Enhancing Venture Capital Investment Decisions: A Domain-Specific Personality Scale for Distinguishing High-Potential Startup Founders

Irena C. Danilovska[1], Manousos Klados[1,2], Catherine Preston[1], Nick E. Barraclough[1*]

[1]Department of Psychology, University of York, Heslington, York, UK, YO10 5DD

[2]University of York Europe Campus CITY College, Thessaloniki 54622, Greece

Author Note

Irena C. Danilovska https://orcid.org/0000-0002-1941-1040

https://www.linkedin.com/in/chaushevskadanilovska/

Manousos Klados https://orcid.org/0000-0002-1629-6446

https://www.linkedin.com/in/mklados/

Catherine Preston https://orcid.org/0000-0001-7158-5382

https://www.linkedin.com/in/catherine-preston-a777202/

Nick E. Barraclough https://orcid.org/0000-0003-2818-326X

https://www.linkedin.com/in/nick-barraclough-0a25711a/

*Corresponding author Nick E. Barraclough, Department of Psychology, University of York, Heslington, York, YO10 5DD, UK. Telephone: +44(0)1904 323141,

Email: nick.barraclough@york.ac.uk

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Ethics statement. This study was conducted in accordance with the 1964 Declaration of Helsinki. On 21 April 2023, the Ethics Committee of the Department of Psychology, University of York waived the requirement for ethics approval for the analysis and publication of retrospectively obtained, anonymized questionnaire data used in this non-interventional study. All respondents provided informed consent online before participation. The scale-validation survey was approved on the same date by the same ethics committee, and all domain and lay panel members provided informed consent online before participation.

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Abstract

Early identification of startup founders with higher success potential is critical for entrepreneurial finance efficiency. We present a domain-specific framework where founder-specific success characteristics—beyond broad personality traits—account for variance in startup success. The 31-item Startup Founder Success Scale (SFSS) was developed from billionaire-founder autobiographies, mentor interviews, and high-return investor insights, then validated on 10,007 participants (Successful Startup Founders, Corporate Managers, and Aspiring Entrepreneurs). Exploratory and confirmatory factor analysis revealed six-dimensions—Relentless Resilience, Value-Creating Opportunism, Intrinsic Curiosity, Courageous Decision-Making, Strategic Innovativeness, and Transformational Leadership—explaining 71% of variance in success-relevant characteristics. SFSS yields large effect-size separations (Cohen's d = 0.83–1.77) between successful founders and comparison groups, substantially exceeding established benchmarks of broad personality models (~10–15% variance; d ~ 0.2–0.5). This 5--7× improvement distinguishes potential for real success from mere intent, reducing false positives. Conceptually, the findings specify a multi-level framework linking founder characteristics to decisions and behaviors under uncertainty, serving as a foundation for future theoretical developments with longitudinal studies. Practically, SFSS offers a validated tool that could potentially enhance investment portfolios by informing early-stage screening for venture capitalists, angel investors, public investment bodies, and innovation funds, while guiding entrepreneurial education and founder training programs.

Keywords

Startup Founders; Entrepreneurship; Entrepreneurial Finance; Venture Capital; Founder Personality, Investment Selection; Human Capital; Startup Success; Economic Impact.

Introduction

Early identification of startup founders that are more likely to succeed has significant economic and policy implications in entrepreneurial finance. Directing funding, mentorship, and specialized training toward high-potential individuals can materially improve the efficiency of scarce resources and downstream impact on investment performance and exits. Yet existing frameworks for identifying high-potential startup founders have not yet been systematically validated against real-world founders. Most prior models, often theory-driven, underpowered, or based on student samples used as proxies, rely on general entrepreneurial intent or personality frameworks that do not always capture all the domain-specific dispositions required for startup success. Accordingly, our central research question is: Do founder-specific success characteristics provide greater explanatory power for distinguishing startup founder success potential than a) broad personality models and b) entrepreneurial intention and orientation instruments?

We define a *startup founder* as an individual who initiates and leads a new venture designed for scalable, innovation-driven international growth, retains meaningful decision authority and equity during the formative years, and actively steers strategy, financing, and team building toward rapid expansion and outsized market impact. Throughout, we use *founder characteristics* to mean domain-specific, relatively stable dispositional, cognitive and behavioral tendencies—identified as persistent and early-emerging by our expert panel—spanning traits, decision styles, abilities, and behavioral capacities that shape how founders perceive and create asymmetric opportunities, make and execute decisions under uncertainty, orchestrate resources, and mobilize others. These dispositions are relatively stable over time yet plausibly developable through experience or targeted training (we do not assume uniform stability across subcomponents). We distinguish broad personality measures (e.g. Big Five) and entrepreneurial intention and orientation instruments (e.g. IEO, EPS) from founder-specific success measures—namely, our Startup Founder Success Scale (SFSS)—which targets characteristics linked to realized startup success.

