.140
LR - *baseline*	0	0.681	0.984	0.805	-	-	-
	1	0.703	0.075	0.135	-	-	-
	Total	-	-	-	0.681	0.752	0.151

Appendix I: ROC curve comparison for NME



Appendix J: Feature importance rank for predicting NME



Appendix K: Data description and sources

Variable	Description	Type	Level	Source
Dependent				
Entrepreneurial activity (TEA)	Is the individual involved in total early-stage entrepreneurial activity? (*TEAyy*: *1 = yes; 0 = no*)	Binary	Individual	GEM
Explanatory				
Self-efficacy (ESE)	Do you think you possess the knowledge, skills, and experience to start a new business? (*suskill*: *1 = yes; 0 = otherwise*)	Binary	Individual	GEM
Fear of failure (FOF)	Would fear of failure prevent you from starting a new business? (*fearfail: 1 = yes; 0 = otherwise*)	Binary	Individual	GEM
Opportunity recognition (OPPORT)	In the next six months, will there be good opportunities for starting a business in the area you live? (*opport*: *1 = yes; 0 = otherwise*)	Binary	Individual	GEM
Digital infrastructure (log)	A country's digital infrastructure (log) as an index from the six information and communication technology indicators (*Broadband subscribers (per 100 people); Internet users (%); mobile phone subscribers (per 100 people); personal computers (Percentage of households with computer, %); international internet bandwidth (Mbits/s); secure internet servers (per 1 million people*)	Continuous	Country	International Telecommunication Union
Controls				
Know entrepreneur	Do you personally know someone who started a business in the past two years? (*knowent*: *1 = yes; 0 = otherwise*)	Binary	Individual	GEM
Age	The age of the respondent at the time of GEM survey	Continuous	Individual	GEM
Female	Coded 1 if individual is female and otherwise, 0		Individual	GEM
Household size	How many members make up your permanent household, including you?	Continuous	Individual	GEM
Labortstat	Identifies the occupational status at the moment of the survey (*full-time employment; part-time employment; retired or disabled; full-time homeworker; student; not working or other; self-employed*)	Categorical	Individual	GEM
Educ	Identifies the highest educational degree (*primary; some secondary; secondary; post-secondary; graduate*)	Categorical	Individual	GEM
Population	Size of population (in millions)	Continuous	Country	World Bank
Population (Growth)	Population growth (annual %)	Continuous	Country	World Bank
GDP (per capita)	GDP per capita at purchasing power parity (current international $)	Continuous	Country	World Bank
GDP (Growth)	GDP growth (annual %)	Continuous	Country	World Bank
Unemployment (%)	The share of labor force that is out of work but seeking employment	Continuous	Country	World Bank
Exports (per GDP)	Exports per GDP (%)	Continuous	Country	World Bank
IPP	Intellectual property protection	Continuous	Country	World Bank
EFI	Economic freedom index. It evaluates countries on five dimensions of freedom: freedom from government, protection of property rights and rule of law, freedom from regulation, freedom to trade internationally, and freedom from monetary policy	Continuous	Country	Fraser Institute
Authority	The authority measure of the World Values Survey (WVS) captures the cross-cultural variation between traditional societal values and secular-rational values	Continuous	Country	World Values Survey
Well-being	The well-being measure of the WVS captures the cross-cultural variation between survival social values and self-expression social values	Continuous	Country	World Values Survey

