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AI, Big Data and Entrepreneurship

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Hong Kong Shue Yan University, Sept 22, 2020

Literature

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1) Special Issue: AI, Big Data & Entrepreneurship, SBEJ 2020

Small Bus Econ (2020) 55:529–539
https://doi.org/10.1007/s11187-019-00202-4

Check for updates

Artificial intelligence and big data in entrepreneurship: a new era has begun

Martin Obschonka · David B. Audretsch

Accepted: 19 April 2019 / Published online: 6 June 2019

Abstract While the disruptive potential of artificial intelligence (AI) and big data has been receiving growing attention and concern in a variety of research and application fields over the last few years, it has not received much scrutiny in contemporary entrepreneurship research so far. Here we present some reflections and a collection of papers on the role of AI and big data for this emerging area in the study and application of entrepreneurship research. While being mindful of the ... entrepreneurship scholars, educators, and practitioners to proactively prepare for future scenarios.

Keywords Entrepreneurship · Artificial intelligence · AI · Big data · Machine learning · Smart entrepreneurship

JEL classification L26 · M13 · B41

2) ETP article on AI in research

Entrepreneurship Theory and Practice
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Pursuing Impactful Entrepreneurship Research Using Artificial Intelligence

Moren Lévesque[1], Martin Obschonka[2], and Satish Nambisan[3]

Abstract

It is time for the entrepreneurship field to come to terms with leading-edge artificial intelligence (AI). AI holds great promise to transform entrepreneurship into a more relevant and impactful field, but it must overcome conflicts between the AI-driven research approach and that of the traditional, theory-based research process. We explore these opportunities and challenges and suggest concrete approaches that entrepreneurship researchers can use to harness the power of AI with rigor and enhance research relevance. We conclude that incorporating the power of AI in entrepreneurship research and managing the associated risks offer a new and "grand challenge" for the field.

Keywords

entrepreneurship research, theory building, theory testing, research relevance, artificial intelligence

Job Creation in an Agile Economy

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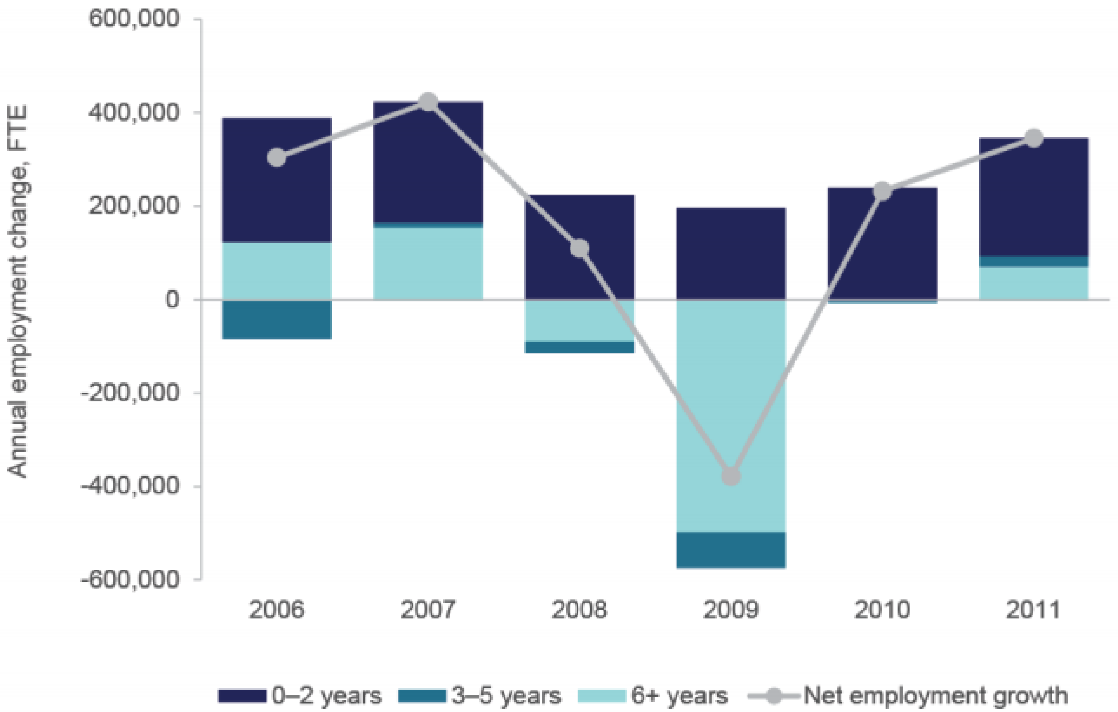
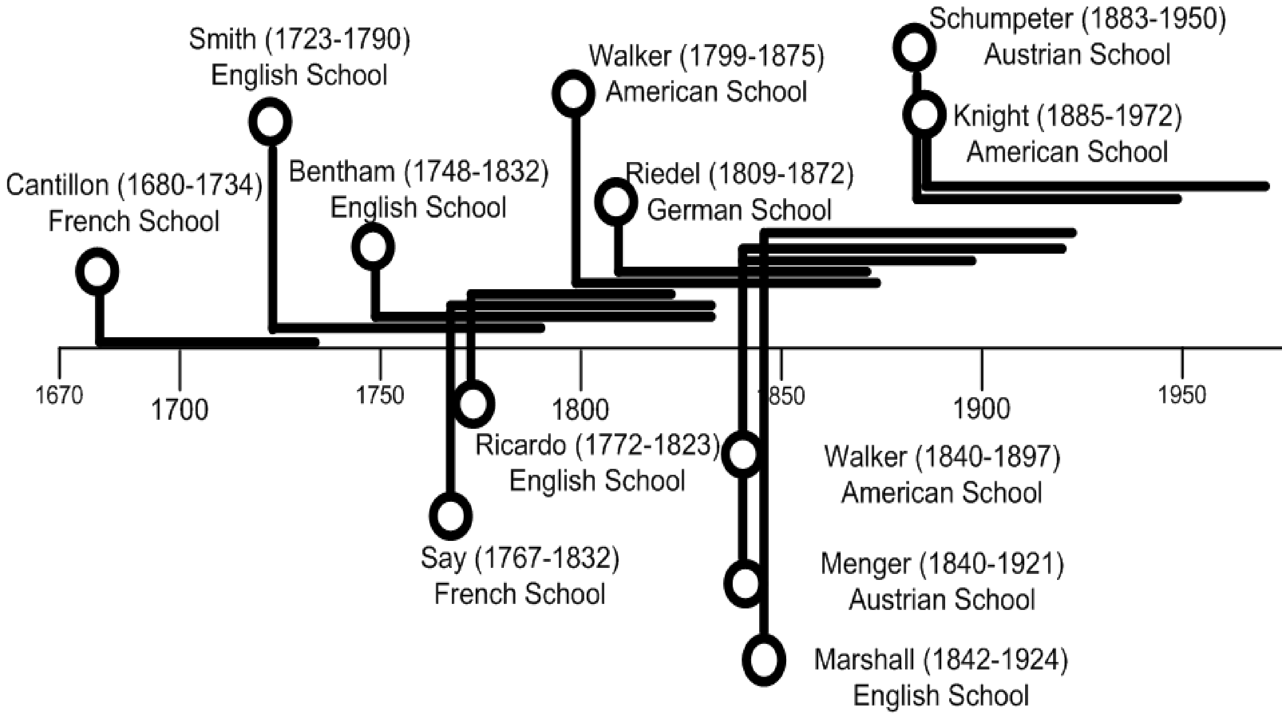
Figure 2.3: Net employment growth by firm age, 2006–2011

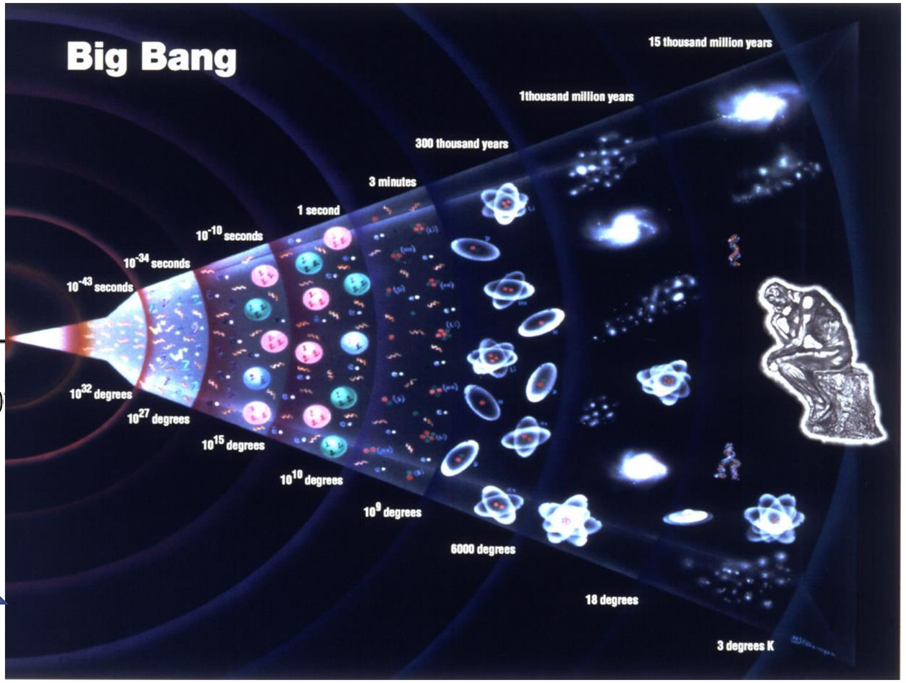


Notes: Employment is measured in Full Time Equivalents (See Appendix A). Results are for all non-government sectors and exclude non-employing firms. Young firms are 0–5 years and mature firms are 6+ years. Start-ups are defined as a subset of young firms that are 0–2 years of age.

Source: ABS (2015) Expanded Analytical Business Longitudinal Database 2001–02 to 2012–13

History of ENT Research





Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of Management Review*, *25*(1), 217-226.

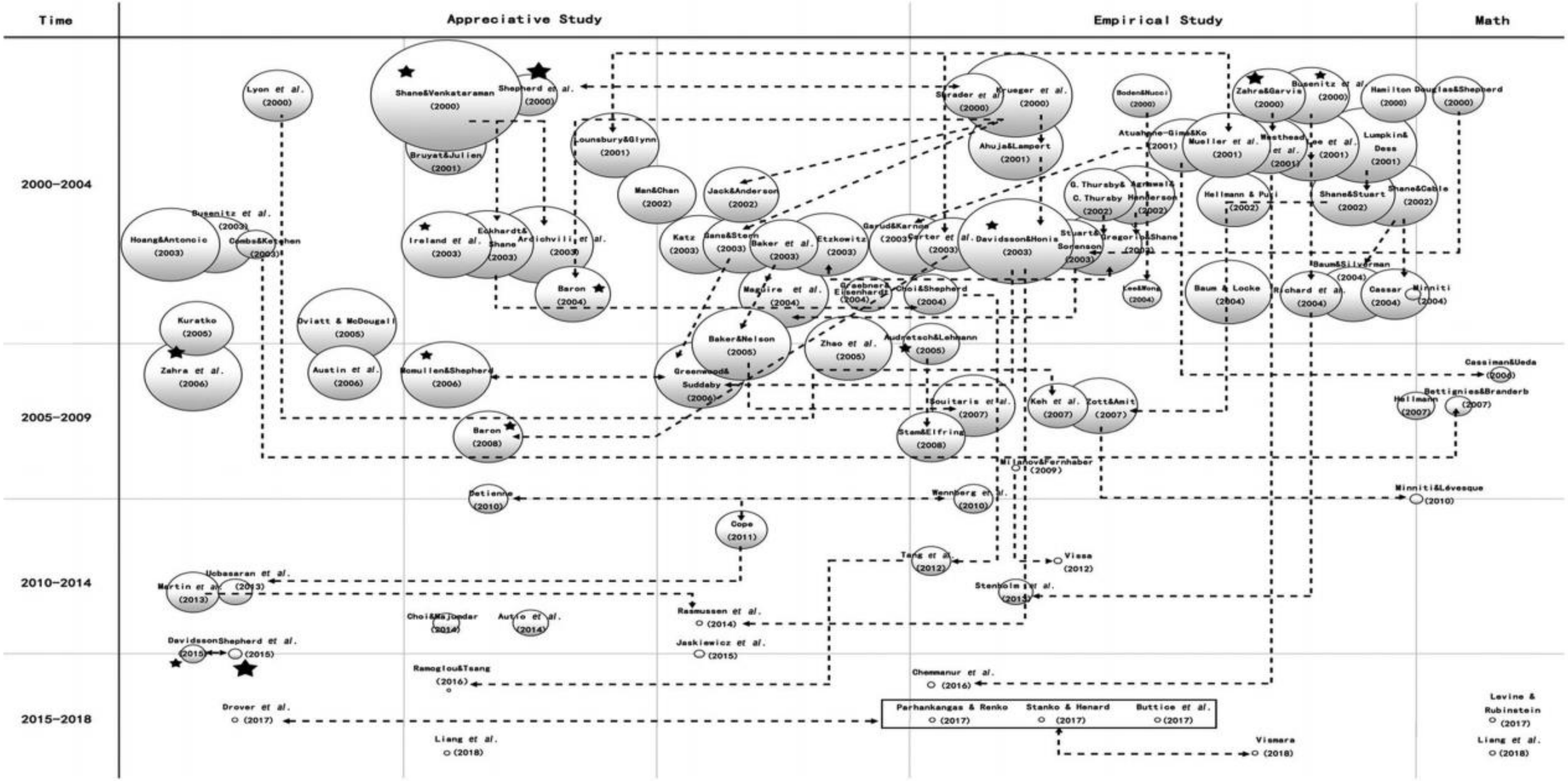


Figure 5. Mapping the Literature in the Entrepreneurship Field.

Note: Circles where the papers are inscribed vary in size according to the number of citations; arrows indicate linkages between the authors' perspective; stars indicate prolific authors.

Lu et al., 2020, JoES

History of ENT Research

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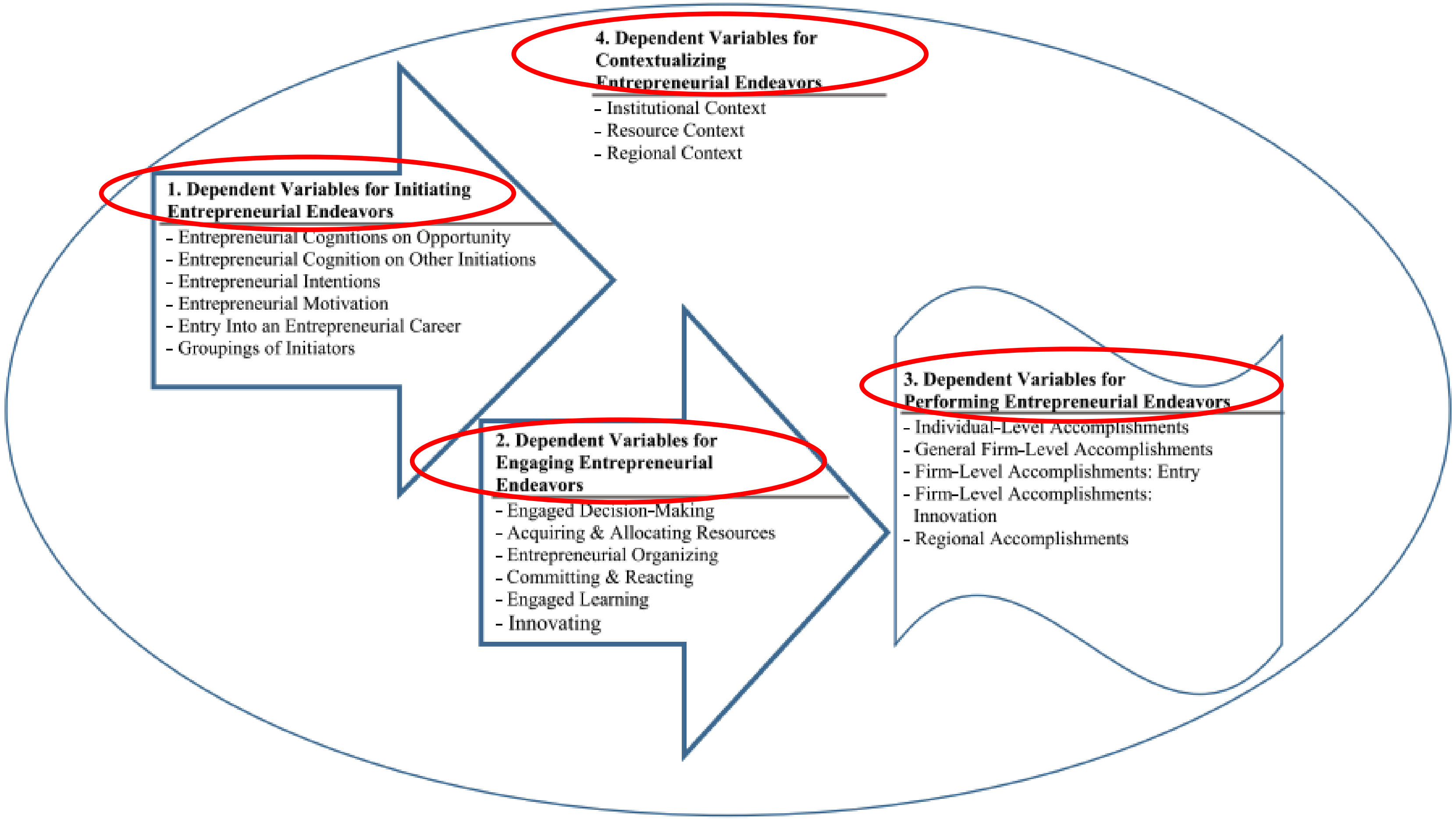
A Meta-Framework Organizing a Review of Entrepreneurship's Dependent Variables