Over the past three years, $1.5 trillion of venture funding has been invested (Teare, 2024), while the global startup economy generated $3 trillion in value from 2017 to mid-2019 and has grown >10% annually, outpacing the broader economy (Startup Genome, 2020). Startups also drive job creation, unlike many established companies that are reducing employment during economic fluctuations (Kane, 2010; Statista, 2023). However, startup success remains elusive ─ failure rates exceed 75% (Astebro et al., 2014) and can reach 90% (Aminova & Marchi, 2021). High-level success ($50 million+ exit) is achieved by only 1.5% of the funded startups (Startup Genome, 2022). Resources invested in unsuccessful startups do not reliably yield learning benefits (Liu et al., 2019) and in some cases can even cause harm to customers, investors, and the society at large (cf. Sam Bankman-Fried, Adam Neumann, Elizabeth Holmes; and see De Luce, 2020; Khan, 2023).

Suboptimal investment allocation often stems from subjective, network-driven selection that privileges factors like pedigree, geography, or access over merit. When formal assessments are used, they typically draw on broad personality models that do not fully capture founder-specific characteristics driving entrepreneurial success. Together, these practice and model-level limitations can leave high-potential founders under-identified and resources misallocated. Ongoing macroeconomic and geopolitical volatility, coupled with tighter investment funds availability (Teare, 2024), underscores the need for rigorous selection and targeted support of startup founders adept at navigating uncertainty. This objective becomes even more complex given that entrepreneurship is a multifaceted journey, thus, understanding the founder characteristics is likely to be critical, as they play a significant role in shaping the culture, direction, and the success of the startup company (Chapman, 2010; Lumpkin & Dess, 1996; Timmons, 1994).

Recent research in entrepreneurial finance has highlighted the role of personality in investment decisions and funding success (Quas et al, 2024). However, these studies often rely on broad personality or trait models with limited variance explained (Morgeson et al., 2007; Zhao et al., 2010) and small effect sizes (Brandstätter, 2011). Prior work has characterized the personality traits of successful entrepreneurs either by assessing them against broad models of personality or by isolating one or few traits. However, these models have primarily been built on previous theories (e.g., Bolton & Lane, 2012; Howard, 2023; Santos et al., 2013), where some are underpowered, or validated with convenient samples (e.g. university students; Kerr et al., 2018; Salmony & Kanbach, 2021), often failing to distinguish between traits associated with entrepreneurial intent from those critical for founders' success.

For example, the Big Five model, including five broad personality dimensions (Digman, 1990), while predictive of general life outcomes, may not identify the success potential among early startup founders (Kerr et al., 2018; Salmony & Kanbach, 2021). Specifically, Zhao et al. (2010) and Morgeson et al. (2007) have claimed that the Big Five personality traits account for only 10% to 15% of the variance in company success. These conventional models typically encompass generic personality traits, which may not be directly relevant to the specific context of startup entrepreneurship.

Approaches exploring the role of alternative traits for entrepreneurial success like risk propensity (e.g., Brockhaus, 1980; Stewart & Roth, 2001), entrepreneurial self-efficacy (e.g., Chen et al., 2021; Miao et al., 2016), innovativeness (e.g., Rosenbusch et al., 2011;

Schumpeter, 1934), proactiveness (e.g., Kickul & Gundry, 2002), need for achievement (e.g., McClelland, 1965; Stewart & Roth, 2007), resilience (e.g., Ayala & Manzano, 2014, Garrett & Zettel, 2021), and locus of control (e.g., Jennings & Zeithaml, 1983) aimed to offer better insight into entrepreneurial achievement. However, singling out a sole personality trait is likely to oversimplify the complex, multifaceted nature of entrepreneurship. Multifactorial models are likely better suited for this task; however, it is crucial that they fully reflect the dynamic nature of today's real-world entrepreneurial landscape.