Appendix L: Summary statistics

	Mean	Std. dev.	Min.	Max.
Individual-level variables				
Entrepreneurial activity	.105	.306	0	1
Self-efficacy	.462	.499	0	1
Fear of failure	.406	.491	0	1
Opportunity recognition	.331	.471	0	1
Controls				
Know entrepreneur	.360	.480	0	1
Age	42.041	14.789	18	99
Female	.502	.500	0	1
Household size	3.332	1.683	1	94
Labortstat1-full-time	.436	.496	0	1
Labortstat2-part-time	.098	.298	0	1
Labortstat3-retired/disabled	.107	.309	0	1
Labortstat4-homemaker	.057	.231	0	1
Labortstat5-student	.049	.215	0	1
Laborstat6-not working	.093	.291	0	1
Laborstat7-self-employed	.145	.352	0	1
Educ1	.182	.386	0	1
Educ2	.416	.493	0	1
Educ3	.339	.473	0	1
Educ4	.063	.243	0	1
Country-level variables				
Digital infrastructure (log)	36.633	3.470	26.074	43.631
Controls				
Population (log)	17.167	1.343	13.253	21.050
Population (growth)	.659	.664	-1.201	2.431
GDP per capita (log)	10.338	.539	8.880	11.632
GDP (growth)	2.792	2.199	-3.546	25.163
Unemployment (%)	9.644	6.718	.600	27.040
Exports (per GDP)	42.580	30.654	11.320	221.197
IPP	4.837	.920	2.970	6.580
Authority	.109	.789	-1.781	1.672
Well-being	.939	1.041	-1.399	3.108
EFI	7.601	.510	5.980	8.460

Appendix M: Observations and digital infrastructure per country

Country	Frequency	Percent	Average digital infrastructure (log)
United States	7,509	2.18	42.22
Russia	2,005	0.58	39.15
South Africa	8,567	2.49	32.15
Greece	5,284	1.53	35.71
Netherlands	6,418	1.86	40.66
Belgium	1,862	0.54	38.73
France	3,741	1.09	39.05
Spain	66,707	19.38	37.02
Hungary	3,432	1.00	37.07
Italy	5,742	1.67	36.65
Romania	1,954	0.57	34.97
Switzerland	8,391	2.44	39.11
Austria	4,409	1.28	38.35
United Kingdom	23,975	6.96	42.09
Sweden	14,169	4.12	38.15
Norway	1,986	0.58	38.63
Poland	8,766	2.55	36.26
Germany	11,647	3.38	40.37
Peru	5,012	1.46	30.38
Mexico	12,467	3.62	33.03
Argentina	1,766	0.51	33.67
Brazil	4,362	1.27	35.26
Chile	21,516	6.25	36.19
Colombia	6,540	1.90	34.48
Malaysia	5,146	1.49	35.29
Australia	5,552	1.61	38.37
Indonesia	10,123	2.94	30.48
Philippines	1,698	0.49	29.02
Thailand	6,222	1.81	33.57
Japan	1,835	0.53	36.38
China	3,463	1.01	34.17
Canada	7,220	2.10	39.32
Portugal	3,183	0.92	36.87
Luxembourg	5,596	1.63	40.92
Ireland	5,577	1.62	37.34
Finland	3,864	1.12	38.61
Estonia	6,789	1.97	36.83
Croatia	5,918	1.72	35.12
Slovenia	5,544	1.61	36,19
Bosnia and Herzegovina	1,693	0.49	31.10
Slovakia	5,154	1.50	35.71
Guatemala	4,324	1.26	26.94
Ecuador	4,252	1.24	30.04
Uruguay	5,103	1.48	33.55
Kazakhstan	5,797	1.68	33.91
Georgia	1,985	0.58	33.94
Total	**344,265**	**100.00**	