Review of entrepreneurship research 2000-2017

Shepherd et al., 2019 JoM

Technological Progress

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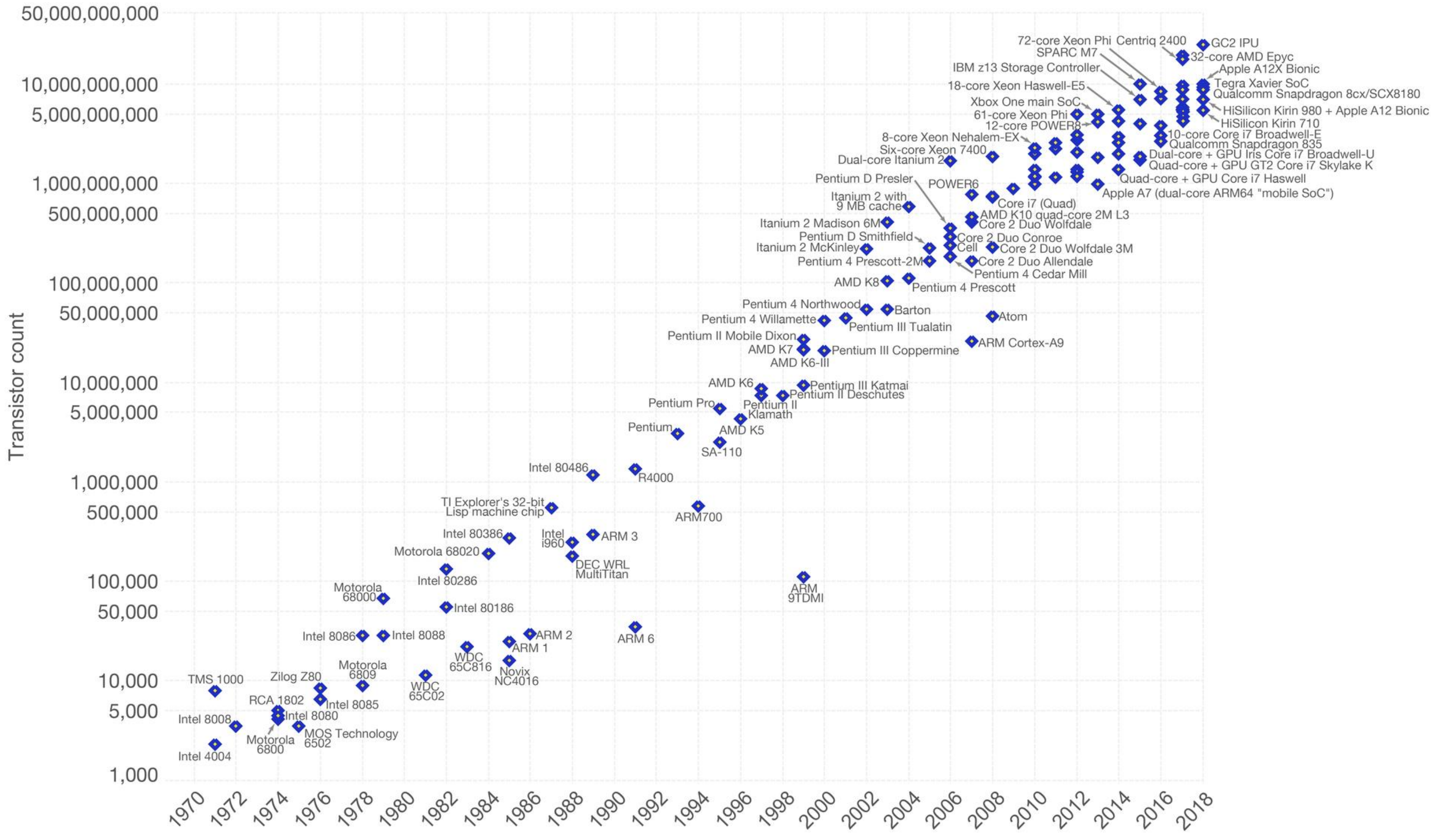
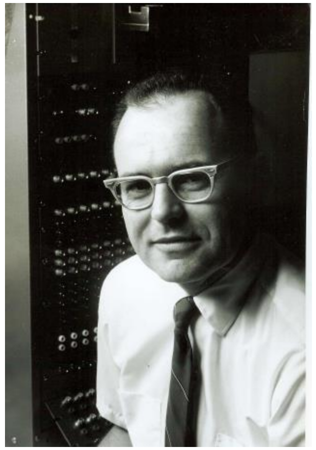
Moore's Law – The number of transistors on integrated circuit chips (1971-2018)

Our World in Data

Moore's law describes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. This advancement is important as other aspects of technological progress – such as processing speed or the price of electronic products – are linked to Moore's law.



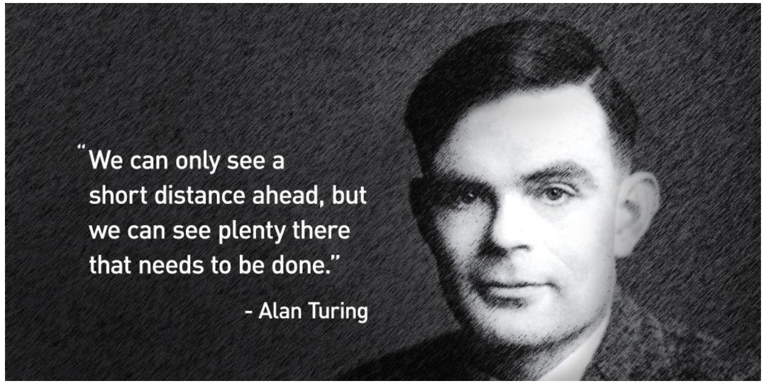
Data source: Wikipedia (https://en.wikipedia.org/wiki/Transistor_count)
The data visualization is available at OurWorldinData.org. There you find more visualizations and research on this topic.



Gordon Moore
Co-founder Intel Corp.

Entrepreneurial AI

- "A lake of data but no boat"?
- Links to entrepreneurship
- Human vs. machine
- Replaces entrepreneurs vs. Supports Entrepreneurs



Entrepreneurial AI

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- "Over the next decade, AI won't replace managers, but managers who use AI will replace those who don't" (Brynjolfsson & Mcafee, 2017)

- If AI is indeed a manifestation of **intelligence** where the latter is defined in a sense of **human intelligence** (Turing 1950), we can ask whether entrepreneurship really benefits from extremely high levels of human intelligence.

- Interestingly, so far research has not shown a clear link between (extremely high) intelligence and entrepreneurship.

- Intelligence researcher Robert J. Sternberg hypothesized that "successful entrepreneurship requires a blend of analytical, creative, and practical aspects of intelligence" (Sternberg 2004).

- Hence, successful entrepreneurship might not be "a story about intelligence in the traditional sense" (e.g., general human intelligence; Spearman 1904) but rather about certain facets of intelligence that help entrepreneurs in their analytic, creative, and practical capacities.

Entrepreneurial AI

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- AI and uncertainty (McMullen & Shepherd 2006; Parker 2009)

- Rule-driven AI vs. Entrepreneurial rule-breaking

- It seems that AI is better suited to create a “synthetic homo economics” (Parkes & Wellman 2015) than a rule-breaking, intuitive, and creative entrepreneur
- “Blind trust” in algorithms (Logg et al. 2019)

Entrepreneurial Process

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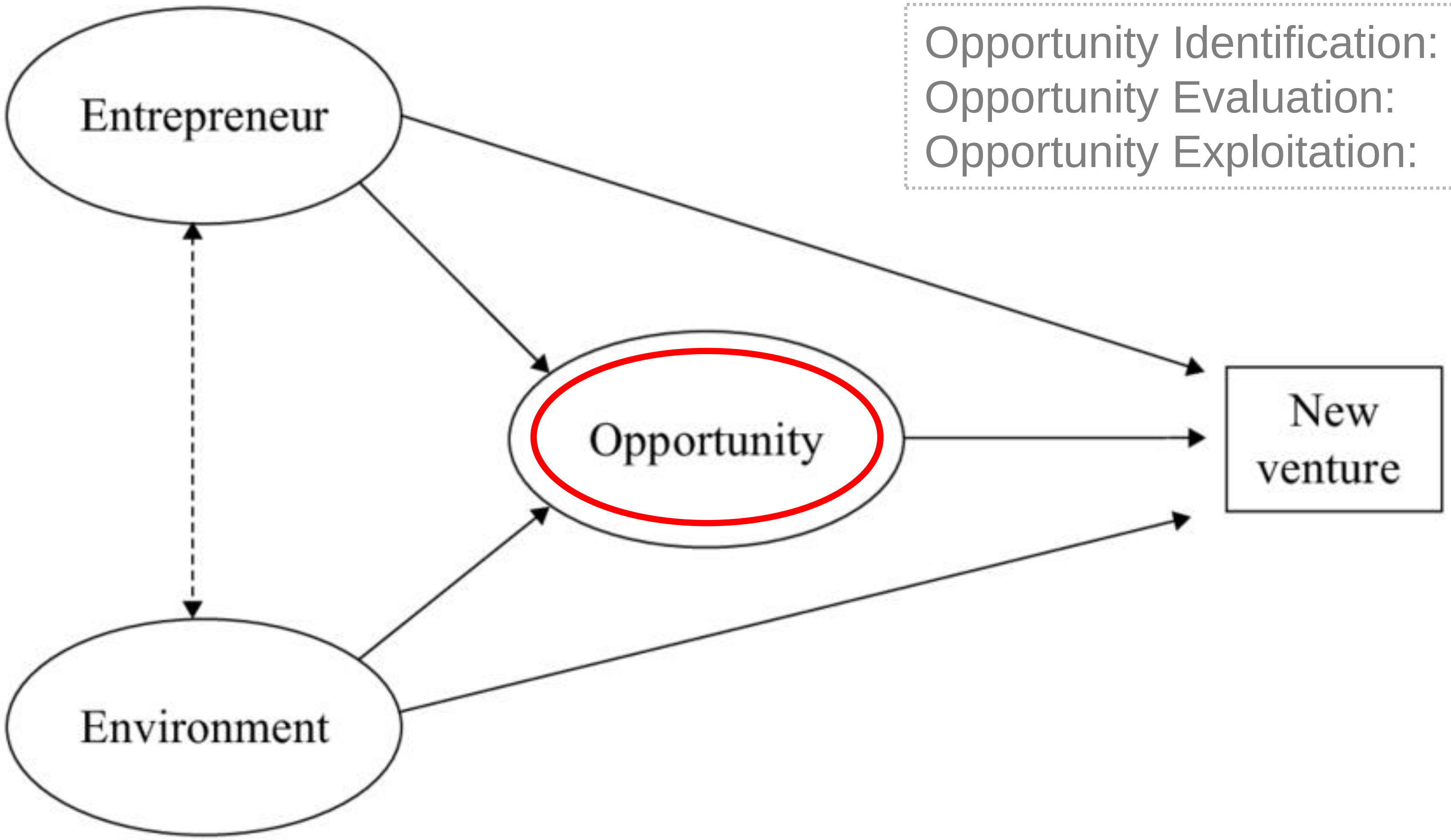

Opportunity Identification: Prospecting
Opportunity Evaluation: Developing
Opportunity Exploitation: Venturing

AI – The “Golden Opportunity”?

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AI startups raised $6.9 billion in Q1 2020, a record-setting pace before coronavirus
venturebeat.com • Lesedauer: 2 Min.

Data from National Venture Capital Association, USA

Entrepreneurial Process

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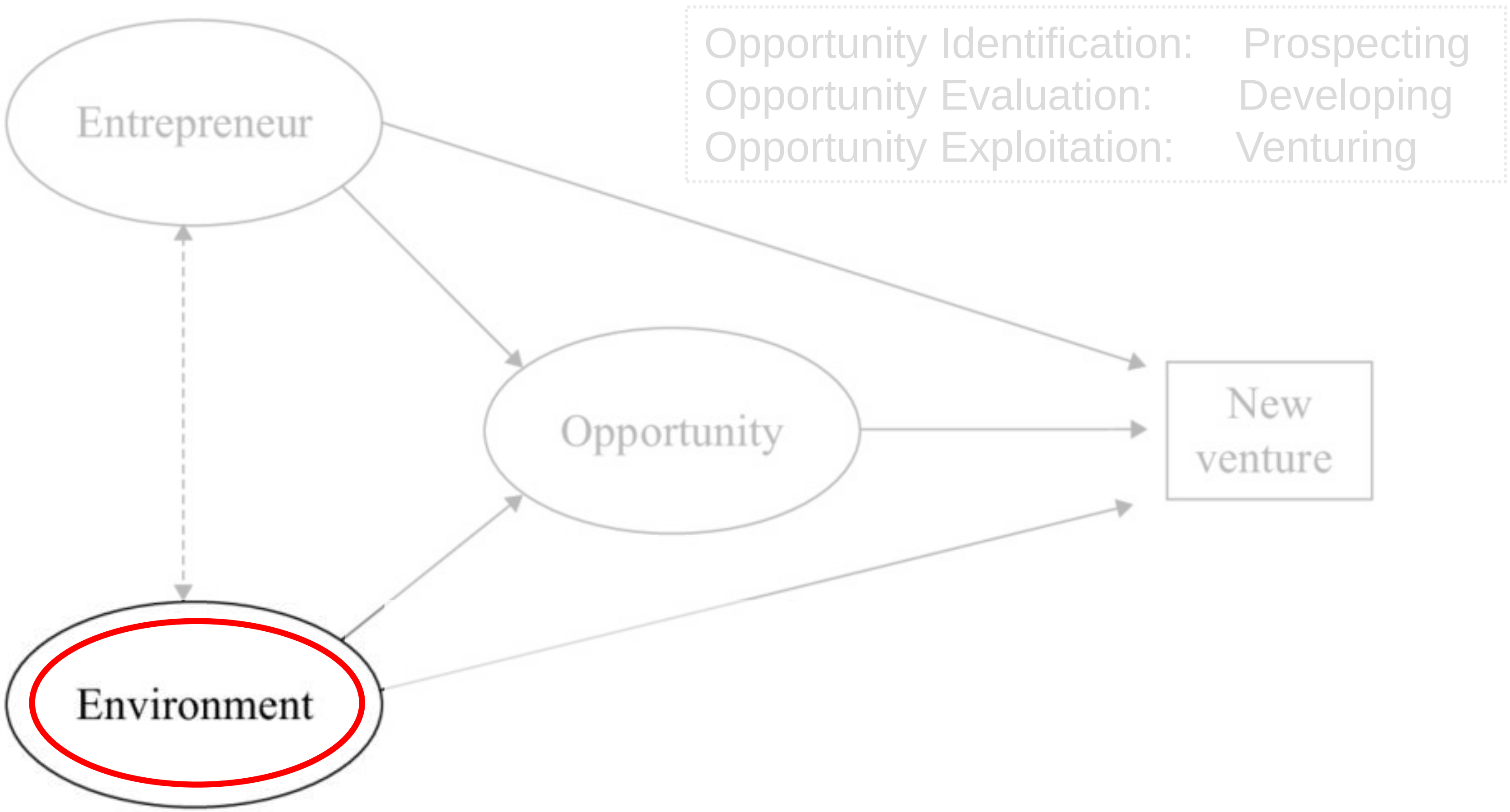

The External Enabler Framework

(Davidson, 2016)

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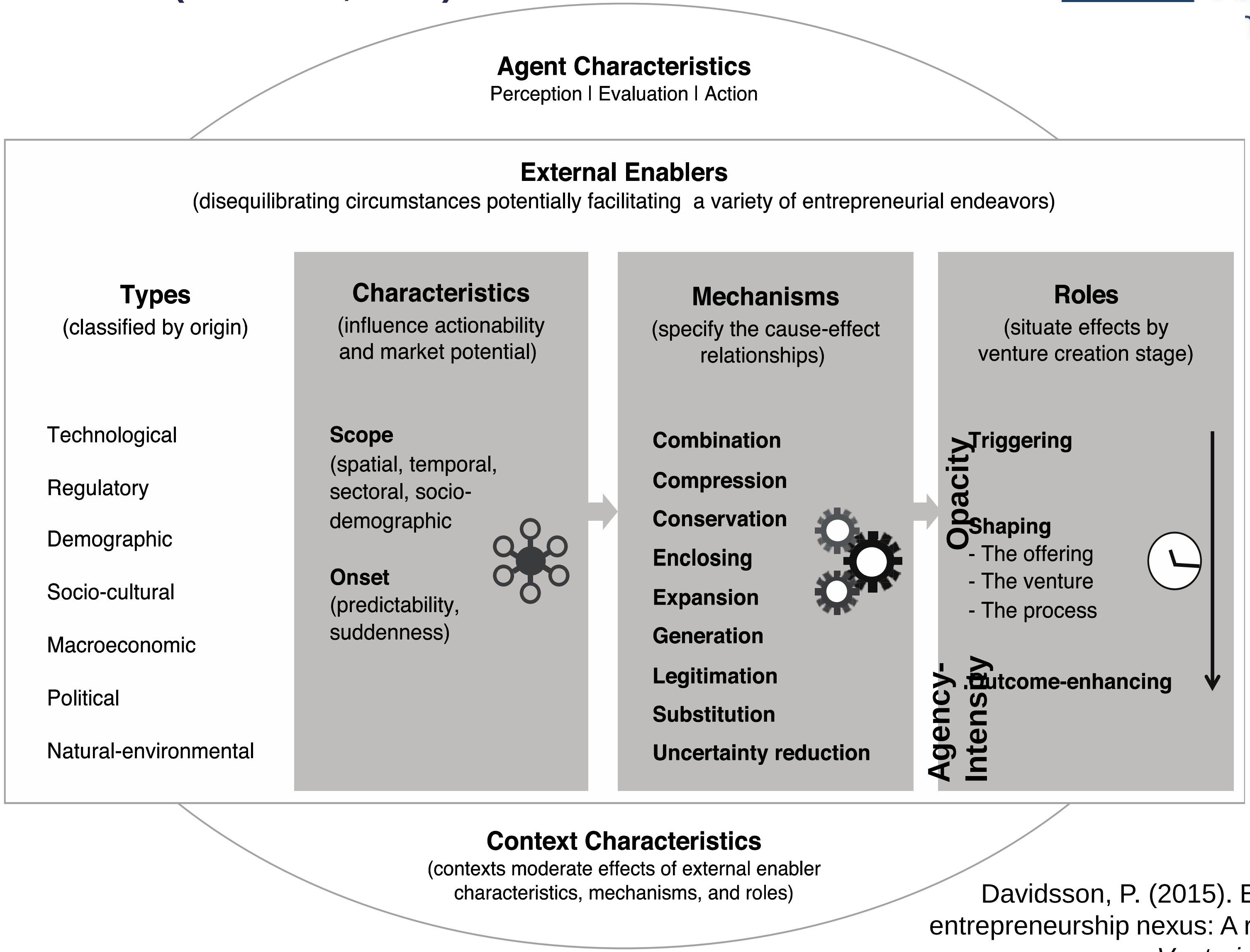
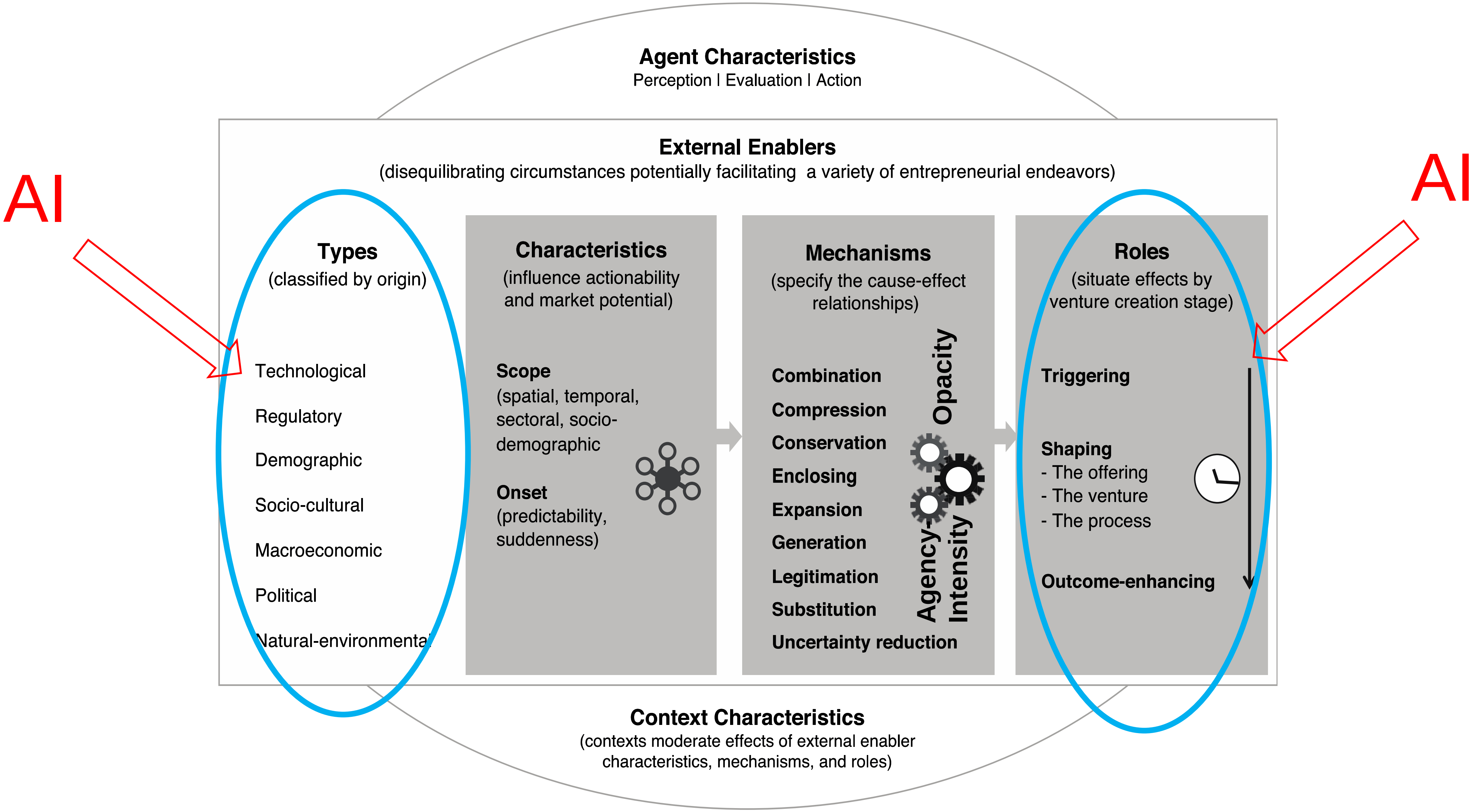