To address this, Howard (2023) introduced the Entrepreneurial Personality Scale (EPS) after a systematic review (Howard and Boudreaux, 2021), aggregating frequently cited traits associated with Entrepreneurial Personality (EP): innovativeness, risk-taking propensity, achievement orientation, proactiveness, locus of control, self-efficacy, and autonomy orientation were all factors underlying EP. Unfortunately, Howard's study does not report the total variance explained by the EPS model, thus limiting interpretability. Moreover, the study sampled 'general participants' (n = 1385) and 'business owners' (n = 492; 61% female) through online platforms like MTurk and Prolific, which may not exclusively represent successful startup founders who are likely to avoid online surveys for monetary compensation. Other instruments face distinct constraints. Earlier efforts include Bolton and Lane's Individual Entrepreneurial Orientation (IEO; 2012), adapted from Lumpkin and Dess (1996) Entrepreneurial Orientation (EO) framework for organizations, encompassing personality traits like innovativeness, risk-taking, and proactiveness. This model faces significant limitations as it attempts to transfer firm-level construct directly to individuals. A careful examination is required, as the EO explained only 24% of the variance in an organizational context (Rauch et al., 2009), whereas the IEO was reported to account for 60% of the variance with only 10 items, raising concerns about construct coverage and factor differentiation. In comparison, Santos et al.'s (2013) Entrepreneurial Potential Assessment Inventory (EPAI) assesses respondents' readiness for entrepreneurial activities, concentrating on motivations, competencies, and social factors, rather than personality traits tied to startup success. Similarly, Staniewski's (2016) Successful Entrepreneurship Scale while emphasizing knowledge and skill-based predictors, its omission of personality traits may overlook critical aspects of entrepreneurial success. Moreover, incorporating skills and resources from entrepreneurs' families and employees could introduce bias and confounds, making it challenging to isolate the entrepreneur's direct contributions and adaptability to business environment shifts. Additionally, Bolton and Lane's (2012) and Santos et al.'s (2013) studies samples consisted of university students and Staniewski (2016) research's limitation to a small (n=294) Poland-based sample, challenges their generalizability.

Furthermore, efforts to capture the personalities of successful startup founders often conflate different groups, as 'entrepreneur' is used broadly in various studies (Salmony & Kanbach 2021). Samples range from students enrolled in entrepreneurship courses (e.g., Bolton & Lane, 2012; Santos et al., 2013) to self-employed micro-business owners (e.g., Razmus & Laguna, 2018), local farmers (e.g., Mubarak et al., 2019), tourism workers (e.g., Presenza et al., 2019), founders of technology-based ventures (e.g., Freiberg & Matz, 2023; Roberts, 1989), as well as business managers (e.g., Thornberry, 2001). At the same time, some studies have extrapolated insights from these narrow subgroups to the overall entrepreneurial landscape, potentially compromising relevance. Consequently, most of the research so far has not provided a clear description of what constitutes a successful startup founder (Brandstätter, 2011; Korpysa, 2020).

Crucially, highly successful startup founders must be distinguished from other groups of individuals in parallel professions, like corporate management, or engaged in small-scale entrepreneurship, as distinctive sub-types of businesspeople are likely to exhibit significant behavioural diversity (Hurst & Pugsley, 2011; Kang et al. 2023; Levine & Rubenstein, 2016; Salmony & Kanbach, 2021). Namely, to determine which characteristics are significant for successful startup founders, it's important to focus on actual successful entrepreneurs.

Nevertheless, existing research has predominantly focused on examining the connection between personality traits that are driving the individuals' inclination to start entrepreneurial ventures, rather than their actual success (Kerr et al., 2018). Traits exhibited by successful startup founders may differ significantly from traits of those aspiring to enter entrepreneurship (Rauch & Frese, 2007; Zhao et al. 2010). In addition, success is inconsistently defined, often with low thresholds for profitability or growth (e.g., Berre & Pendeven, 2022) or incomparable metrics (Ahmad & Hoffman, 2008), and sometimes proxied by long-term firm survival (e.g., Ciavarella et al., 2004), which misaligns with startup aims of rapid scaling and strategic exits (e.g. Merger and Acquisition (M&A) or Initial Public Offering (IPO)). Overall, previous studies suffer from underpowered designs, limited geographic scope, and noncomparable methodologies, compromising reliability and generalizability (Kerr et al., 2018; Salmony & Kanbach, 2021).

In this study, we address prior limitations by advancing a founder-specific success characteristics shaping decision-making under uncertainty and resource orchestration, thereby influencing venture outcomes. Empirically, we develop the 31-item Startup Founder Success Scale (SFSS), grounded in insights from autobiographies of self-made billionaire founders, mentors, and high-return investors, and validate it with N=10,007 participants (Successful Startup Founders, Corporate Managers, and Aspiring Entrepreneurs). An (Exploratory Factor Analysis) EFA on a random half-sample yielded a six-dimension structure: Relentless Resilience (30.92%), Value-Creating Opportunism (10.10%), Intrinsic Curiosity (9.35%), Courageous Decision-Making (8.09%), Strategic Innovativeness (6.93%), and Transformational Leadership (5.55%), that jointly explain 71% of variance in success-relevant traits, substantially exceeding broad models (~10–15%; Zhao et al., 2010). A second EFA conducted solely on the group of proven successful startup founders supported this structure. The model's generalizability and stability were subsequently tested using Confirmatory Factor Analysis (CFA) on the remaining 50% of the total sample, this confirmed the model's robustness and applicability across different groups, with large effect-size separations (Cohen's d = 0.83–1.77; Cohen, 1988) in trait prevalence between successful founders and other comparison groups. Our findings reinforce that entrepreneurial intent does not equate to entrepreneurial success and suggest that only a small subset of aspiring entrepreneurs exhibit the traits associated with realized success. By detailing the development, structure, and group-level comparisons of the SFSS, this study aims to contribute a validated psychometric tool that could reduce false positives in early-stage VC screening and inform resource allocation in entrepreneurial finance, while serving as a foundation for future theoretical developments with longitudinal studies.