Appendix N: Additional analyses and robustness checks

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
Individual-level effects												
Entrepreneurial self-efficacy (ESE)	0.0809***	0.0051	0.0910***	0.0054	0.0813***	0.0053	0.0670***	0.0042	0.0220***	0.0633	0.0825***	0.0056
Fear of failure (FOF)	-0.0183***	0.0025	-0.0207***	0.0029	-0.0186***	0.0025	-0.0195***	0.0022	0.0640 n.s.	0.0425	-0.0203***	0.0031
Opportunity recognition (OPPORT)	0.0341***	0.0034	0.0374***	0.0035	0.0350***	0.0027	0.0332***	0.0019	0.0323 n.s.	0.0563	0.0336***	0.0018
Country-level effect												
Digital infrastructure (log)	0.0019 n.s.	0.0023	0.0015 n.s.	0.0026	-0.0074 n.s.	0.0081	-0.0001 n.s.	0.0021	0.0001 n.s.	0.0012	0.0031 n.s.	0.0019
Cross-level interactions												
ESE × Digital infrastructure	0.0042***	0.0007	0.0047***	0.0009	0.0122***	0.0029	0.0038***	0.0007	0.0016***	0.0007	0.0037***	0.0005
FOF × Digital infrastructure	-0.0007**	0.0004	-0.0009**	0.0004	-0.0019 n.s.	0.0014	-0.0009***	0.0004	-0.0001 n.s.	0.0005	-0.0014***	0.0004
OPPORT × Digital infrastructure	0.0009**	0.0003	0.0009**	0.0004	0.0012 n.s.	0.0013	0.0010***	0.0003	0.0002 n.s.	0.0004	0.0016***	0.0004
Individual-level controls included	Yes		Yes		Yes		Yes		Yes		Yes	
Country-level controls included	Yes		Yes		Yes		Yes		Yes		Yes	
Year dummies included	Yes		Yes		Yes		Yes		Yes		Yes	
Random part estimates												
Variance of random intercept	0.2598	0.1182	0.3095	0.1163	0.1939	0.0923	0.1686	0.0658	0.5040	0.1736	0.1761	0.0650
Number of groups (countries)	46		45		46		46		46		53	
Number of observations (N)	344,265		277,558		344,265		344,265		344,265		391,119	

Notes: Compared with the baseline results in Model 1, we excluded Spain in Model 2 because of over-represented observations. In Model 3, we built a sub-construct of digital infrastructure and only included indicators that were more related to application characteristics (i.e., broadband subscribers, internet users, and mobile phone subscribers). In Model 4, we used opportunity-motivated entrepreneurship (OME) as the dependent variable. In Model 5, we used necessity-motivated entrepreneurship (NME) as the dependent variable. In Model 6, we replicated and reran our main analysis for the period 2012–2014. The superscript n.s. explicitly indicates statistically insignificant values. Standard errors are cluster-robust. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix O: Sensitivity test

	Model 1		Model 2		Diff. Models 1–2	
	dy/dx	Std. Err.	dy/dx	Std. Err.	dy/dx	Std. Err.
Individual-level effects						
Entrepreneurial self-efficacy (ESE)	0.0809***	0.0051	0.0815***	0.0054	-0.0006	-0.0003
Fear of failure (FOF)	-0.0183***	0.0025	-0.0186***	0.0024	0.0003	0.0001
Opportunity recognition (OPPORT)	0.0341***	0.0034	0.0348***	0.0028	-0.0007	0.0006
Country-level effect						
Digital infrastructure (log)	0.0019 n.s.	0.0023	-0.0005 n.s.	0.0016	0.0024	0.0007
Cross-level interactions						
ESE × Digital infrastructure	0.0042***	0.0007	0.0042***	0.0008	0.0000	-0.0001
FOF × Digital infrastructure	-0.0007**	0.0004	-0.0008**	0.0004	0.0001	0.0000
OPPORT × Digital infrastructure	0.0009**	0.0003	0.0008**	0.0003	0.0000	0.0000
Individual-level controls included	Yes		Yes		–	
Country-level controls included	Yes		Yes		–	
Year dummies included	Yes		Yes			
Random part estimates						
Variance of random intercept	0.2598	0.1182	0.2912	0.1473	-0.0314	-0.0291
Number of groups (countries)	46		46		0	
Number of observations (*N*)	344,265		344,265		0	
Model fit statistics						
Degrees of freedom	32		30		2	
Wald χ^2 (sig.)	20582.19***		11656.81***		8925.38	
Log-pseudolikelihood	-84,876.66		-84,936.01		59.35	

Notes: Model 1 reports the baseline findings with TEA as the dependent variable. In Model 2, we re-estimated the baseline model but excluded the highest non-orthogonal country-level variables, namely, *GDP per capita (log)* and *Well-being.* The Diff. column reports the parameter stability for the direct cross-level interaction term of interest. Standard errors are cluster-robust. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix P: CRE and LPM model for country-fixed effects