Davidsson, P. (2015). Entrepreneurial opportunities and the entrepreneurship nexus: A re-conceptualization. *Journal of Business Venturing 30*, no. 5, 674-695.

The External Enabler Framework

(Davidson, 2016)



Towards an AI-Augmented Entrepreneurial Process

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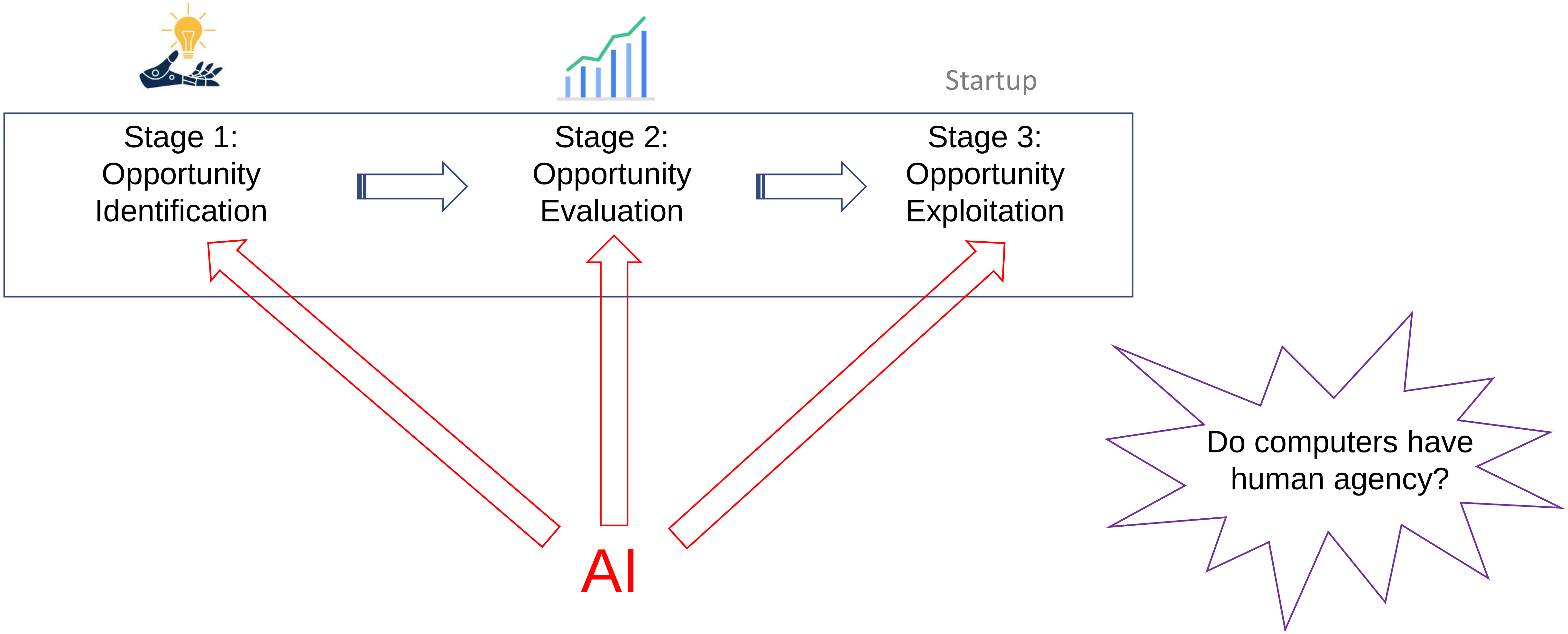

Entrepreneurial Process

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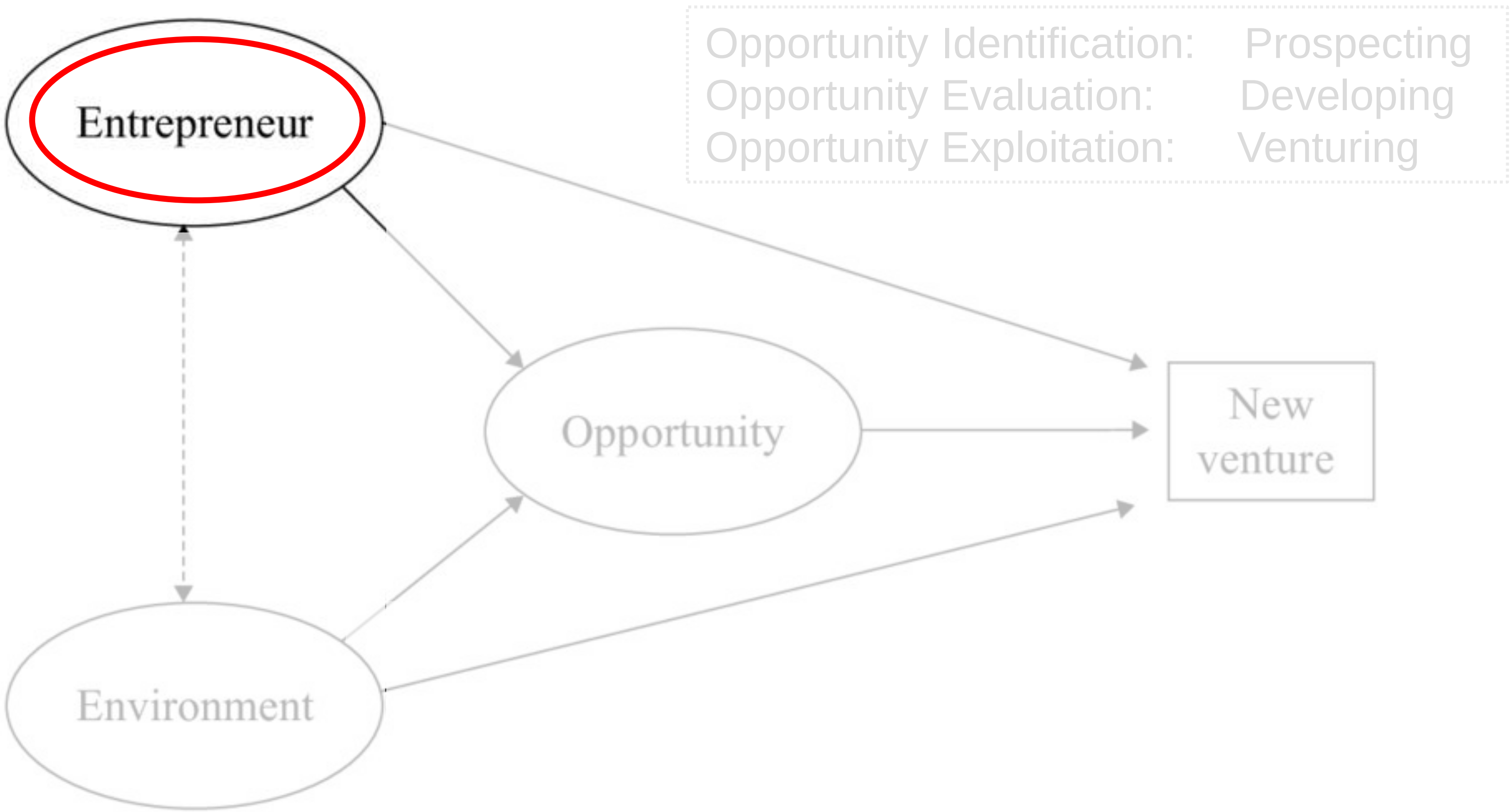

Challenges

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- Prior Knowledge

- Cognitive Bias

Entrepreneurship as a Private Trait

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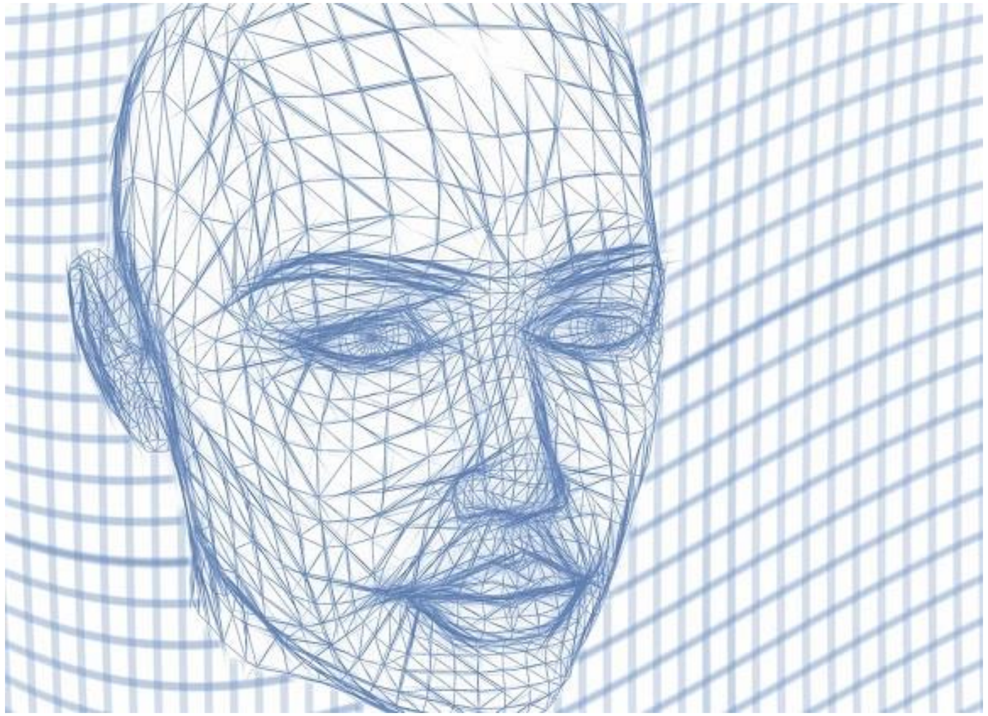

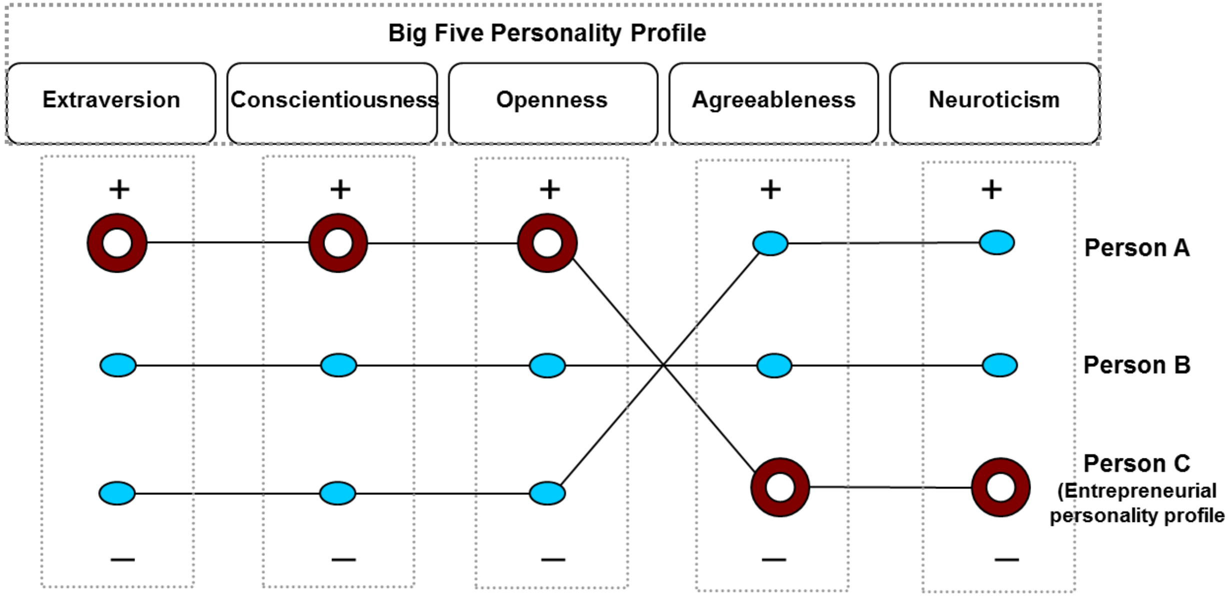

Big Data (self-report personality tests)

GEOGRAPHY OF ENTREPRENEURIAL PERSONALITY

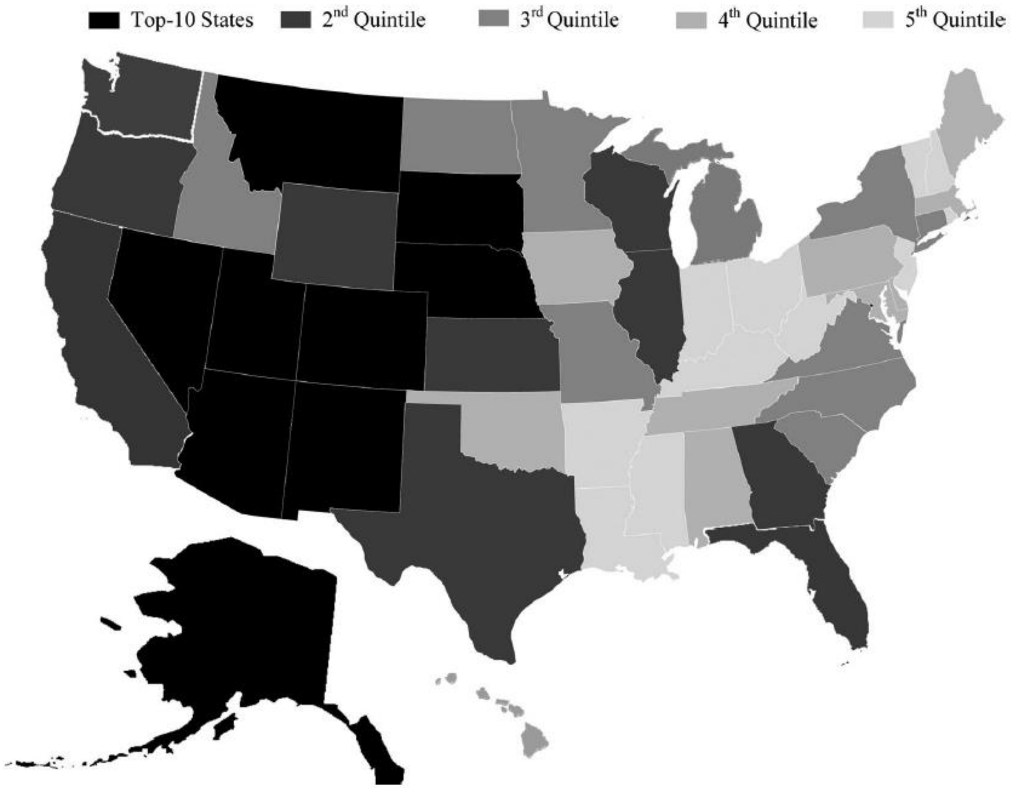

Figure 1. Map of state-level variation in an entrepreneurship-prone personality profile across the United States. The variable entrepreneurship-prone personality profile represents the fit between a person's individual Big Five profile and a statistical reference profile (highest possible value in extraversion, conscientiousness, and openness and lowest possible value in agreeableness and neuroticism).

Obschonka, et al. (2013) JPSP

Big Data (self-report personality tests)

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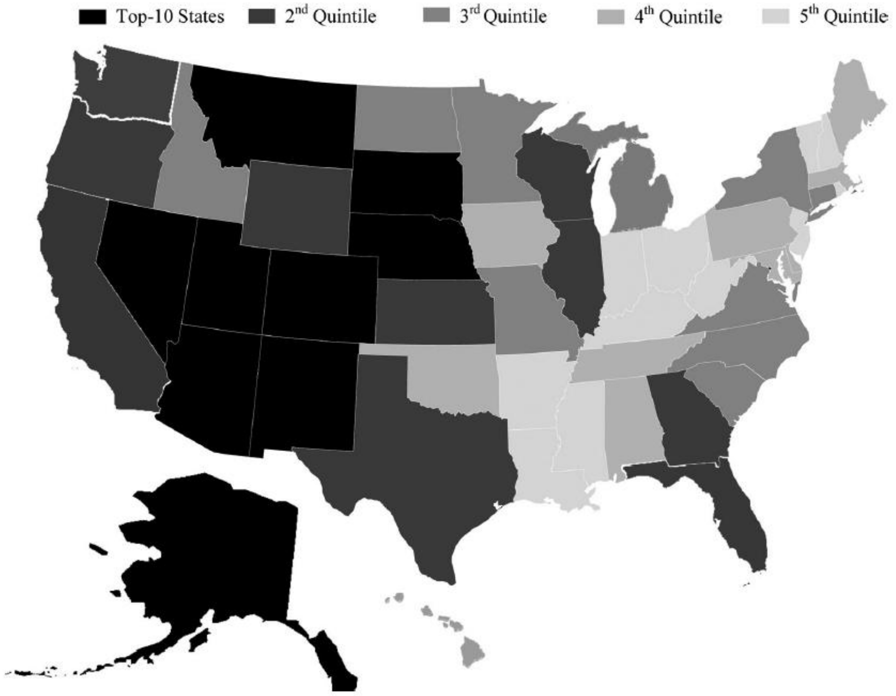

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OBSCHONKA ET AL.