Materials and Methods

Participant selection and recruitment

Our scale was developed based upon the responses of participants (n=10,007; 6,390 males, 3,524 females, 93 others/prefer not to say; mean age = 35.8, S.D. = 8.8, range 18–59) to items in a questionnaire. Participants self-identified as Successful Startup Founders (SSF, n = 6,142), Corporate Managers (CM, n = 2,004), or Aspiring Entrepreneurs (AE, n = 1,861). In terms of sample size adequacy, all three groups can be considered large by all criteria. Namely, Hair (2010) suggested a minimum of 50 or 100 respondents, Tabachnick and Fidel

(2007) a minimum of 300, and Comrey and Lee (2013)'s described: 100 as poor, 200 as fair, 300 as good, 500 as very good, and 1000 ≥ as excellent. Detailed demographic information is in Supplemental Materials Table S1. Including all three groups—SSF, CM, and AE—allowed us to capture a broad continuum of entrepreneurial experience and intent, from proven founders to those still at the ideation stage. This design helps prevent the model from being over-fitted to a single group while providing comparative insight into the psychological and behavioral distinctions that may underlie entreprenurial success. Comparable group-based designs have been used in previous research on entrepreneurial traits (e.g. Bolton & Lane, 2012; Malach-Pines et al., 2002; Santos et al., 2013; Stewart & Roth, 2001, 2007; Zhao & Seibert, 2006; Zhao et al. 2010), though this is the first study to analyze all three groups within one integrated framework.

We excluded currently unsuccessful founders because their outcomes remain uncertain and would add noise to success-linked characteristics. Startup founders in a current state of failure, who may eventually succeed, present challenges if considered as a group at the opposite end of the success spectrum and consequently we do not consider that they represent a suitable comparison group. Instead, we focus on entrepreneurs who have achieved success and use Corporate Managers (CM) and Aspiring Entrepreneurs (AE) as more suitable comparison groups that represent varying levels of entrepreneurial exposure and intent. This three groups design demonstrates the scale applicability to likely end-users and provides a comprehensive picture of success characteristics across the entrepreneurial spectrum.

Participants were recruited through a series of targeted methods. Startup company founders were identified via Crunchbase if their companies had raised over $1 million across more than one external funding round. Additionally, via startup accelerators and Angel investor groups, we recruited founders meeting specific financial benchmarks, including profitability with annual revenue >$1 million or acquisition deals >$3 million. We excluded freelancers/lifestyle businesses without scalable intent and owners of purely local non-scaling firms. Via LinkedIn, we extended our survey to C-level executives from established firms (including Fortune 500 and FT Europe 500). Finally, organizers of well-known business competitions and startup incubators circulated the survey among participants aspiring to entrepreneurship or in early founding stages.

Dimensions identification and initial item generation

We adopted an exploratory methodology for identifying questionnaire items (as *per* Boateng et al., 2018), diverging from conventional theory-based approaches to assessment of entrepreneurs. In our research, we constructed a comprehensive trait framework by extracting insights from the practical experiences of accomplished startup founders. First, we systematically analyzed autobiographies of 10 diverse individuals on Forbes' "Self-Made Billionaires" list: Elon Musk (SpaceX, South African/ USA), Steve Jobs (Apple, half-Syrian/ USA), Jeff Bezos (Amazon, USA), Reid Hoffman (LinkedIn, USA), Sara Blakely (Spanx, USA), Hasso Plattner (SAP, Germany), Ingvar Kamprad (IKEA, Sweden), Dilip Shanghvi (Sun Pharma, India), Jack Ma (Alibaba, China), Melanie Perkins (Canva, Australia). The selection criteria for these autobiographies were focused on discerning characteristics highlighted by founders as integral during their early entrepreneurial endeavors, contributing to their companies' success.