	Model 1		Model 2		Model 3	
	dy/dx	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Random effects (between)						
Entrepreneurial self-efficacy (ESE)	0.0811***	0.0043	0.0946***	0.0134	0.0429***	0.0155
Fear of failure (FOF)	-0.0167***	0.0024	-0.0261***	0.0053	-0.0132***	0.0037
Opportunity recognition (OPPORT)	0.0332***	0.0030	0.0446***	0.0057	0..0289***	0.0036
Fixed effects (within)						
Digital infrastructure (log)	-0.0055***	0.0020	0.0007 n.s.	0.0051	-0.0015 n.s.	0.0015
Cross-level interactions						
ESE × Digital infrastructure	0.0042***	0.0008	0.0028 n.s.	0.0044	0.0038*	0.0000
FOF × Digital infrastructure	-0.0009**	0.0004	-0.0009 n.s	0.0014	-0.0009*	0.0001
OPPORT × Digital infrastructure	0.0004 n.s	0.0004	-0.0036***	0.0012	0.0013*	0.0000
Individual-level controls included	Yes		Yes		Yes	
Country-level controls included	Yes		Yes		Yes	
Country dummies included	No		Yes		Yes	
Year dummies included	Yes		Yes		Yes	
Individual-level cluster means included	Yes		No		No	
Random part estimates						
Variance of random intercept	-	-	9.4476	15.0965	1.2767	5.0052
Number of countries	46		24		23	
Number of country-years	-		56		56	
Number of observations (N)	344,265		135,848		208,417	
Country-level var.	0.3447	0.1491	1.81e-16	2.14e-14	8.12e-17	7.93e-15
Country-year-level var.	-	-	0.0004	0.0002	0.0000	7.35e-06
Individual-level var.	-	-	0.1060	0.0096	0.05363	0.0055
Model fit statistics						
Degrees of freedom	41		23		23	
AIC	168880.30		80908.93		-18123.46	
Log-pseudolikelihood	84397.16		-40,399.47		9115.73	

Notes: In Models 1, 2, and 3, TEA is the dependent variable. Model 1 reports unstandardized average marginal effects for the correlated random effects (CRE) model. Following Mundlak (1978), we included individual-level cluster means instead of country dummies to perform the maximum likelihood estimation for fixed effects. In both Models 2 and 3, we report coefficients for the linear probability model (LPM). Model 2 reports the country-fixed effects for factor- and efficiency-driven economies. Model 3 shows the country-fixed effects for innovation-driven economies. As the sample consists of repeated cross-sectional data, the individual-level effects represent random effects. Standard errors are cluster-robust at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Q: Data description and source

Variable	Description	Type	Level	Source
Dependent				
Number of CVC investments	Number of CVC investments per year	Continuous	Firm	Refinitiv Eikon
Independent				
CEO humility	CATA with annual LTS: Reversed LIWC ‘clout’ score, calculated through CATA with annual LTS (clout score = 1 – 100)	Continuous	Individual	LTS
BM dependence on I. & K	Business model dependence on knowledge and information, calculated as: (intangible assets – goodwill) / total assets	Continuous	Firm	S&P Capital IQ
Emerging digital competition	Ratio of digital VC-backed ventures / non-digital VC-backed ventures in the same industry (two-digit SIC code). Classification as ‘digital’ by selection of pre-defined filters by the Private Equity Module of the Eikon database	Continuous	Industry	Refinitiv Eikon
Controls				
CEO age	Number of years	Continuous	Individual	S&P Capital IQ
CEO change	Coded 0 if CEO already in position before year t; coded 1 if new CEO in year t	Binary	Individual	S&P Capital IQ
CEO digital orientation	CATA with annual LTS: Percentage of words belonging to “digital orientation“ dictionary by Kindermann et al. (2021)	Continuous	Individual	LTS
CEO education	1 = no degree, 2 = undergraduate, 3 = graduate, 4 = doctorate	Categorical	Individual	S&P Capital IQ
CEO gender	Coded 1 if an individual is female and otherwise, 0	Binary	Individual	S&P Capital IQ
CEO tenure	Number of years in the position	Continuous	Individual	S&P Capital IQ
Firm advertising exp.	In million USD	Continuous	Firm	S&P Capital IQ
Firm age	Years since foundation	Continuous	Firm	S&P Capital IQ
Firm available slack	Total current assets / total liabilities	Continuous	Firm	S&P Capital IQ
Firm R&D exp.	In million USD	Continuous	Firm	S&P Capital IQ
Firm size	Number of total employees	Continuous	Firm	S&P Capital IQ
Industry R&D expenditures	In million USD	Continuous	Industry	S&P Capital IQ
Industry size	Denoted in total revenue	Continuous	Industry	S&P Capital IQ