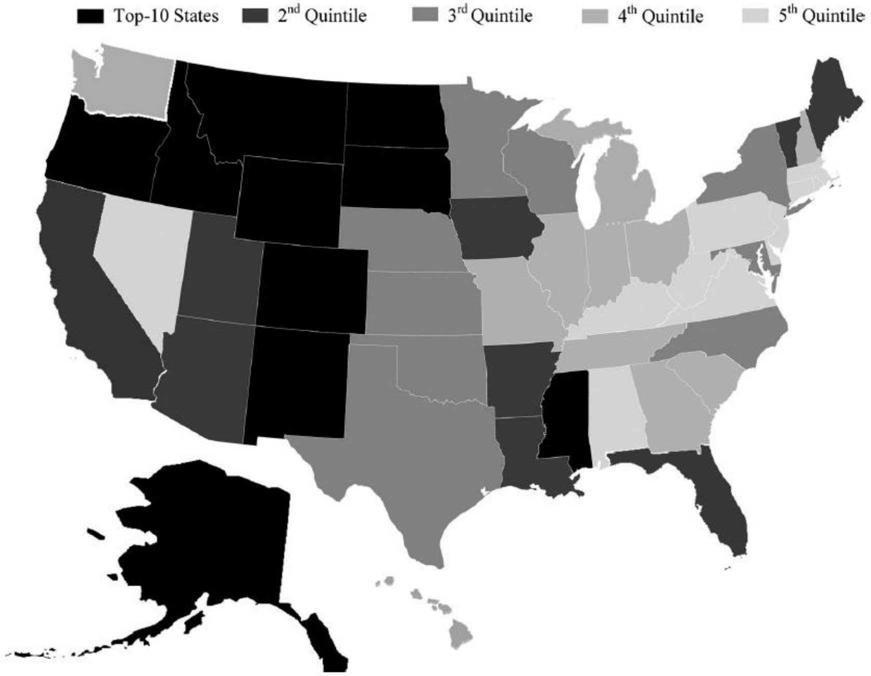

Figure 2. Map of state-level entrepreneurial activity across the United States (Kauffman index of entrepreneurial activity 1998–2000).

Obschonka, et al. (2013) JPSP

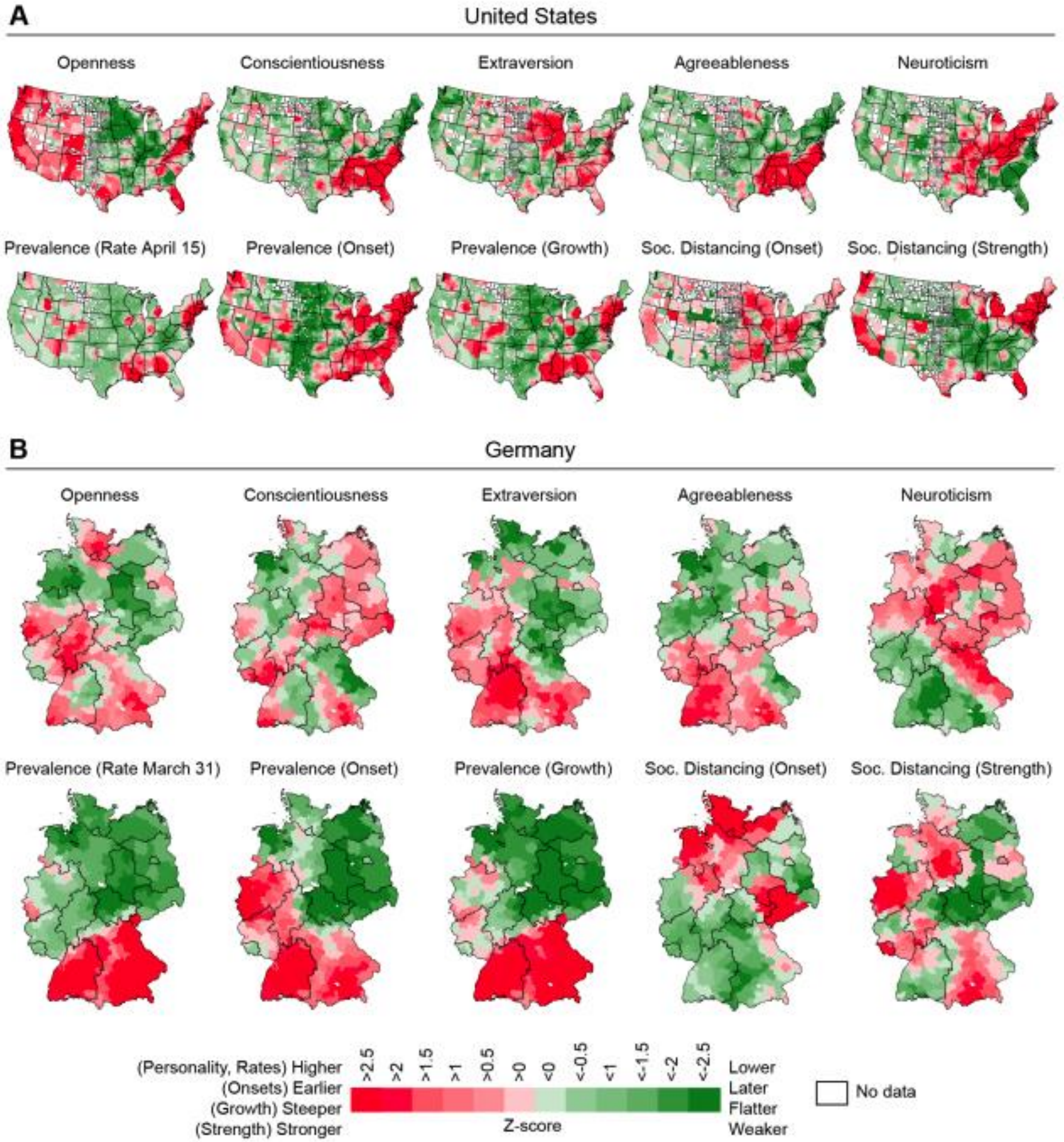

Figure 2. Maps of the geographic distribution of the Big Five personality traits, COVID-19 spread, and social distancing behavior in the US (A) and Germany (B). We applied Getis-Ord-Gi* analysis to identify areas where high/low values of a variable geographically cluster (so-called hotspot analysis, 23). To do so, we used a binary spatial weight matrix in which we classified regions that are less than a specific threshold (i.e., 75 miles in the US and 75 kilometers in Germany) apart from each other as proximal, while regions whose distance exceed this threshold are classified as distal.

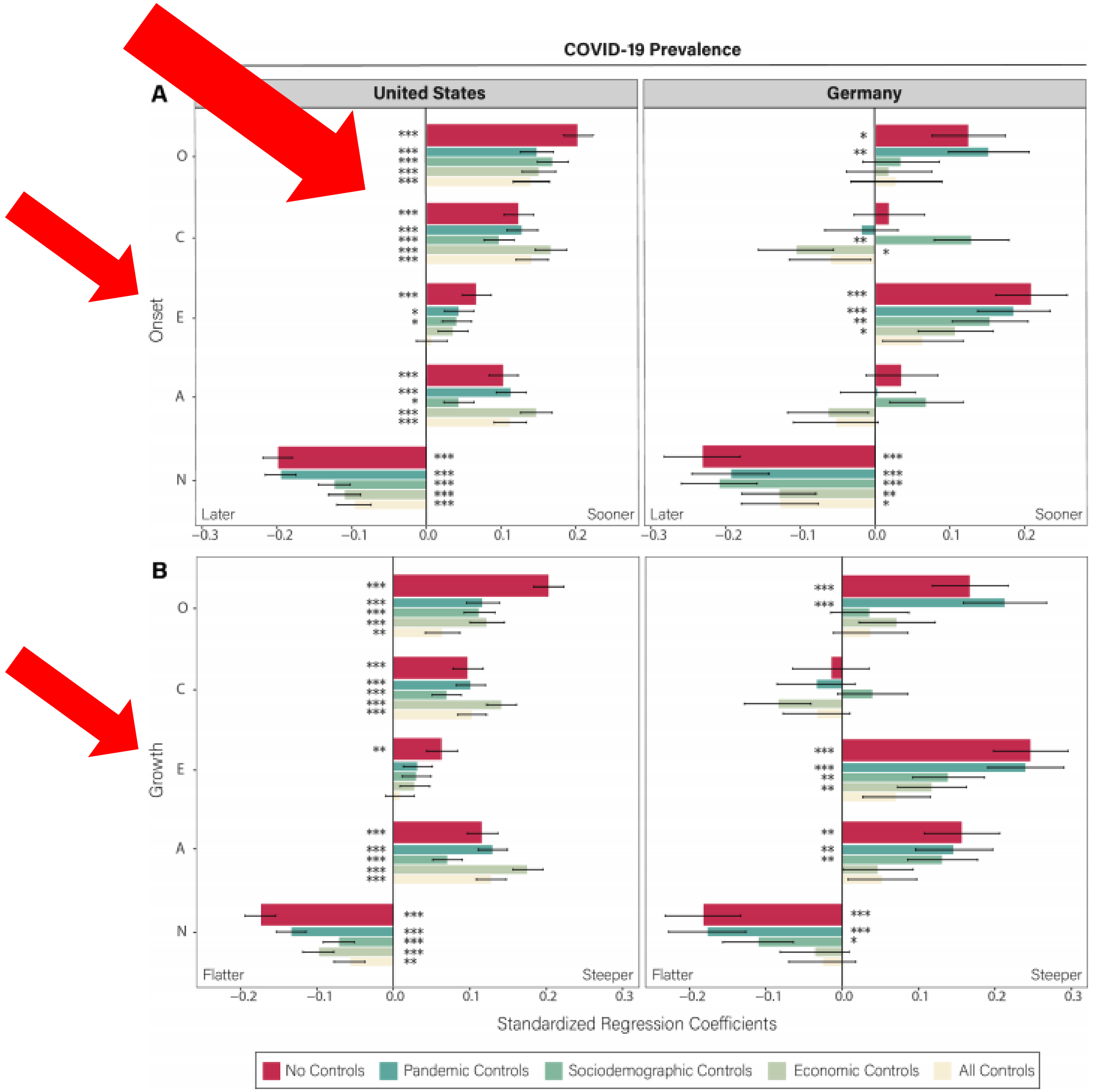

Figure 3. Effects of regional personality on COVID-19 onset (Panel A) and growth rates (Panel B) in the US and Germany. Error bars represent standard errors (SE). O = Openness, C = Conscientiousness, E = Extraversion, A = Agreeableness, N = Neuroticism. * $p < 0.05$, ** $p < 0.01$, *** $p < 001$.

Entrepreneurship as a Private Trait

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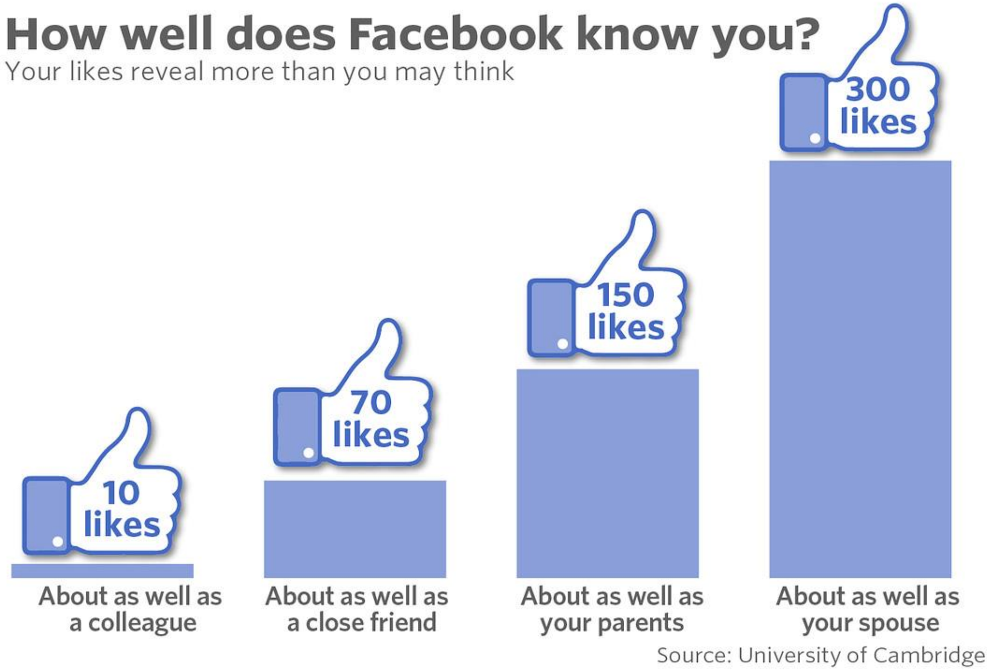