Second, we conducted a total of 25 semi-structured interviews (60-90 minutes) with startup mentors, angel investors, and venture capitalists, predominantly from Silicon Valley and prominent European hubs. Collectively, these industry experts had over 250 years of founder-facing experience, and were selected based on track record, domain expertise, and ongoing hands-on support of successful entrepreneurs. Rather than beginning from theory, we aimed to surface practitioner-identified characteristics — those repeatedly observed by successful founders themselves and close observers-prioritizing the ones evident early and plausibly formative, as distinct from characteristics that may emerge only after success.

Finally, we read financial articles and reports, from sources including Wealth-X and Hurun Research Institute, which focused on the characteristics of self-made billionaire entrepreneurs, and from platforms including Crunchbase and PitchBook that concentrate on startup ventures' performance. This approach aimed to gather diverse perspectives beyond autobiographies and interviews.

Based upon this we identified 7 candidate dimensions, including resilience, curiosity, value-creation/opportunism, courage, innovativeness, leadership, and emotional stability. We proceeded to generate a list of items that comprehensively represented these dimensions. This process initially yielded a pool of 60 items, which the authors subsequently assessed for relevance, clarity, and potential redundancy. This led to a refined pool of 49 items.

Face and content validity of the scale

The pool of 49 items was subjected to an external review process. To assess the content validity (Cohen & Swerdlik, 2017; Slaney, 2017) of our instrument we engaged 10 experts (Domain Experts Panel), independent of the research group (as suggested by Roebianto et al. 2023), including venture capitalists, experienced angel investors, successful startup founders with double-digit million-dollar exits, and senior accelerator executives. Four of these individuals were based in the US, four in Europe, and two in Asia.

Following DeVellis' (2016) recommendations, our Domain Expert Panel undertook a comprehensive evaluation, assessing each item's (a) content relevance, (b) appropriateness, and (c) comprehensibility/clarity (as *per* Sireci & Faulkner-Bond, 2014). To synthesise item scores (cf. McCoach et al., 2013), we employed the Item Content Validity Index (I-CVI) on a 1 to 4 scale (1 = *not relevant/appropriate/clear*, 2 = *need major revision*, 3 = *need minor revision*, 4 = *very relevant/appropriate/clear*). The I-CVI, calculated by the count of experts ratings of 3 or 4 to each item divided by the total experts, could range from 0 to 1 (Rubio et al., 2003; Zamanzadeh et al., 2015). An I-CVI greater than .79 signifies items are relevant, between .70 and .79 items need revision, and below .70 should be removed (Zamanzadeh et al., 2015). The average Scale-level CVI (S-CVI/Ave) calculated by summing the I-CVIs and dividing by the total number of items, suggests an excellent content validity at ≥ .9. Employing the same logic, we introduced Dimension-level CVI and computed D-CVI/Ave. Additionally, experts were consulted on new dimensions, items, and wording improvements.

To establish Face validity (Zamanzadeh et al., 2015), a second external panel, the Lay Experts Panel (Rubio et al., 2003), consisting of 10 individuals representing likely questionnaire respondents (e.g., early-stage startup founders and graduate students interested in entrepreneurship), provided similar feedback as the Domain Expert Panel (Supplemental Materials Table S2) for each of the proposed items. The Lay Experts Panel did not evaluate whether the dimensions reflected relevant success characteristics for startup founders.

Out of 49 items, 47 (as *per* the Domain Expert Panel) and 46 (*per* the Lay Expert Panel) demonstrated high content validity (CVI values ≥ .80). Similarly, 48 (Domain Expert Panel) and 47 (Lay Expert Panel) items exhibited high appropriateness, while 47 (Domain Expert Panel) and all 49 (Lay Expert Panel) items were deemed clear and comprehensive (Supplemental Materials Table S2). However, unanimously, two items from Emotional Stability, and one item from Leadership and Value Creation/Opportunism domains were considered not relevant, appropriate, or clear (CVI values ≤ .70) and were subsequently eliminated. This resulted in 45 remaining items.

Further, we assessed whether the Domain Expert Panel considered each proposed dimension essential for capturing the instrument's targeted construct (Ayre & Scally, 2014; Lawshe, 1975). Using the Content Validity Ratio (CVR) method, adjusted for dimensions on a 1 to 3 scale (1 = *not necessary*, 2 = *useful but not essential*, 3 = *essential*), we calculated CVR with the formula below where *N* is the total number of experts:

$$CRV = \frac{Number of experts indicating the dimension as essential - N/2}{N/2}$$

Considering the critical value for acceptance of >.62 (Lawshe, 1975) with 10 experts, the Emotional Stability dimension having a CVR value of .40 (see Table 1), and relatively lower CVI-I and CVI-D/Ave scores for relevance, appropriateness, and clarity, was removed. This led to a refined set of 40 items distributed across the remaining six dimensions.