Appendix R: Fixed-effects negative binomial panel regression

	Model 1			Model 2			Model 3		
DV: No. of CVC investments (t+1)	Coef.	p-value	Sig.	Coef.	p-value	Sig.	Coef.	p-value	Sig.
CEO variables									
CEO age	0.007 (0.008)	0.359		0.004 (0.008)	0.593		0.004 (0.008)	0.555	
CEO change	0.108 (0.080)	0.175		0.108 (0.079)	0.172		0.116 (0.079)	0.145	
CEO digital orientation	0.111 (0.036)	0.002	***	0.107 (0.036)	0.003	***	0.112 (0.036)	0.002	***
CEO education	0.004 (0.059)	0.946		0.008 (0.059)	0.886		0.011 (0.059)	0.846	
CEO gender (female = 1, male = 0)	-0.458 (0.229)	0.046	**	-0.530 (0.231)	0.022	**	-0.501 (0.231)	0.030	**
CEO tenure	-0.007 (0.009)	0.446		-0.009 (0.009)	0.321		-0.008 (0.009)	0.368	
Firm variables									
Firm advertising exp. (ln)	0.042 (0.016)	0.009	***	0.043 (0.016)	0.008	***	0.043 (0.016)	0.007	***
Firm age (ln)	0.260 (0.120)	0.031	**	0.273 (0.120)	0.023	**	0.285 (0.121)	0.019	**
Firm available slack	0.083 (0.039)	0.035	**	0.079 (0.039)	0.044	**	0.075 (0.039)	0.053	*
Firm R&D exp. (ln)	0.026 (0.029)	0.364		0.024 (0.029)	0.407		0.023 (0.290)	0.411	
Firm size (ln)	0.078 (0.078)	0.320		0.087 (0.078)	0.267		0.078 (0.791)	0.321	
BM dependence on I. & K	0.829 (0.577)	0.151		0.791 (0.580)	0.173		0.909 (0.589)	0.123	
Industry variables									
Emerging digital competition	0.005 (0.009)	0.517		0.006 (0.008)	0.448		0.006 (0.008)	0.474	
Industry R&D expenditures (ln)	0.008 (0.049)	0.863		0.013 (0.048)	0.778		0.011 (0.048)	0.814	
Industry size (ln)	0.049 (0.141)	0.728		0.028 (0.142)	0.839		0.036 (0.142)	0.797	
Main effect									
CEO humility				0.017 (0.004)	0.000	***	0.016 (0.004)	0.000	***
Cross-level interaction effects									
CEO humility × Emerging digital competition							0.001 (0.001)	0.044	**
CEO humility × BM dependence on I. & K.							0.015 (0.445)	0.724	
Additional information									
Degrees of freedom	31			32			34		
Wald χ2 (sig.)	287.19***			305.13***			308.94***		
Log-likelihood	-2412.39			-2405.66			-2403.67		
AIC	4888.79			4877.32			4877.34		

Notes: N = 1,564 years from 183 firms. Year-fixed and industry-fixed effects included. AIC refers to Akaike's information criterion. Standard errors in parentheses. Two-tailed tests with *** p<0.01, ** p<0.05, * p<0.1.