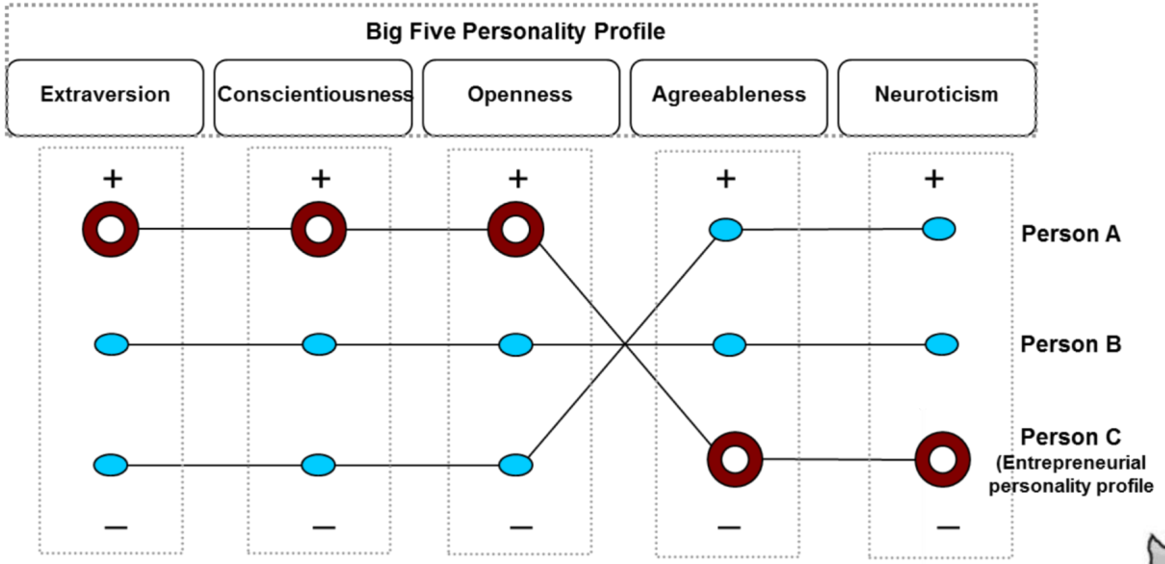

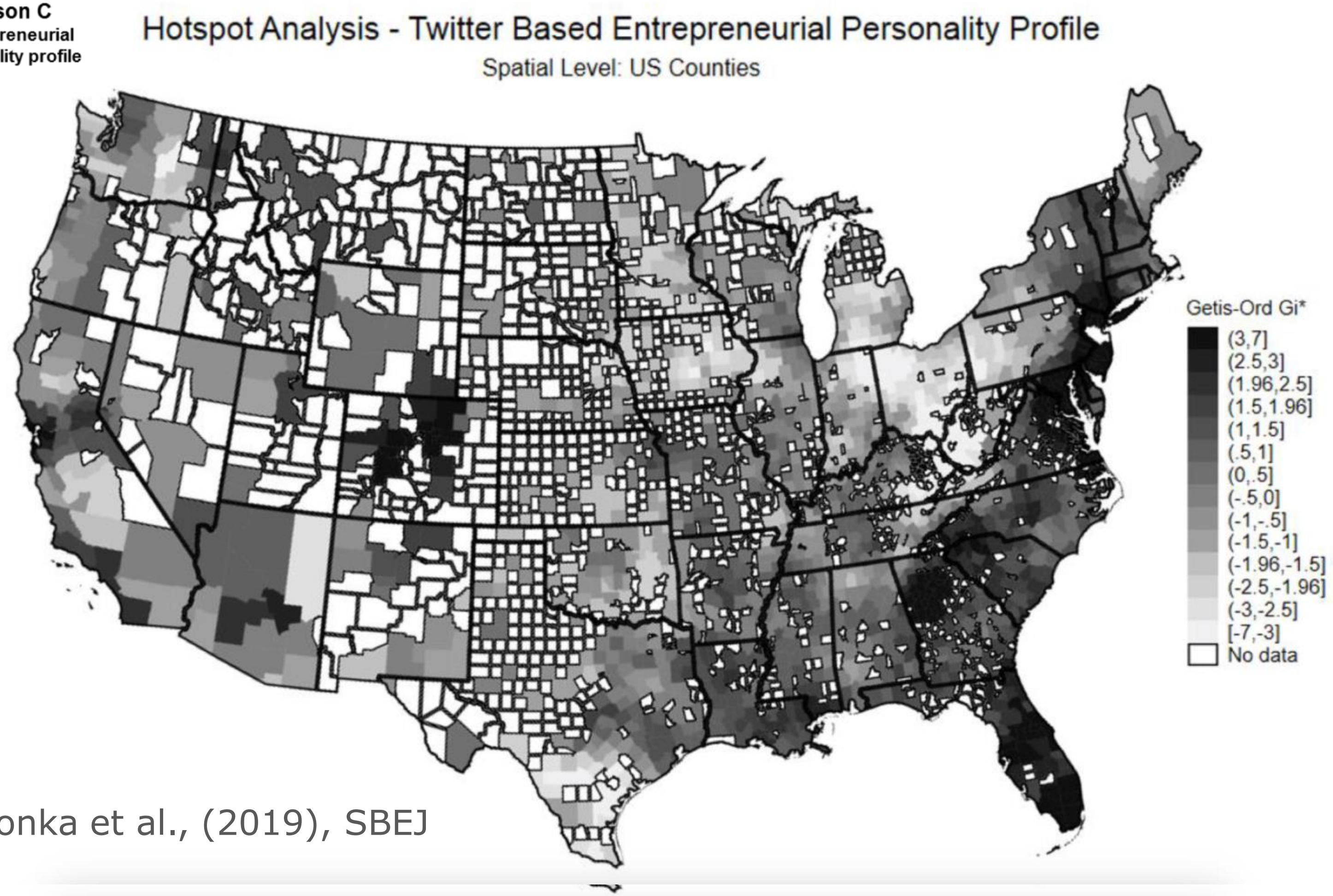

Obschonka et al., (2019), SBEJ

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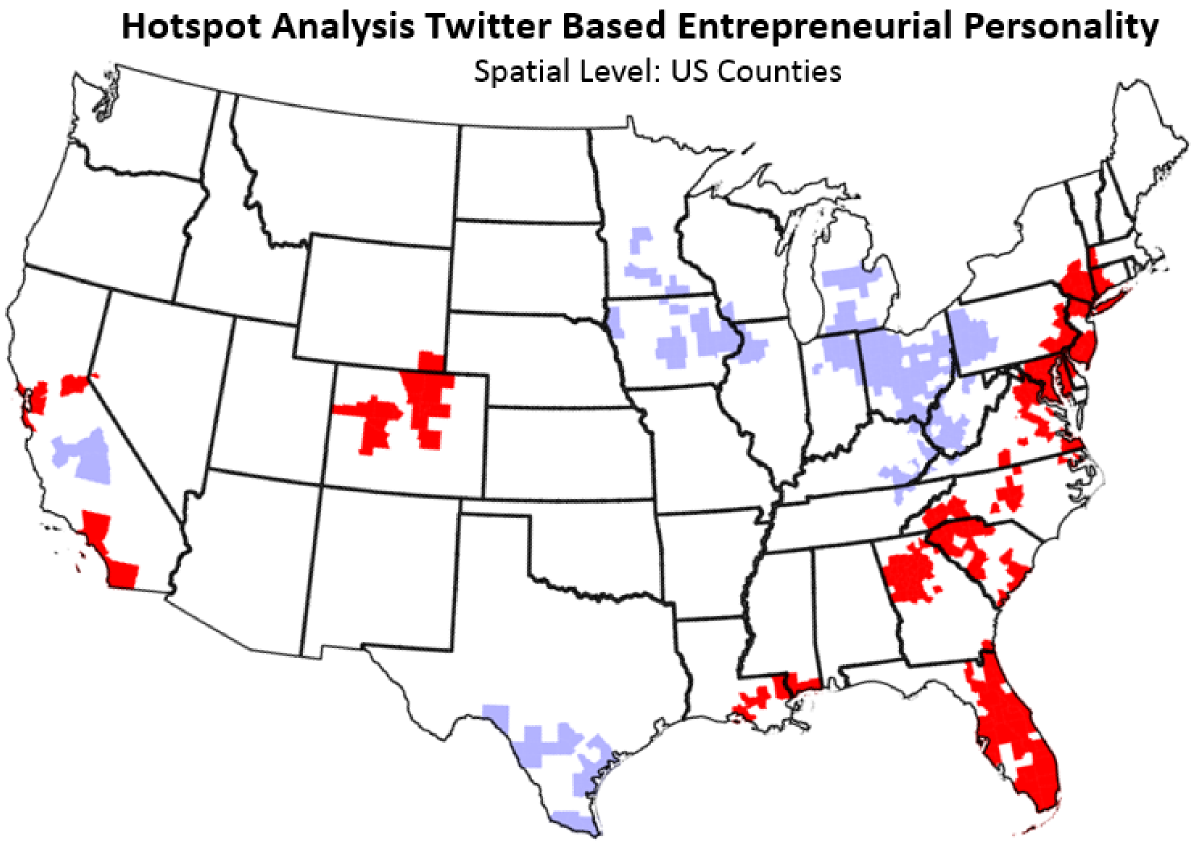
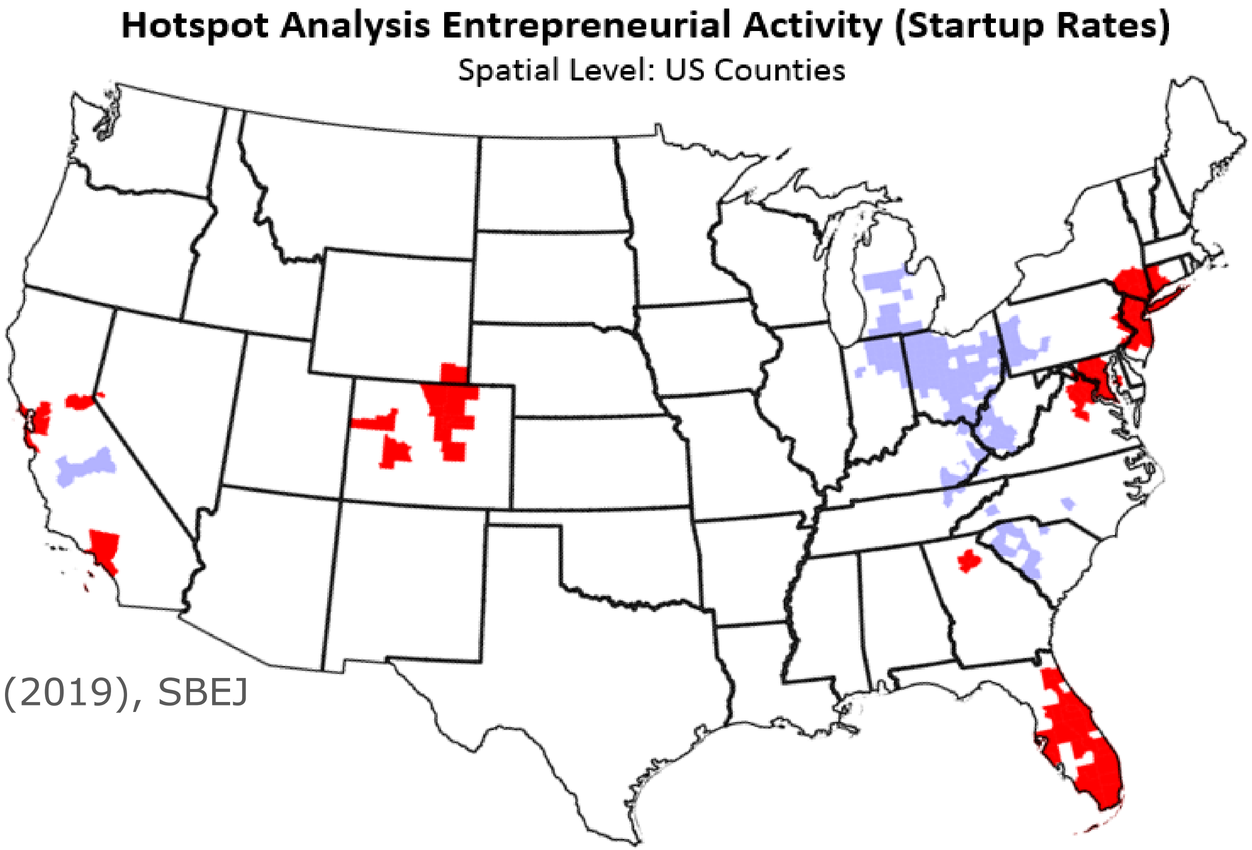
AI Map



Economic Map

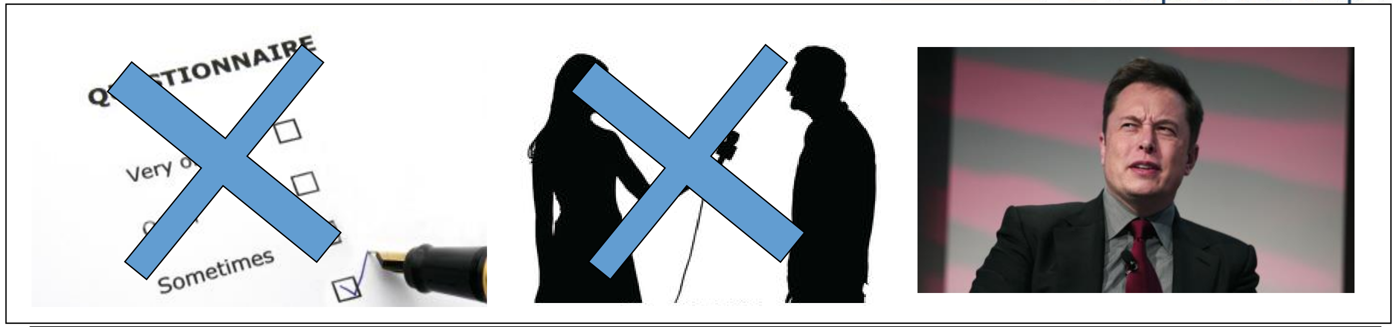


Obschonka et al., (2019), SBEJ


Elon Musk

Musk in 2015

Born	Elon Reeve Musk June 28, 1971 (age 46) Pretoria, Transvaal (now Gauteng), South Africa
Residence	Bel Air, Los Angeles, California, U.S.[1][2]
Citizenship	South African (1971–present) Canadian (1989–present) American (2002–present)
Alma mater	Queen's University University of Pennsylvania[3][4]
Occupation	Entrepreneur, Engineer, Inventor, and Investor
Known for	SpaceX, PayPal, Tesla Inc., Hyperloop, SolarCity, OpenAI, The Boring Company, Neuralink, Zip2
Net worth	US$21.3 billion (August 2017)[5]



Elon Musk @elonmusk · 22. Aug.
Was at a friend's party this weekend and drank wine from a mason jar

Elon Musk @elonmusk · 12. Aug.
Nobody likes being regulated, but everything (cars, planes, food, drugs, etc) that's a danger to the public is regulated. AI should be too.

Elon Musk hat retweetet
Motor Trend @MotorTrend · 29. Juli
INTERGALACTIC EXCLUSIVE: FIRST DRIVE OF THE ALL-NEW @TeslaMotors #MODEL3

Elon Musk @elonmusk · 29. Juli
Couldn't believe how incredibly inspiring and creative they were!!
Original (Englisch) übersetzen

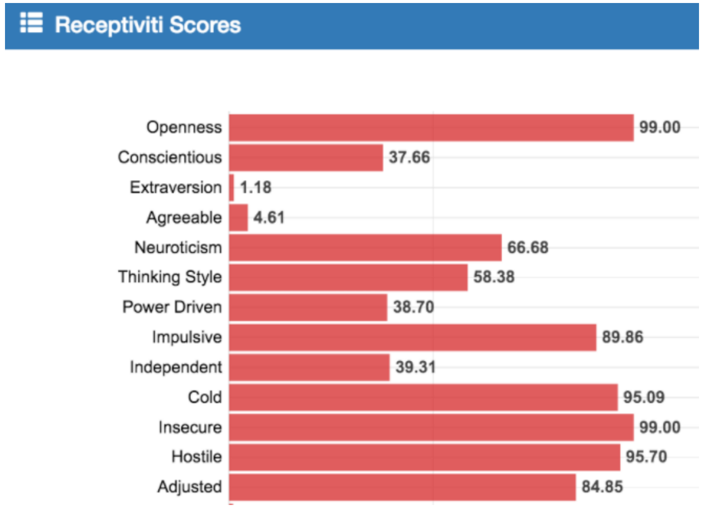
Elon Musk @elonmusk · 20. Juli
Antwort an @elonmusk
If you want this to happen fast, please let your local & federal elected representatives know. Makes a big difference if they hear from you.
Original (Englisch) übersetzen
1,4 Tsd. 3,5 Tsd. 21 Tsd.

Elon Musk @elonmusk · 20. Juli
Antwort an @elonmusk
Still a lot of work needed to receive formal approval, but am optimistic that will occur rapidly

LIWC

Category		Examples	Words
Affective processes	affect	happy, cried	1393
Positive emotion	posemo	love, nice, sweet	620
Negative emotion	negemo	hurt, ugly, nasty	744
Anxiety	anx	worried, fearful	116
Anger	anger	hate, kill, annoyed	230
Sadness	sad	crying, grief, sad	136

Receptiviti



Data: Identifying superstar entrepreneurs and managers

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- **Individual wealth identifies successful individuals:**
  - **Forbes 400:** First and foremost, we draw on the Forbes 400 2016 ranking, which lists the 400 wealthiest US Americans (e.g., Kaplan and Rauh, 2013; Klass et al., 2006). 66/400 individuals with Twitter.
  - **Forbes "America's richest entrepreneurs under 40"**: This ranking includes the 40 wealthiest entrepreneurs under 40 years. 37/40 individuals with Twitter.
  - **Fortune 500:** CEOs of Fortune 500 companies (e.g., Feldman and Montgomery, 2015; Shleifer and Vishny, 1986). 53 individuals with Twitter.
- Next, we **distinguish entrepreneurs and managers** manually and exclude accounts with missing values.
- **Final sample of 106 individuals**, 57 (superstar) entrepreneurs and 49 (superstar) managers. In total, our sample consists of 215,252 words (average of 2,031 words per individual).

Sample

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#	Name	DOB	Follower[a]	Tweets	Role	Source	O	C	E	A	N
1	Oprah Winfrey	1954	36,186,528	11,940	Founder Harpo Productions Inc.	Forbes 400	-1.320	-1.256	0.627	-0.018	0.279
2	Bill Gates	1955	34,144,402	2,306	Founder Microsoft	Forbes 400	1.961	0.361	-0.114	-1.515	0.156
3	Donald Trump	1946	27,359,166	34,701	Former CEO of Trump Org.	Forbes 400	1.229	-0.230	-1.329	-1.623	1.702
4	Elon Musk	1971	8,066,368	2,821	Founder Paypal and Tesla	Forbes 400	0.791	-1.412	-1.507	-0.420	0.876
5	Mark Cuban	1958	6,703,918	1,802	Founder Broadcast.com	Forbes 400	-0.571	-1.479	-2.057	-1.265	1.815
6	Timothy D. Cook	1960	4,549,234	349	CEO Apple	Fortune 500	0.614	0.669	1.138	0.443	-0.887
7	Jack Dorsey	1976	4,021,091	21,703	Founder Twitter	Forbes 400	-0.289	-0.450	-0.157	0.076	-1.256
8	Ralph Lauren	1939	1,976,751	3,843	Founder Ralph Lauren	Forbes 400	0.219	0.078	-0.835	-0.224	-1.238
9	Michael Bloomberg	1942	1,937,301	9,513	Founder Bloomberg	Forbes 400	1.855	1.065	0.211	-0.875	0.134
10	Eric Schmidt	1955	1,850,750	494	Ex-CEO Google	Forbes 400	0.611	0.369	-0.154	0.151	0.331
11	Satya Nadella	1967	1,279,496	593	CEO Microsoft	Fortune 500	0.376	1.064	1.380	0.640	-0.998
12	Michael Dell	1965	1,157,852	3,555	Founder Dell	Forbes 400	-0.508	1.433	1.449	1.365	-1.324
13	Rupert Murdoch	1931	774,142	1,717	Founder News Corp.	Forbes 400	0.916	-0.597	-1.388	-1.140	2.497
14	Marc Benioff	1964	684,406	14,343	Founder salesforce	Forbes 400	-0.002	0.453	-0.207	0.066	0.649
15	Pierre Omidyar	1967	533,809	9,965	Founder ebay	Forbes 400	2.265	-1.251	-2.222	-2.623	2.629
16	John Henry	1949	442,850	521	Founder John W. Henry	Forbes 400	0.751	0.244	-0.895	-0.431	-0.155
17	Reid Hoffman	1967	430,058	1,816	Founder LinkedIn	Forbes 400	0.270	1.099	0.344	0.222	-0.045
18	Sean Parker	1979	429,503	498	Founder Napster	Forbes 400	1.102	-1.220	-1.345	-2.129	1.648
19	Carl Icahn	1936	329,982	319	Founder Icahn Capital Man.	Forbes 400	-0.372	0.908	-0.765	-0.228	0.266
20	John Doerr	1951	287,835	809	Investor	Forbes 400	-0.175	0.169	-0.271	-0.720	-0.532

Superstar CEO's and Entrepreneurs

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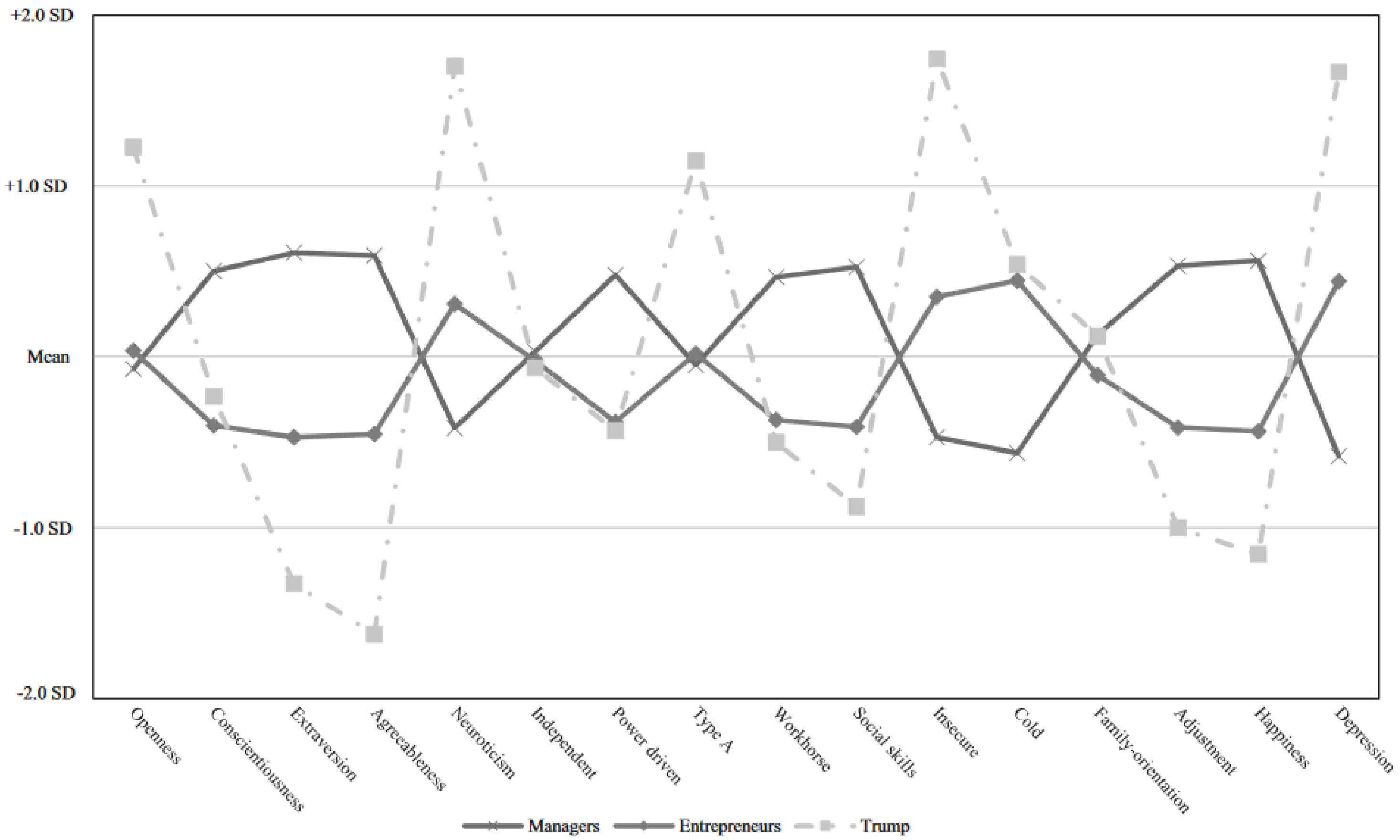