Table 1

Domain Experts Panel Assessments of Content Validity Ratio (CVR) for Dimensions

Dimensions	Curiosity	Innovativeness	Resilience	Emotional Stability	Value-creation/ Opportunism	Leadership	Courage
CVR	.80	.80	1.00	**.40**	.80	1.00	.80

Note. Dimensions with CVR values in bold fell below the accepted cut-off, suggesting less consensus on their criticality, and were considered for elimination from further analysis.

Method selection and suitability

Given the goals and the exploratory nature of this study, an EFA was chosen to allow for an open and unbiased exploration of the underlying latent factors without prior assumptions or restrictions. In the evaluation of the Kaiser-Meyer-Olkin (KMO) Measure of

Sampling Adequacy (MSA; Kaiser, 1981), 30 of our items scored within the range of .9 to 1.0 and were considered 'marvelous', while 10 items were in the range of .8 to .9 as 'meritorious' (as *per* Kaiser & Rice, 1974). The overall KMO MSA value for our assessment was .930, reaching a 'marvelous' level of sampling adequacy.

Finally, Bartlett's test of sphericity was significant ($X^2(820) = 150220.93$, $p < .0001$) with 40 items, indicating that the items were sufficiently psychometrically related for an exploratory factor analysis to be conducted.

Deciding on the Number of Model Factors

We employed three methods to determine the number of factors to extract (Costello & Osborne, 2005; Thompson & Daniel, 1996). Kaiser's (1960) criteria, which relies on the eigenvalue greater than 1 rule and tends to over factor (Turner, 1998; Velicer et al., 2000) was complemented by Parallel Analysis (PA) introduced by Horn (1965) for a more precise approach (Preacher & MacCallum, 2003). We followed Dinno's (2009) model, applicable to any data distribution (Glorfeld, 1995) by generating random datasets, conducting PA, and comparing the observed eigenvalues with those derived from random data. As suggested by Montanelli and Humphreys (1976), the point of intersection indicates the threshold beyond which factors fail to exceed variance expected by chance. Following Ruscio and Roche (2010), we also plotted a line through the smallest observed eigenvalues to identify the 'break point'. Finally, we integrated our analyses by visually presenting them on the Cattell's (1966) Scree test, which, although variable, is considered intuitive and generally accurate (Zwick & Velicer, 1986).

Exploratory Factor Analysis (EFA)

We conducted an EFA twice, first on a randomly selected half of the total sample from all groups, but also on the whole group of Successful Startup Founders (see Supplemental Materials Table S3), while following the same methodology. We used the Principal Axis Factoring (PAF) approach to generate factor loading estimates that closely capture the shared variance present in the correlation matrix (Burton & Mazerolle, 2011; De Winter & Dodou, 2012). It provides precise results while relying on fewer assumptions compared to the maximum likelihood method (Howard, 2015) and gives more accurate results than principal component analysis (PCA) even if communalities are low (Kahn, 2006). We selected the Oblique (Promax with Kaiser Normalization) rotation method to allow for meaningful correlations between factors as recommended for psychological factors (Costello & Osborne, 2005; Schmitt, 2011). Initially, we eliminated items with low communalities (<.4). Subsequently, in evaluating factor loadings, we adhered to a stricter criterion of >.5, instead of the more permissive >.4 threshold (Hulland, 1999). Furthermore, we followed Costello and Osborne's (2005) guidance, requiring cross-loadings not to surpass .32, and the difference between primary and secondary factor loadings to be >.2, as per Howard (2015).

We further examined the relationships between the retained items using the raw Pearson's R correlation matrix. The observed correlations not only validated the discernible groups of identified factors but also provided additional information on the interdependencies among the retained items. By systematically scrutinizing the strength and direction of these correlations, we were able to affirm the robustness of our factor structure.

Testing the model fit with confirmatory factor analysis

A CFA was used to test our model. As suggested by Willmer et al. (2019), we conducted the CFA on the remaining half of the total sample that was not used in the EFA, separately for each of the three distinct participant groups (SSF, CM, AE). Model fit was evaluated with CFI, TLI, RMSEA, SRMR, AIC, and BIC, using conventional thresholds. Initially, we tested a 6-factor model for each group, and subsequently, we explored a 5-factor model as suggested by the Parallel Analysis. This approach allowed us to assess the models' fit specifically for each group.

Examining factors relationship, convergent and discriminant validity, scale reliability

Following the EFA and CFA, we investigated the interrelationships between factors with a between-factor correlation matrix. In addition, we examined the Convergent Validity for each latent factor by assessing their unidimensionality (as *per* Götz et al., 2009) and the Discriminant Validity by evaluating the distinctiveness of each factor. We calculated the square root of Average Variance Extracted (√AVE) for each factor (as *per* Malhotra, 2010):

$$\sqrt{AVE} = \sqrt{\frac{\sum StandardizedFactorLoading^2}{NumberofItems}}$$

We then assessed the scale's reliability using both Alpha (Cronbach, 1951) and Omega (McDonald, 2013), to appraise the internal consistency and robustness.