Appendix S: Random-effects negative binomial panel regression

	Model 1			Model 2			Model 3		
DV: No. of CVC investments (t+1)	Coef.	p-value	Sig.	Coef.	p-value	Sig.	Coef.	p-value	Sig.
CEO variables									
CEO age	-0.006 (0.007)	0.417		-0.008 (0.007)	0.265		-0.007 (0.007)	0.288	
CEO change	0.088 (0.079)	0.266		0.090 (0.078)	0.252		0.094 (0.078)	0.233	
CEO digital orientation	0.107 (0.034)	0.002	***	0.102 (0.033)	0.002	***	0.107 (0.033)	0.002	***
CEO education	0.008 (0.053)	0.870		0.009 (0.053)	0.865		0.011 (0.053)	0.826	
CEO gender (female = 1, male = 0)	-0.372 (0.204)	0.069	*	-0.421 (0.205)	0.040	**	-0.381 (0.20)	0.064	*
CEO tenure	0.003 (0.008)	0.702		0.001 (0.008)	0.866		0.001 (0.008)	0.841	
Firm variables									
Firm advertising exp. (ln)	0.040 (0.014)	0.005	***	0.040 (0.014)	0.004	***	0.040 (0.014)	0.005	***
Firm age (ln)	0.189 (0.079)	0.017	**	0.187 (0.079)	0.019	**	0.188 (0.079)	0.018	**
Firm available slack	0.090 (0.035)	0.011	**	0.087 (0.034)	0.013	**	0.085 (0.034)	0.015	**
Firm R&D exp. (ln)	0.047 (0.020)	0.021	**	0.047 (0.020)	0.022	**	0.046 (0.020)	0.025	**
Firm size (ln)	0.168 (0.050)	0.001	***	0.178 (0.050)	0.000	***	0.176 (0.050)	0.000	***
BM dependence on I. & K	0.903 (0.463)	0.051	**	0.960 (0.039)	0.039	**	1.104 (0.471)	0.019	**
Industry variables									
Emerging digital competition	0.009 (0.008)	0.238		0.010 (0.008)	0.201		0.010 (0.008)	0.189	
Industry R&D expenditures (ln)	0.029 (0.032)	0.366		0.028 (0.032)	0.385		0.027 (0.032)	0.402	
Industry size (ln)	0.113 (0.097)	0.244		0.108 (0.098)	0.268		0.114 (0.097)	0.242	
Main effect									
CEO humility				0.015 (0.004)	0.000	***	0.014 (0.004)	0.001	***
Cross-level interaction effects									
CEO humility × Emerging digital competition							0.001 (0.001)	0.031	**
CEO humility × BM dependence on I. & K.							0.045 (0.043)	0.288	
Additional information									
Degrees of freedom	31			32			34		
Wald $\chi 2$ (sig.)	329.91***			346.67***			353.38***		
Log-likelihood	-3225.95			-3219.62			-3216.99		
AIC	6519.90			6509.24			6507.98		

Notes: N = 1,564 years from 183 firms. Year-fixed and industry-fixed effects included. AIC refers to Akaike's information criterion. Standard errors in parentheses. Two-tailed tests with *** p<0.01, ** p<0.05, * p<0.1.

Affidavit

I hereby declare that I completed the papers submitted and listed hereafter independently and only with those forms of support mentioned in the relevant paper. When working with the authors listed, I contributed no less than a proportionate share of the work. In the analyses that I have conducted and to which I refer in the papers, I have followed the principles of good academic practice, as stated in the Statute of Justus Liebig University Giessen for ensuring good scientifc practice.

Submitted Papers:

1. **Schade, P.,** & Schuhmacher, M.C. (2023). "Predicting Entrepreneurial Activity Using Machine Learning". Available online in *Journal of Business Venturing Insights, 19*, e00357, https://doi.org/10.1016/j.jbvi.2022.e00357 (Chapter 2)

2. **Schade, P.,** & Schuhmacher, M.C. (2022). "Digital Infrastructure and Entrepreneurial Action-Formation: A Multilevel Study". Available online in *Journal of Business Venturing, 37*(5), 106232, https://doi.org/10.1016/j.jbusvent.2022.106232 (Chapter 3)

3. Ademi, P, **Schade, P.,** & Schuhmacher, M.C. (2023). "Responding to the Situational Urgency of Digital Transformation: A Multilevel Analysis of CEO Humility and Corporate Venture Capital". *Working Paper* (Chapter 4)

Philipp Schade, Giessen, August 2023