Fig. 1 Illustration of differences between the group of managers, entrepreneurs, and Donald J. Trump

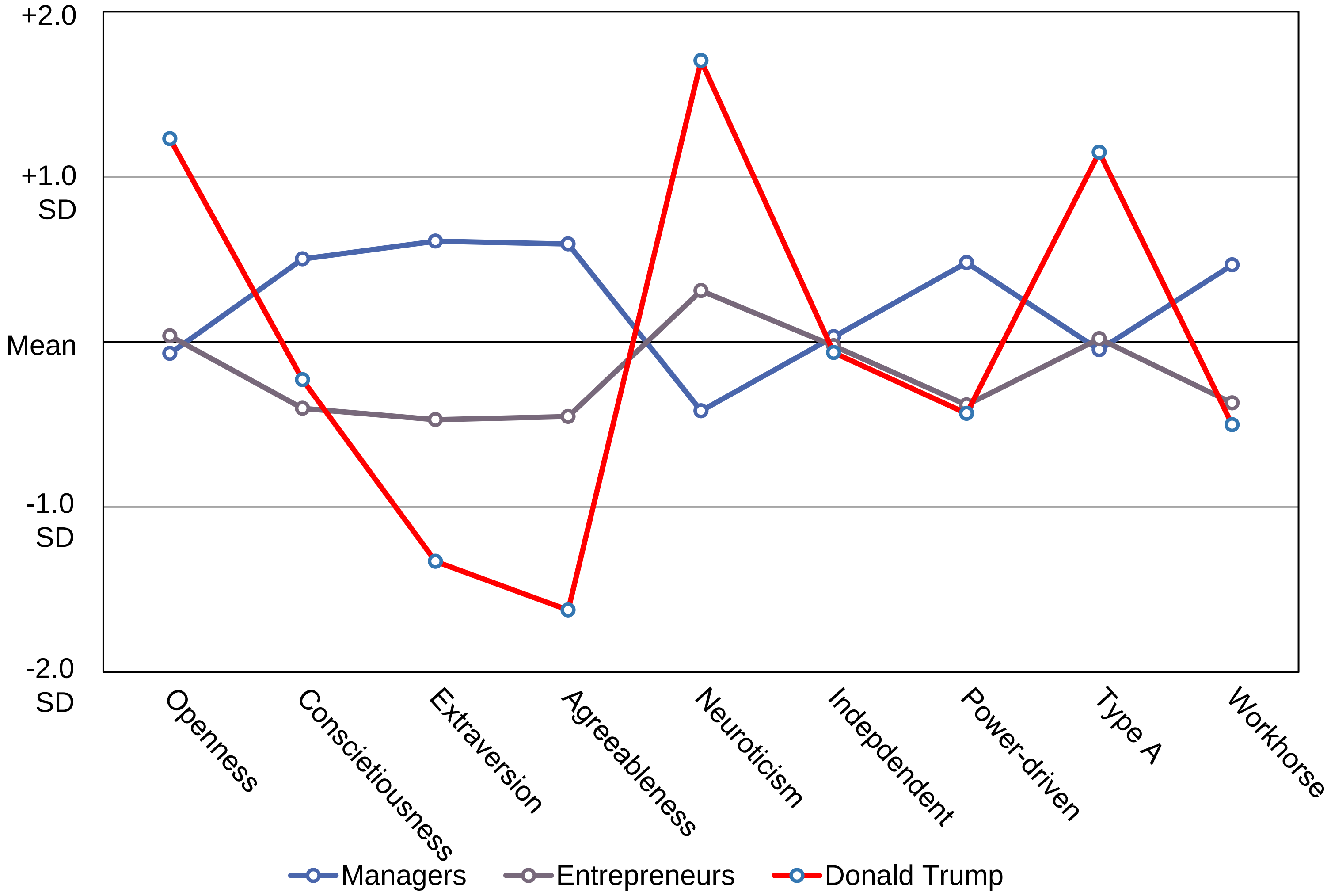
Springer

Obschonka & Fisch, 2018, SBEJ

- Tool: **LIWC**

(Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K.(2015). *The development and psychometric properties of LIWC2015*. Austin: University of Texas at Austin)

	Openness	Conscientiousness	Extraversion	Agreeableness	Neuroticism	Independent	Power-driven	Type A	Workhorse
Managers	-0.071	0.502	0.610	0.593	-0.418	0.030	0.480	-0.049	0.467
Entrepreneurs	0.036	-0.403	-0.471	-0.453	0.309	-0.023	-0.381	0.020	-0.369
Donald Trump	1.229	-0.230	-1.329	-1.623	1.702	-0.064	-0.433	1.148	-0.501

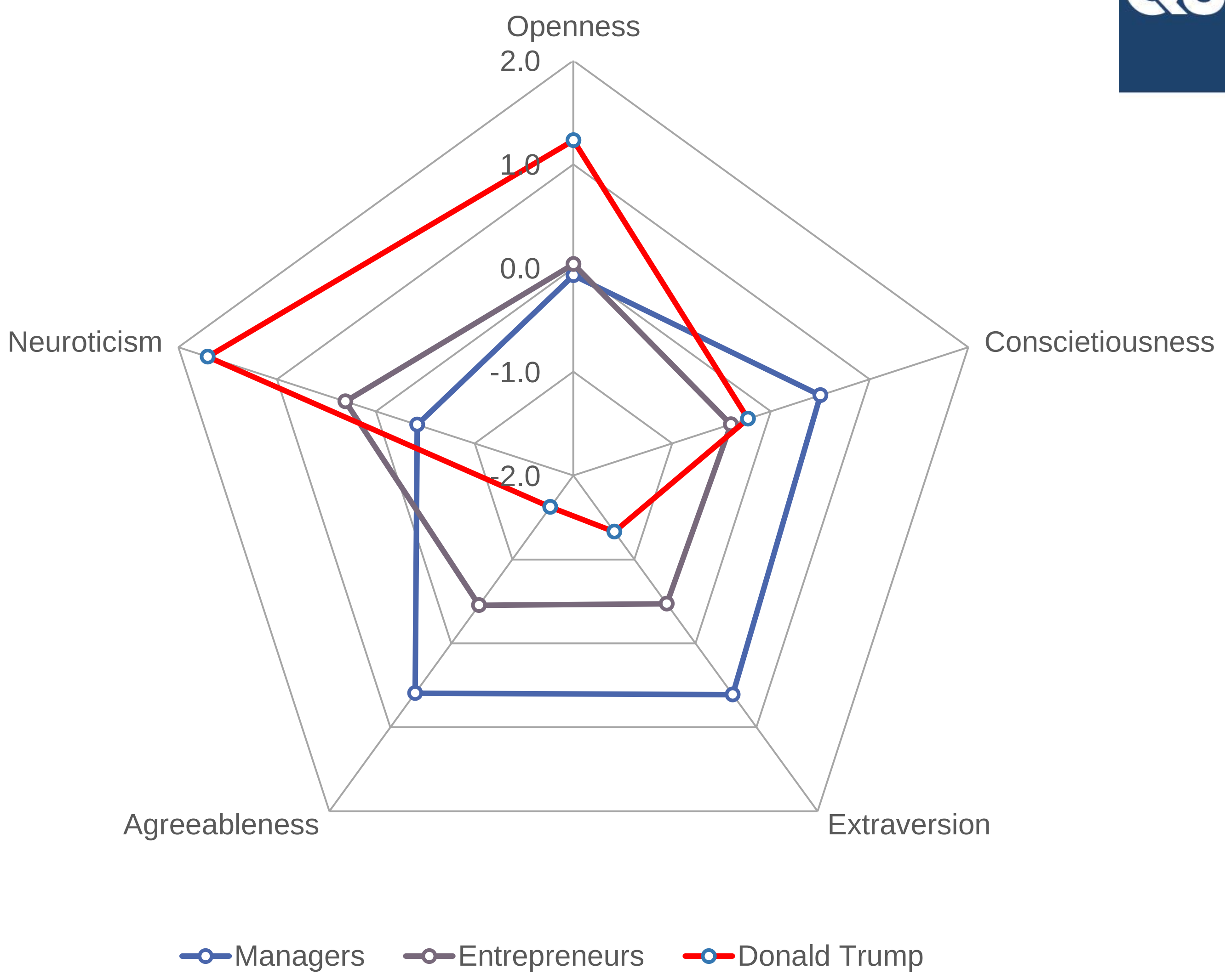


Big Five

Openness	… is open to new ideas and new experiences.
Conscientiousness	… is reliable.
Extraversion	… feels energized and uplifted when interacting with others or engaging in activity.
Agreeableness	… is inclined to please others.
Neuroticism	… expresses strong negative emotions.

Achievement-orientation

Independent	… is a non-conformist.
Power driven	… is driven by the desire for power.
Type A	… is driven and competitive, intolerant of setbacks.
Workhorse	… has a strong work ethic vs. preference for leisure and non-work activity.



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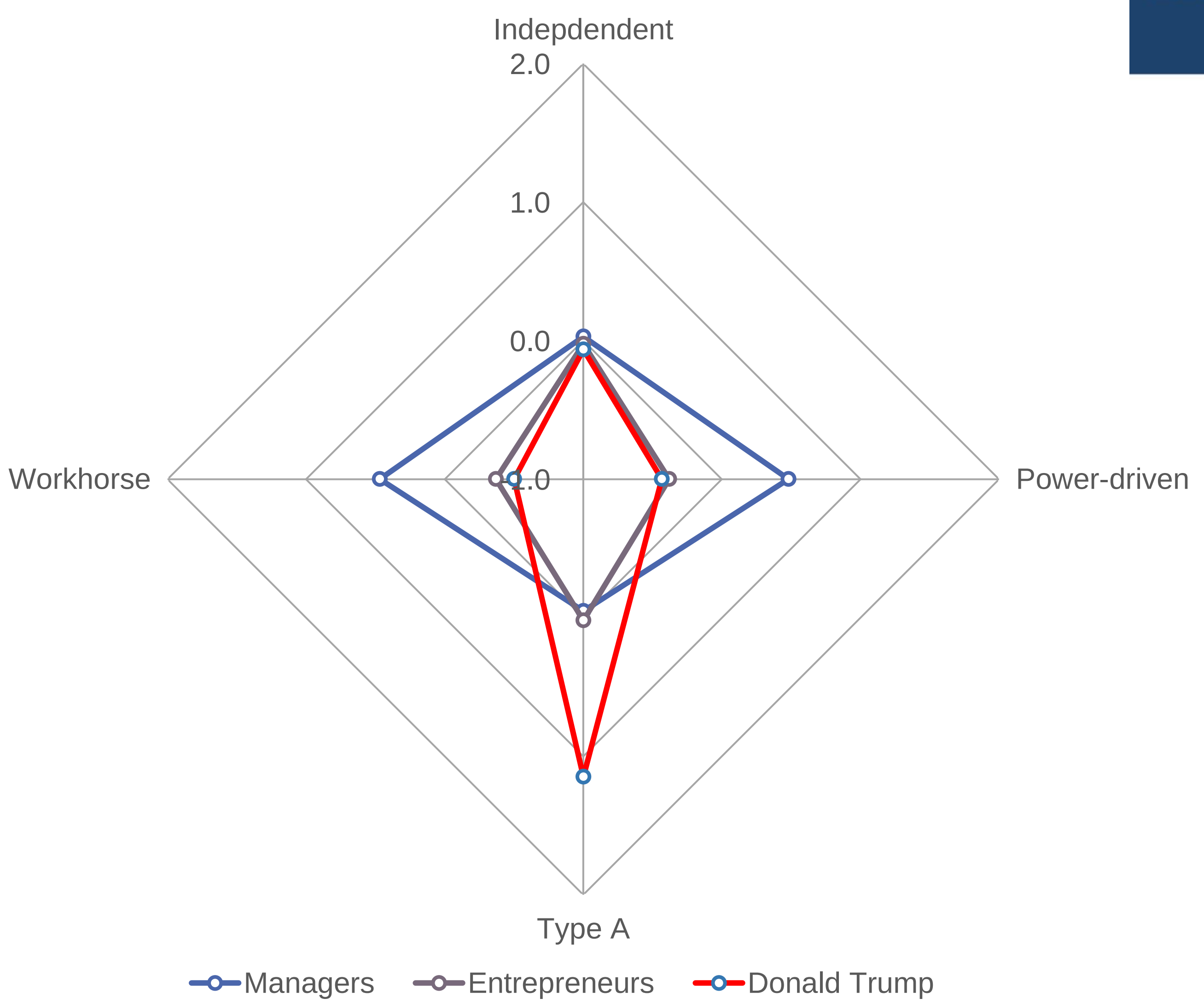

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Using tweets to decrypt the personality of Donald Trump and other powerful people

SOCIAL MEDIA

What Do President Trump's Tweets Say About His Personality? New Research Gives Insight

Almost every day a new tweet from President Donald Trump arrives, but what do they mean about the man?

BY KAREN TIBER LELAND, PRESIDENT, STERLING MARKETING GROUP @KARENFLELAND

www.research.qut.edu.au/ace

Private Entrepreneurial Traits

Private Entrepreneurial Traits

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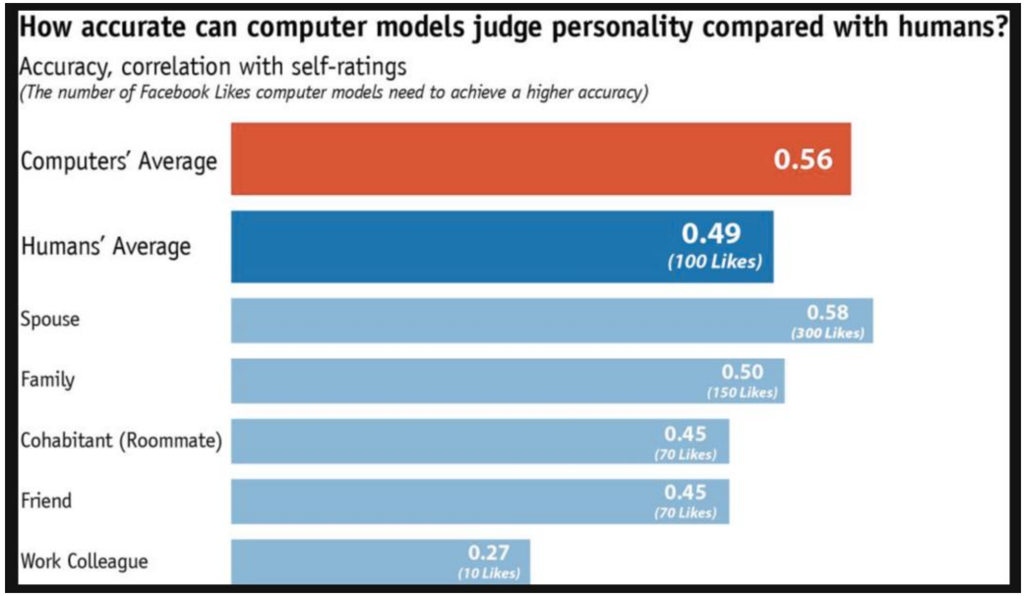

Kosinski et al., (2014), PNAS

"Gaydar"


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'I was shocked it was so easy': meet the professor who says facial recognition can tell if you're gay

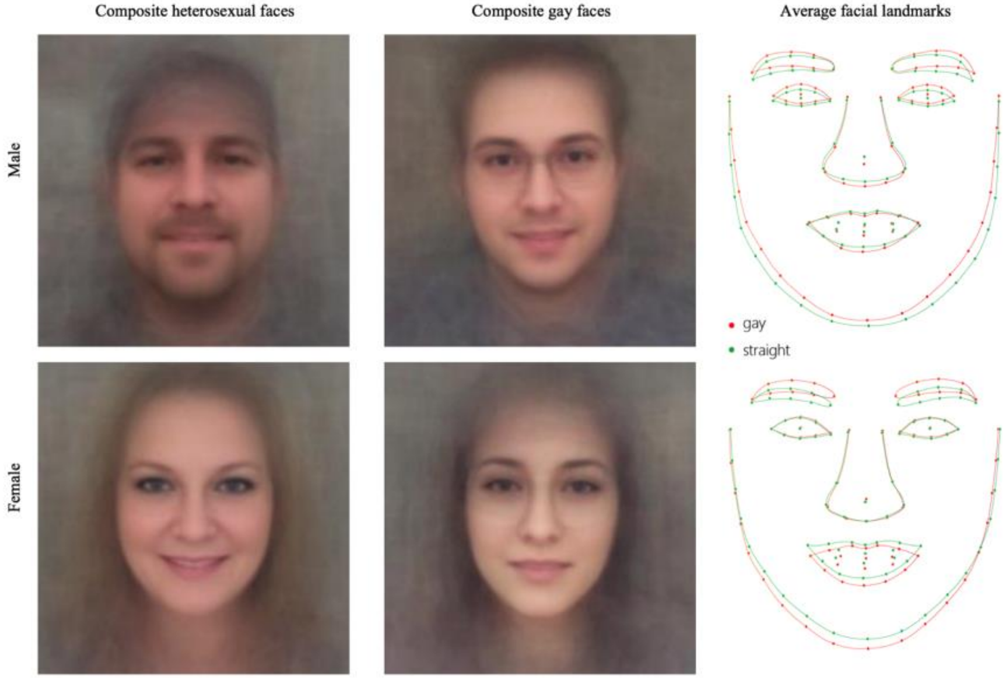

Figure 4. Composite faces and the average facial landmarks built by averaging faces classified as most and least likely to be gay.

Wang & Kosinski (2018), JPSP

Entrepreneurial Traits?

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Entrepreneurial Face?