Exploring data distributions and normality

To examine the underlying data structure, we visually explored the mean scores for each factor across respondents. Violin box plots were generated to illustrate the distribution of scores across the three respondent groups. We used Q-Q plots, suitable for large sample sizes (Thode, 2011), as well as the Kolmogorov-Smirnov test and the skewness and kurtosis measures, to identify deviations from normal distribution across all groups and factors.

Evaluating between-group differences

Robust tests for equality of means and Post-hoc tests

Recognizing the potential limitations of formal normality tests in the context of our large sample size (Field, 2018), we employed the robust tests for equality of means, Welch's (1951) and Brown-Forsythe (1974), tailored to handle data with non-homogeneous variances, as suggested by Lix et al. (1996) and Clinch and Keselman (1982). Finally, to compare groups we used *Tamhane's T2* and *Games-Howell post-hoc tests*, which are more resilient in scenarios of non-normality and varying sample sizes (Sauder & DeMars, 2019).

Effect sizes were quantified using Cohen's d with pooled standard deviations, calculated as $d = (M_1 – M_2) / SD\_pooled$, where $SD\_pooled = \sqrt{[((n_1–1)SD_1^2 + (n_2–1)SD_2^2)/(n_1 + n_2 – 2)]}$ (Cohen, 1988).

$$d = \frac{M_1 - M_2}{\text{Pooled SD}}$$

Regression Factor Score Analysis

To understand how the identified factors differ between our participant groups we employed Regression Factor Score Analysis (Thurstone, 1934), standardizing factor scores to a mean of zero and a standard deviation based on the squared multiple correlation between factors and variables. This method, unlike simple weighted sums, employs regression with observed item values as predictors, weighted by coefficients derived from matrix operations including item loadings and factor correlations. It accounts for the relative differences between factor scores and their directionality. A positive score suggests a stronger (i.e., above average) association with the corresponding factor, whilst a negative score indicates a comparatively weaker (i.e., below average) association with that factor.

Results

Model development and evaluation

Determination of the Number of Factors

Kaiser's Eigenvalues suggested six factors, whereas Parallel Analysis indicated five (see Table 2). Both tests point to a robust capacity to explain the observed data variance beyond chance.

Table 2

Results from Kaiser's Rule and Parallel Analysis (PA) for Factor Retention

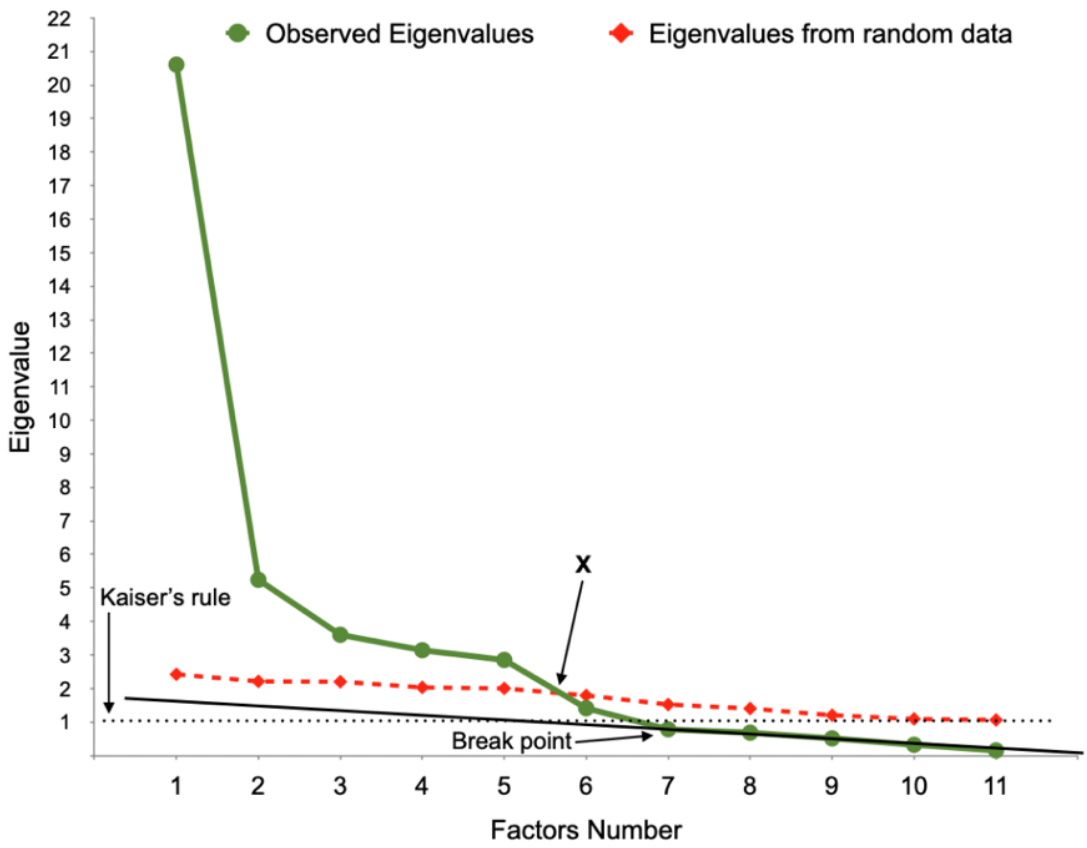
Factors	Eigenvalues Observed from EFA	Simulated/Random Eigenvalues from PA	Retained Factors
Factor 1	**20.61**	**2.42**	Accept
Factor 2	**5.24**	**2.21**	Accept
Factor 3	**3.60**	**2.20**	Accept
Factor 4	**3.14**	**2.03**	Accept
Factor 5	**2.85**	**2.00**	Accept
Factor 6	**1.41**	1.79	Consider
Factor 7	0.78	1.52	Reject