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Angel/Seed Funding / Venture Capital

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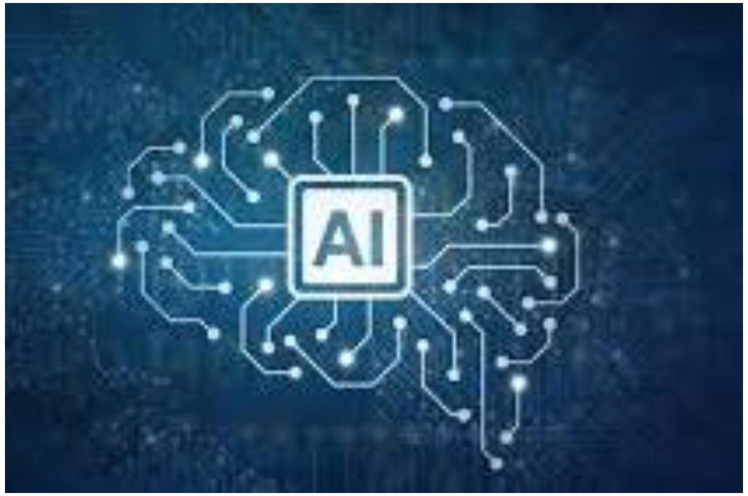

vs.

or

+

Angel/Seed Funding / Venture Capital

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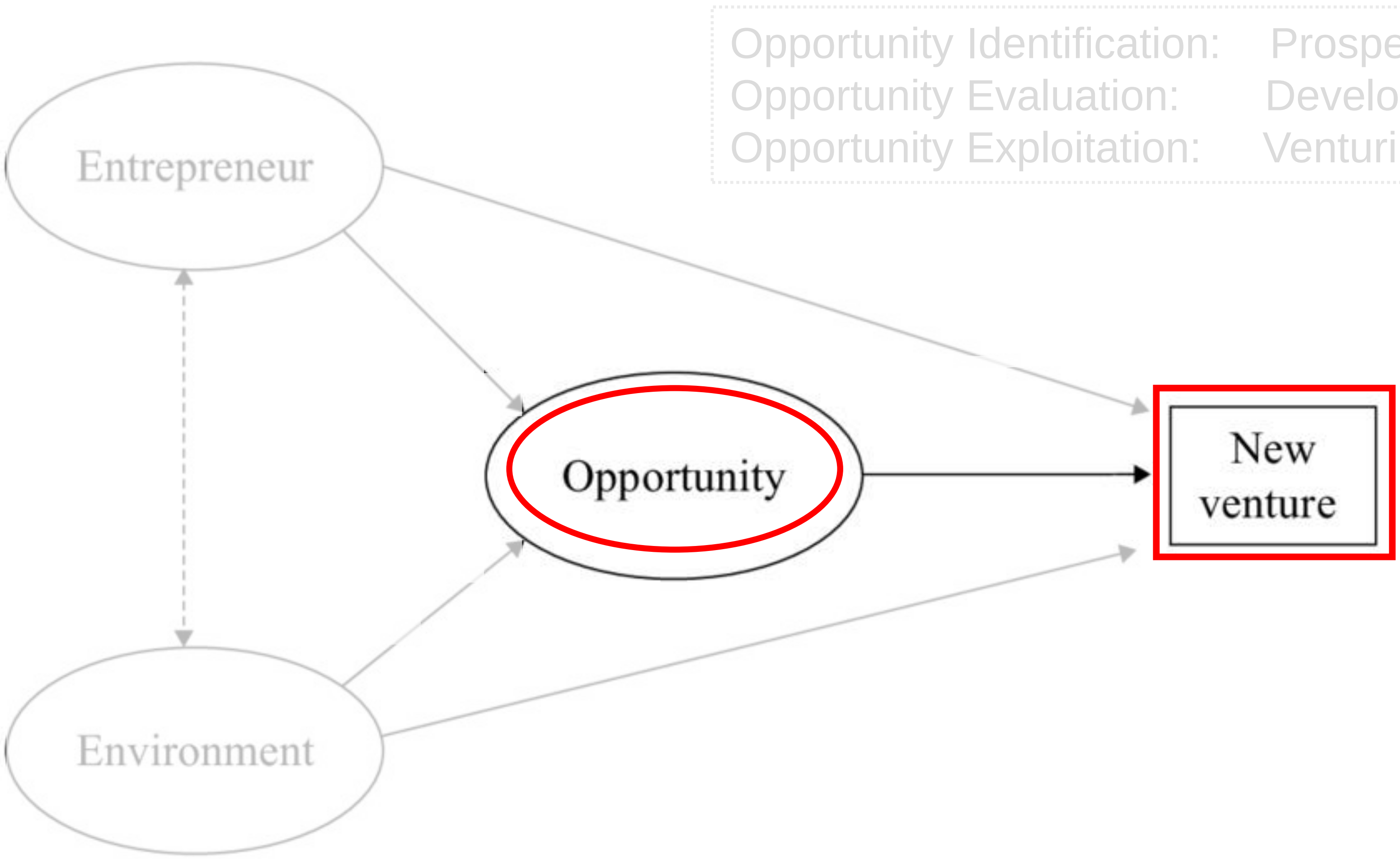

AI and Entrepreneurial Pitches

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Investor Personality

ELSEVIER

Contents lists available at ScienceDirect

Journal of Banking and Finance

journal homepage: www.elsevier.com/locate/jbf

A personality perspective on business angel syndication☆ ☆

Jörn H. Block[a,b,*], Christian O. Fisch[a,b], Martin Obschonka[c], Philipp G. Sandner[d]

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[b] Erasmus School of Economics and Erasmus Institute of Management (ERIM), Erasmus University Rotterdam, P.O. Box 1738, Rotterdam 3000 DR, The Netherlands
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Personality
Twitter data
Digital footprints

A B S T R A C T

The decision to syndicate investments in entrepreneurial finance has been explained through financial, networking, and resource-based perspectives. We posit that a personality perspective exists next to these three perspectives and hypothesize that the personality of business angels influences syndication behavior. Using data from 3,234 syndication decisions of 1,348 business angels, we find evidence for some of our predictions. By measuring personality through a comprehensive language analysis based on digital footprints in Twitter statements of business angels, we show that extraversion makes syndication more likely, whereas conscientiousness reduces the likelihood of syndication. Several sensitivity analyses underline the robustness of our main results. Further exploratory analyses assess the relationship between personality and syndicate composition as well as that between personality and venture success. Our study contributes to the entrepreneurial finance literature by adding and validating a new perspective to explain syndication behavior. In addition, our study contributes to research on the personality of business angels.

Block, J. H., Fisch, C. O., Obschonka, M., & Sandner, P. G. (2019). A personality perspective on business angel syndication☆. *Journal of Banking & Finance*, *100*, 306-327.

Investor personality

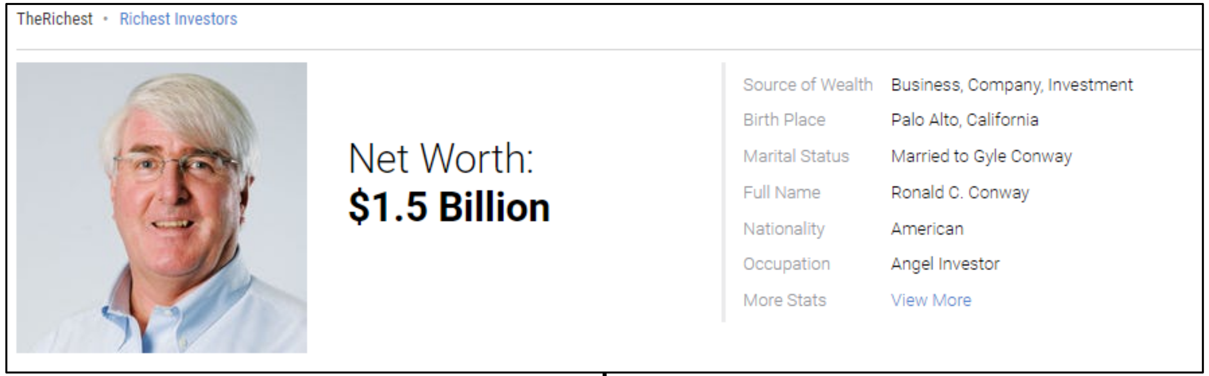
Overview UPDATE

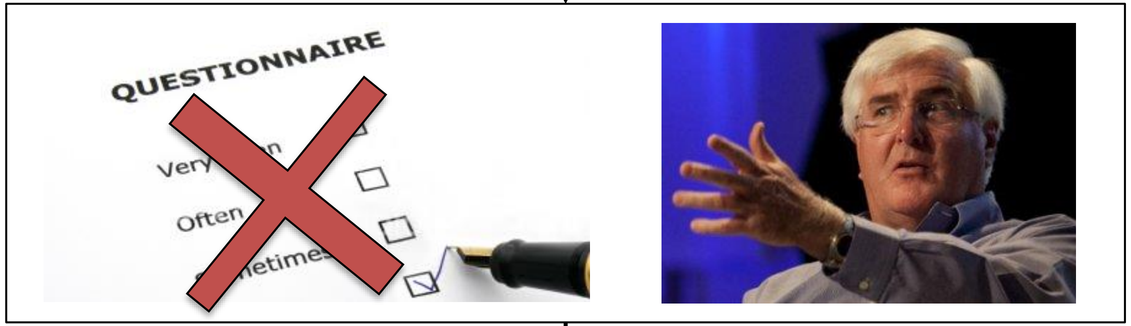
Funding Type:	Angel
Money Raised:	**$500k**
Announced On:	September 1, 2004
Investors:	Peter Thiel, Reid Hoffman, Mark Pincus, Western Technology Investment

Funding Rounds (11) - **$2.34B**

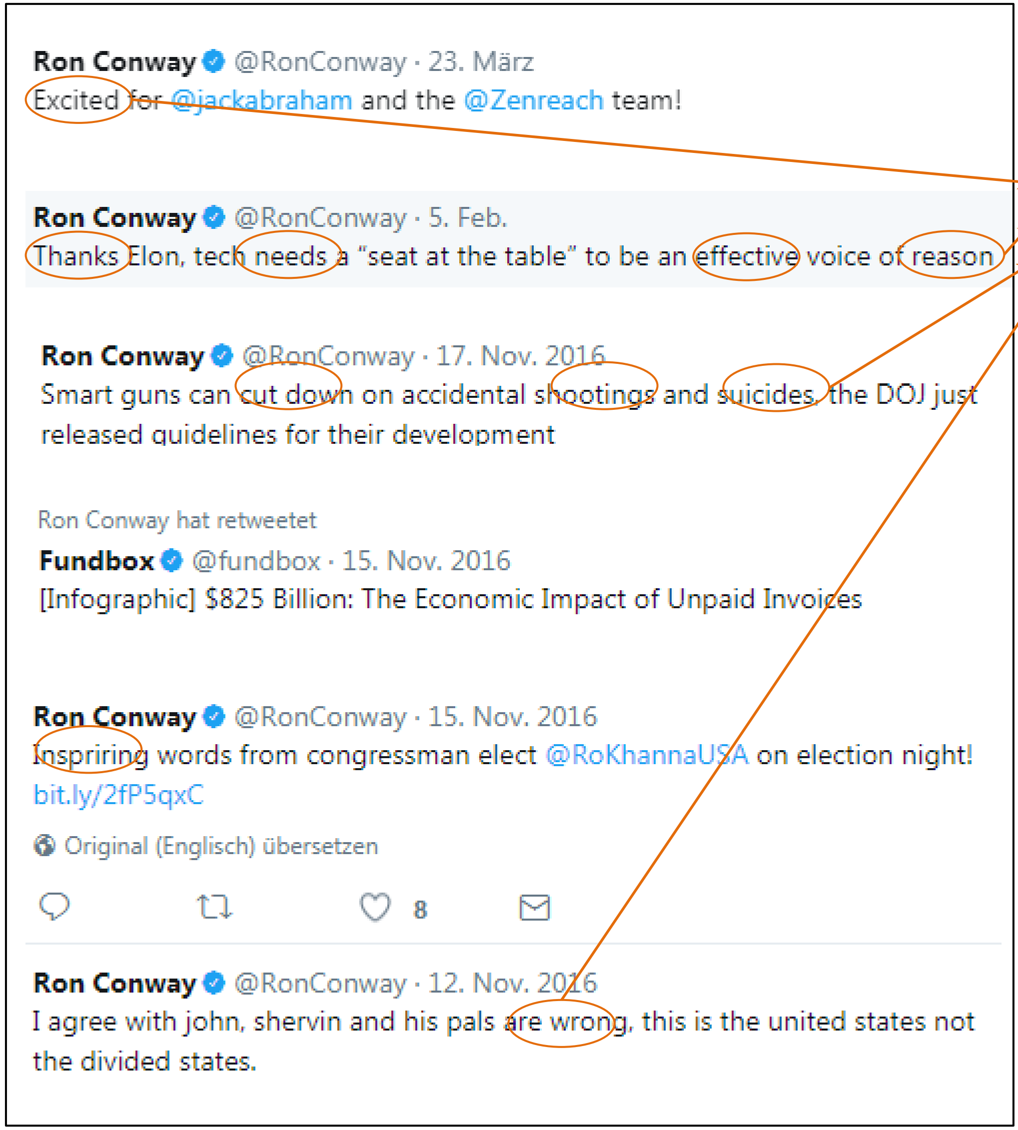
Date	Amount / Round	Valuation	Lead Investor	Investors
Jan, 2011	$1.5B / Private Equity	–	DST Global Goldman Sachs	2
Apr, 2006	$27.5M / Series B	–	Greylock Partners	5
May, 2005	$12.7M / Series A	–	Accel Partners	5
Sep, 2004	$500k / Angel	–	Peter Thiel	4

How do we measure personality?





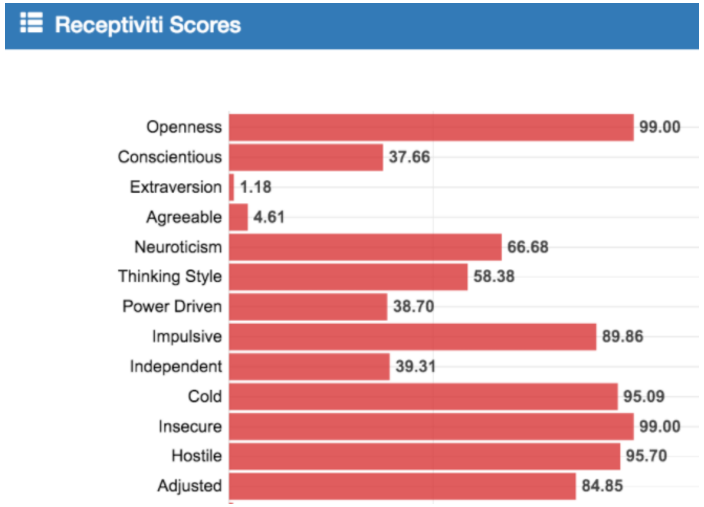
How exactly do we measure personality?



LIWC

Category		Examples	Words
Affective processes	affect	happy, cried	1393
Positive emotion	posemo	love, nice, sweet	620
Negative emotion	negemo	hurt, ugly, nasty	744
Anxiety	anx	worried, fearful	116
Anger	anger	hate, kill, annoyed	230
Sadness	sad	crying, grief, sad	136

Receptiviti



- Tool: **LIWC**

(Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K.(2015). *The development and psychometric properties of LIWC2015*. Austin: University of Texas at Austin)

Sample

We draw on **Crunchbase** (e.g., Ter Wal et al., 2016): We extract all business angel data available in Crunchbase in October 2016, and identify a sample of 2,114 business angels that use Twitter.

Name	Investments	Final sample	Twitter ID	Tweets	Followers	Following
(1) Fabrice Grinda	199	48	@fabricegrinda	1,112	10,473	42
(2) Ron Conway	128	56	@RonConway	465	95,665	63
(3) Alexis Ohanian	118	47	@alexisohanian	53,627	141,376	3,986
(4) Scott Banister	99	41	@nist	6,027	8,258	824
(5) Paul Buchheit	92	41	@paultoo	3[c]	42,856	813
(6) Tim Draper	90	35	@TimDraper	1,332	42,612	2,707
(6) Dave McClure	90	38	@davemcclure	69,627	348,944	17,197
(8) Naval Ravikant	87	45	@naval	13,701	189,241	393
(9) David Tisch	81	40	@davetisch	10,873	39,697	462
(10) Esther Dyson	73	34	@edyson	5,231	55,666	1,455
Total	**1,057**	**425**	**-**	**161,998**	**974,788**	**27,942**

Analysis: Logistic regression on likelihood of syndication

Variables	Model 1 Logit (SE)	Model 2 Logit SE	Model 3 Logit SE	Model 4 Logit SE	Model 5 Logit SE	Model 6 Logit SE
Amount raised (log.)	0.857 (0.076)***	0.844 (0.075)***	0.847 (0.078)***	0.845 (0.076)***	0.845 (0.075)***	0.847 (0.075)***
Round: Seed-stage	0.358 (0.173)**	0.385 (0.174)**	0.364 (0.171)**	0.368 (0.173)**	0.370 (0.174)**	0.395 (0.174)**
Venture: Age (log.)	0.012 (0.333)	0.023 (0.326)	0.002 (0.334)	0.000 (0.333)	0.008 (0.332)	0.030 (0.326)
Venture: Location US	0.409 (0.292)	0.453 (0.296)	0.398 (0.292)	0.422 (0.295)	0.445 (0.296)	0.445 (0.294)
Previous inv. (log.)	0.450 (0.084)***	0.473 (0.094)***	0.449 (0.081)***	0.451 (0.086)***	0.457 (0.086)***	0.470 (0.089)***
BA: Age (log.)	-1.625 (0.438)***	-1.560 (0.425)***	-1.470 (0.470)***	-1.698 (0.430)***	-1.707 (0.429)***	-1.179 (0.437)***
BA: Location US	0.247 (0.278)	0.306 (0.280)	0.269 (0.278)	0.282 (0.280)	0.286 (0.280)	0.270 (0.287)
Male	-0.371 (0.475)	-0.330 (0.462)	-0.378 (0.505)	-0.448 (0.463)	-0.455 (0.455)	-0.210 (0.506)
Tweets (log.)	0.269 (0.106)**	0.301 (0.097)***	0.218 (0.124)*	0.263 (0.113)**	0.277 (0.106)***	0.243 (0.104)**
Followers (log.)	-0.166 (0.085)*	-0.172 (0.072)**	-0.157 (0.094)*	-0.160 (0.085)*	-0.156 (0.077)**	-0.169 (0.076)**
Follows (log.)	-0.096 (0.075)	-0.108 (0.076)	-0.074 (0.074)	-0.091 (0.075)	-0.102 (0.076)	-0.089 (0.074)
IV: Big Five						
Openness (+)	-0.178 (0.084)**					0.031 (0.100)
Extraversion (+)		0.187 (0.079)**				0.313 (0.097)***
Conscientiousness (-)			-0.198 (0.083)**			-0.294 (0.088)***
Agreeableness (+)				0.003 (0.049)		-0.072 (0.066)
Neuroticism (+)					-0.046 (0.052)	-0.030 (0.056)
Pseudo-R^2	0.232	0.235	0.235	0.229	0.230	0.248

Logistic regression on the determinants of syndication. This table shows the results of our main analysis. We perform a logistic regression with the dependent variable syndication (dummy). The total number of observations of investments is 3,549 from 1,456 investors. All variables are defined in Table 1. Logits are reported with robust standard errors clustered by business angels in parentheses. Significance levels are denoted by asterisks, *** 1%, ** 5%, and * 10% (p - values are two-tailed). Education, industry, and year dummies included but omitted for brevity.

Human bias

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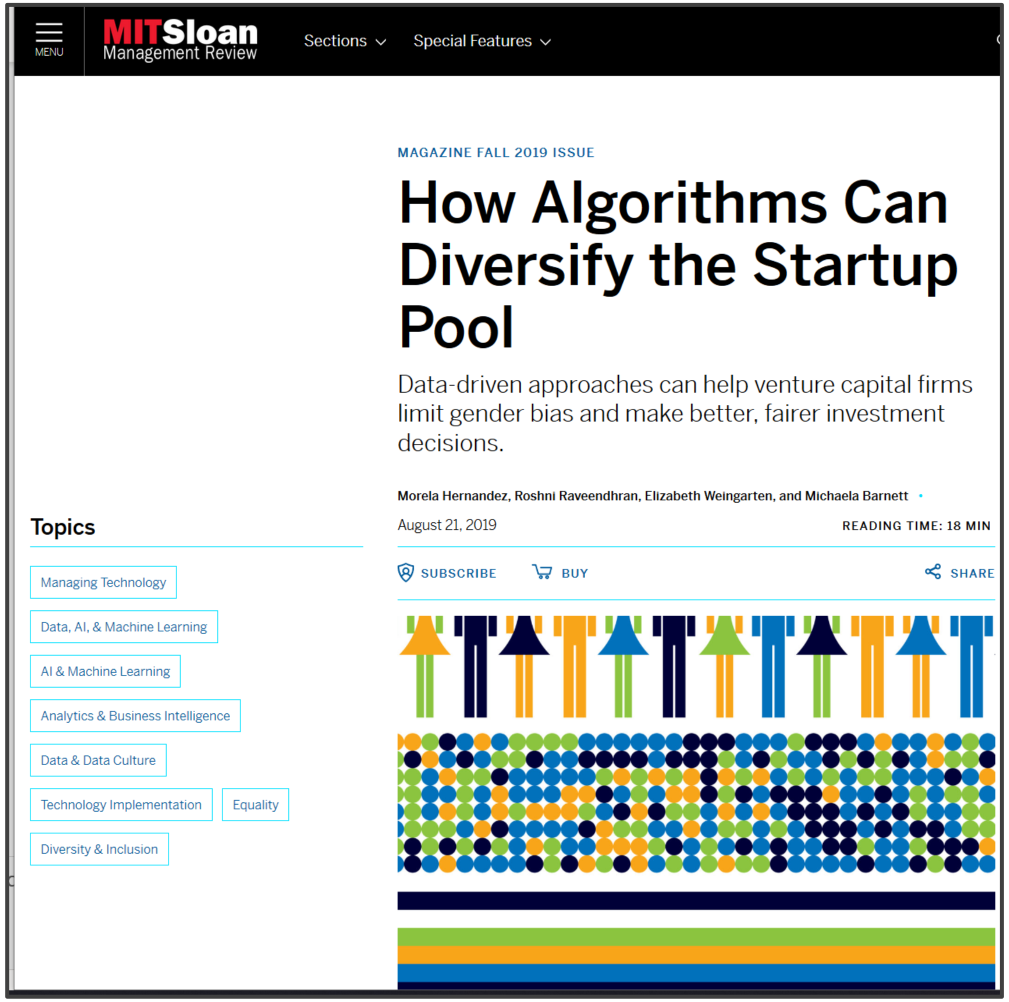
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MAGAZINE FALL 2019 ISSUE

How Algorithms Can Diversify the Startup Pool

Data-driven approaches can help venture capital firms limit gender bias and make better, fairer investment decisions.

Morela Hernandez, Roshni Raveendhran, Elizabeth Weingarten, and Michaela Barnett

August 21, 2019

READING TIME: 18 MIN

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Entrepreneurship Theory and Practice
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It's a Peoples Game, Isn't It?! A Comparison Between the Investment Returns of Business Angels and Machine Learning Algorithms

Ivo Blohm[1*], Torben Antretter[1*], Charlotta Sirén[1,2], Dietmar Grichnik[1], and Joakim Wincent[1,3]

Abstract

Investors increasingly use machine learning (ML) algorithms to support their early stage investment decisions. However, it remains unclear if algorithms can make better investment decisions and if so, why. Building on behavioral decision theory, our study compares the investment returns of an algorithm with those of 255 business angels (BAs) investing via an angel investment platform. We explore the influence of human biases and experience on BAs' returns and find that investors only outperformed the algorithm when they had extensive investment experience and managed to suppress their cognitive biases. These results offer novel insights into the role of cognitive limitations, experience, and the use of algorithms in early stage investing.

Keywords

business angels, artificial intelligence, machine learning, biases, investment experience, decision making

- "Man vs. machine" comparison in early stage investing
- AI method: Gradient boosted decision trees
- DV: New venture survival
- IVs:
  - Legitimacy (social media activity)
  - Human capital (LinkedIn profiles)
  - Business model, industry, market timing
  - Equity capital before BA funding
- BA decision making bias
  - Local bias, overconfidence, loss aversion

- "…on average, our ML algorithm is able to achieve a performance gain of up to 184% when compared to the BAs in our sample. The average Internal Return Rate of 7.26% shown for our ML algorithm is also well above the angel investment returns reported by other studies. BAs are generally considered to have limited cognitive capacities and fall prey to a series of decision biases, such as local bias, over-confidence, and loss aversion. Algorithms, on the other hand, are not sensitive to these biases and can thus be seen as an optimal benchmark to investigate the role of decision biases in early stage investing."

AI and Research

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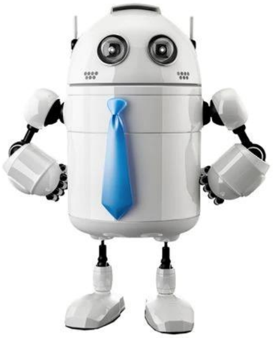

Rigor and Relevance

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Entrepreneurship Theory and Practice
00(0) 1–30

DOI: 10.1177/1042258720927369
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Pursuing Impactful Entrepreneurship Research Using Artificial Intelligence

Moren Lévesque[1], Martin Obschonka[2], and Satish Nambisan[3]

Abstract

It is time for the entrepreneurship field to come to terms with leading-edge artificial intelligence (AI). AI holds great promise to transform entrepreneurship into a more relevant and impactful field, but it must overcome conflicts between the AI-driven research approach and that of the traditional, theory-based research process. We explore these opportunities and challenges and suggest concrete approaches that entrepreneurship researchers can use to harness the power of AI with rigor and enhance research relevance. We conclude that incorporating the power of AI in entrepreneurship research and managing the associated risks offer a new and "grand challenge" for the field.

Keywords

entrepreneurship research, theory building, theory testing, research relevance, artificial intelligence

Rigor and Relevance

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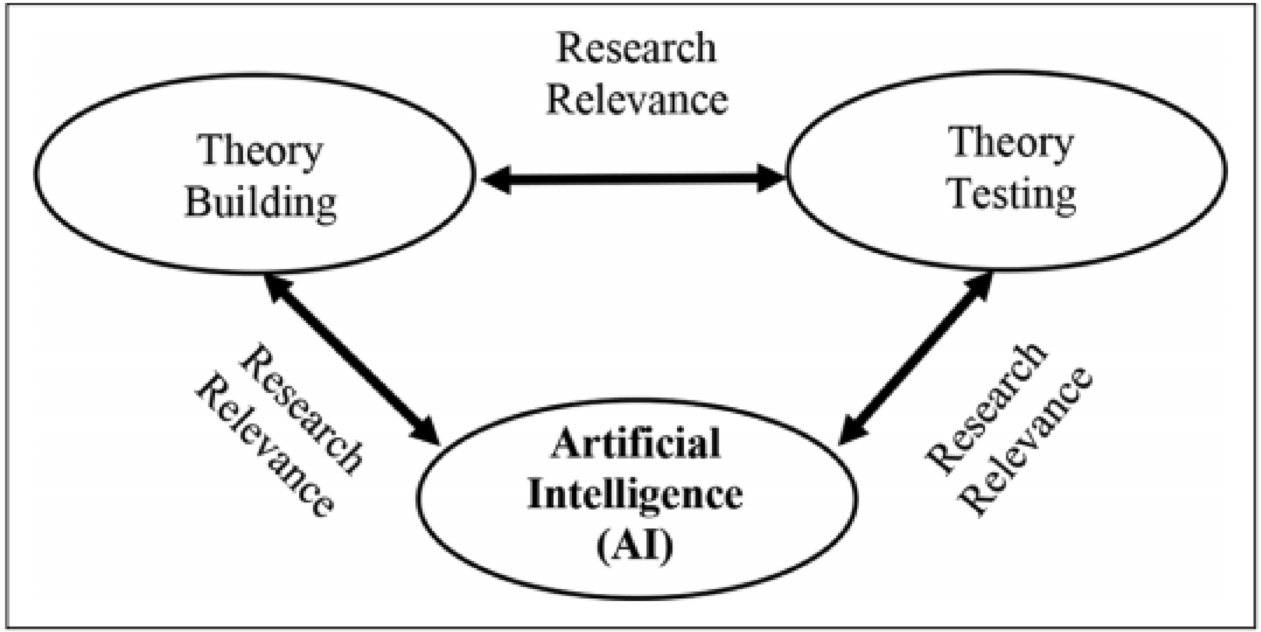

Figure 1. Associating Artificial Intelligence with Entrepreneurship Theory Building and Testing.

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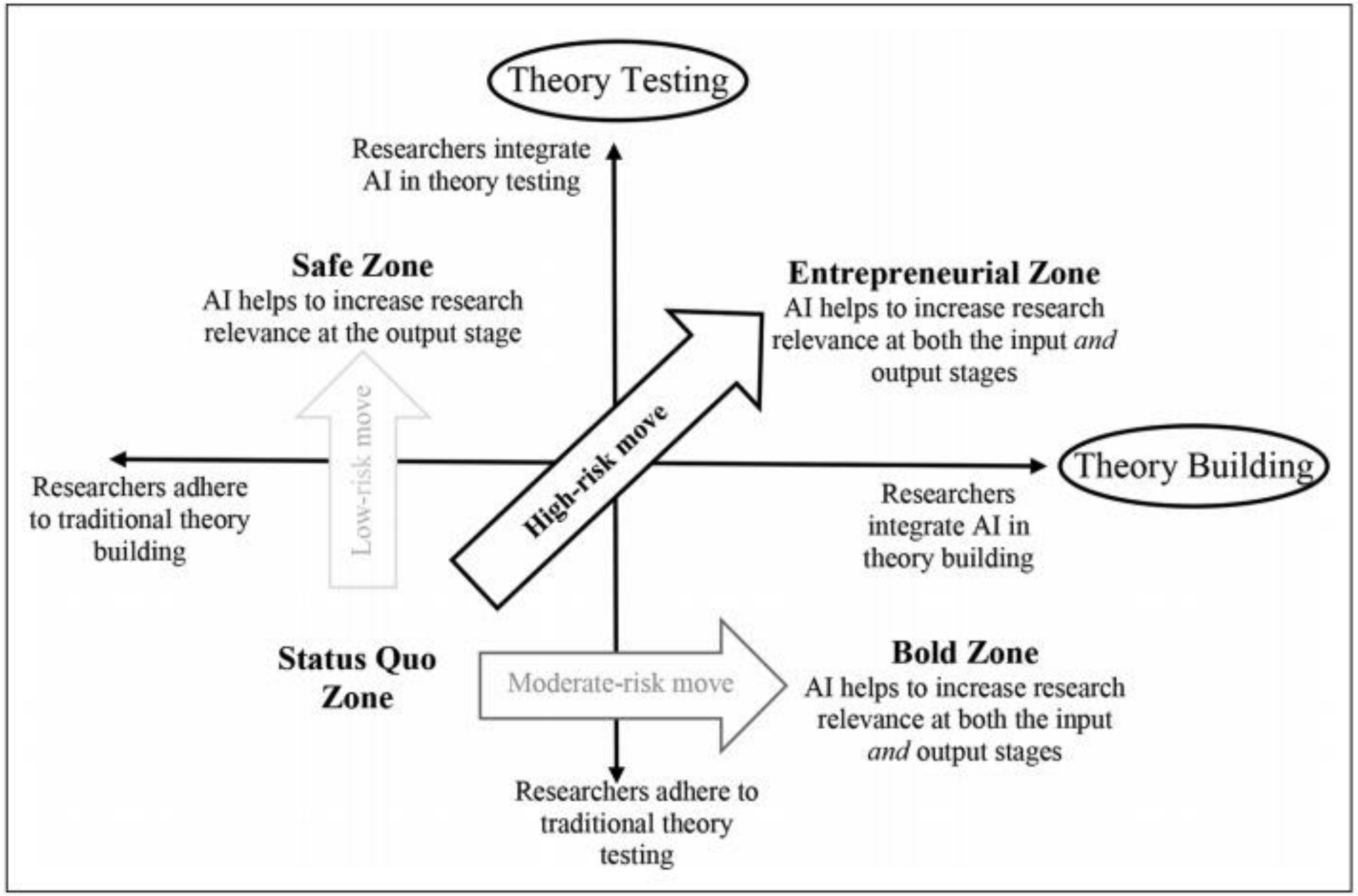


Figure 2. Zones of Artificial Intelligence Application in Entrepreneurship Research

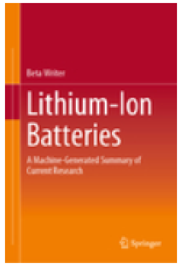
AI as a Researcher

Springer Nature publishes its first machine-generated book

Innovative book prototype provides a compelling machine-generated overview about the latest research on lithium-ion batteries, automatically compiled by an algorithm developed in collaboration with the Applied Computational Linguistics lab of Goethe University Frankfurt/Main (Germany)

London | Heidelberg, 02 April 2019

Springer Nature published its first machine-generated book in chemistry. The book prototype provides an overview of the latest research in the rapidly growing field of lithium-ion batteries. The content is a cross-corpus auto-summarization of a large number of current research articles in this discipline. Serving as a structured excerpt from a huge set of papers, the innovative pipeline architecture aims at helping researchers to manage the information overload in this discipline efficiently.



AI Revolution in Academia

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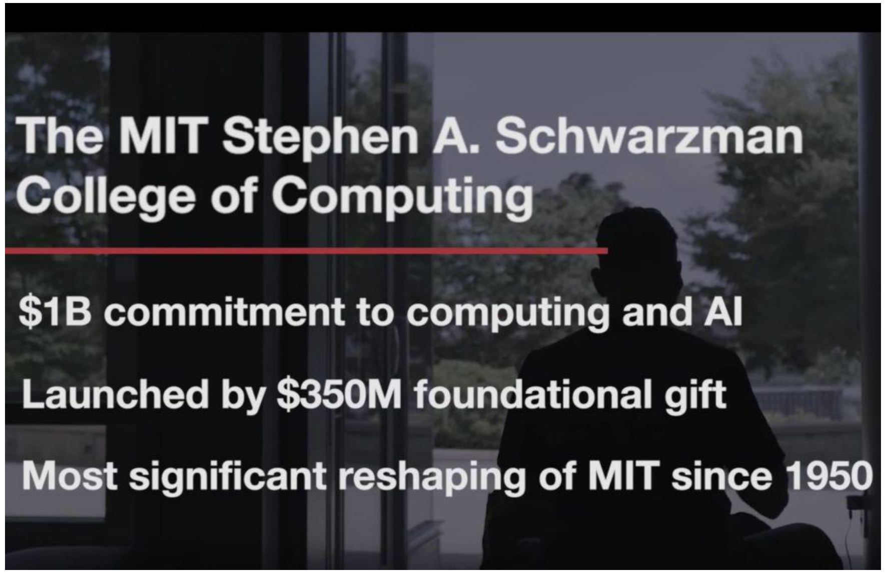
The Alan Turing Institute

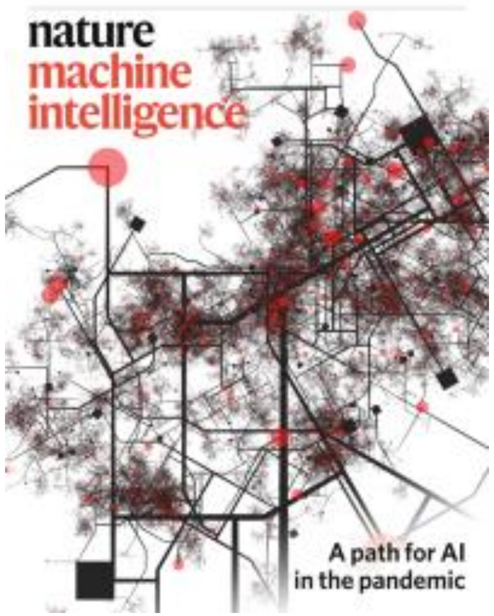
Stanford University

HAI Human-Centered Artificial Intelligence
Stanford University

OXFORD ARTIFICIAL INTELLIGENCE SOCIETY



MIT Schwarzman College of Computing



We conclude by noting that in making the above suggestions to the entrepreneurship field and its various stakeholders, and in offering our thoughts on this broader topic, one theme is central: as a tool, AI is a "servant" to its human masters and their goals. Therefore, let us (strategically) embrace our new grand challenge in entrepreneurship research—to rigorously integrate AI into our research to enhance its scope and relevance.

Я твой слуга
Я твой работник
(I am your servant, I am your worker)
—from "The Robots" by Kraftwerk

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Thank you! 唔該

martin.obschonka@qut.edu.au

Recommended Literature

QUT Business School
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1) Special Issue: AI, Big Data & Entrepreneurship, SBEJ 2020

Small Bus Econ (2020) 55:529–539
https://doi.org/10.1007/s11187-019-00202-4

Check for updates

Artificial intelligence and big data in entrepreneurship: a new era has begun

Martin Obschonka · David B. Audretsch

Accepted: 19 April 2019 / Published online: 6 June 2019

Abstract While the disruptive potential of artificial intelligence (AI) and big data has been receiving growing attention and concern in a variety of research and application fields over the last few years, it has not received much scrutiny in contemporary entrepreneurship research so far. Here we present some reflections and a collection of papers on the role of AI and big data for this emerging area in the study and application of entrepreneurship research. While being mindful of the entrepreneurship scholars, educators, and practitioners to proactively prepare for future scenarios.

Keywords Entrepreneurship · Artificial intelligence · AI · Big data · Machine learning · Smart entrepreneurship

JEL classification L26 · M13 · B41

2) ETP article on AI in research

Entrepreneurship Theory and Practice
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