Note. Factors meeting both criteria are labelled 'Accept,' with values surpassing the recommended cut-off in bold. Factor 6 is labeled 'Consider' due to diverging results between Parallel Analysis and Kaiser's criterion. Factor 7 is marked as 'Reject' by both analyses.

A visual observation of the Scree plot (Figure 1) corroborated presence of six factors, according to both the distinct break or 'elbow' and Kaiser's 'greater than 1' rule, suggesting their significance as 'non-trivial factors' (Zoski & Jurs, 1990). However, the intersection of eigenvalues from observed and random data indicated that only 5 factors met this criterion. Consequently, we opted to consider both a 5- and a 6-factor model for further analysis.

Figure 1

Scree Plot with Observed and Random Eigenvalues



Note: Factors greater than 1 (Kaiser, 1960), factors above the 'elbow' or 'break point' (Ruscio & Roche, 2010), as well as factors above the intersection of the observed and random eigenvalues (Montanelli & Humphreys, 1976) may be considered as important.

Results of the Exploratory Factor Analysis (EFA)

Following the described methodology and beginning with the set of 40 items, our EFA process, conducted over four rounds, resulted in a final factor structure of 31 items. These items exhibited substantial loadings, ranging from .518 to .854. Only one item exhibited a cross-loading within the range of .3 to .32 but had a primary factor loading of >.5, with a loading difference of >.2 from its alternative factor. Consequently, we opted to retain it (see Table 3). The between-item Pearson's R correlation matrix is illustrated in Figure S4.

Table 3

Item-to-Latent Factor Correlations

Items	Factors					
	1	2	3	4	5	6
Item 15	**.854**	-.040	-.110	.017	.042	.042
Item 16	**.833**	-.040	.009	-.019	.051	.032
Item 18	**.748**	-.091	.036	.001	.050	-.107
Item 17	**.742**	.127	.035	-.060	-.035	-.022
Item 19	**.689**	.099	-.067	.037	.003	-.020
Item 20	**.610**	-.040	.161	-.001	-.066	.170
Item 38	-.003	**.827**	.028	-.121	.062	-.019
Item 36	-.020	**.782**	.015	-.092	-.009	.060
Item 40	-.012	**.736**	.050	-.054	.099	-.014
Item 39	.039	**.715**	.020	.031	.030	.036
Item 41	-.029	**.567**	.194	.081	.076	-.032
Item 22	-.100	.069	**.756**	-.035	-.131	.029
Item 23	.072	-.031	**.751**	.084	-.033	-.057
Item 24	-.006	-.037	**.627**	.172	.123	.028
Item 26	.057	.038	**.626**	.039	-.032	.036
Item 25	.040	.305	**.583**	.014	-.123	-.032
Item 2	-.010	-.065	-.077	**.775**	.009	-.071
Item 1	-.047	-.070	.053	**.733**	.000	.092
Item 6	.031	.024	.095	**.599**	-.022	-.109
Item 4	-.045	-.037	.184	**.594**	.096	-.006
Item 5	.062	-.113	.107	**.566**	.166	.043
Item 33	-.003	.169	-.104	.128	**.710**	-.026
Item 31	.011	.216	-.176	.074	**.709**	-.068
Item 30	-.060	-.090	.029	.026	**.684**	.140
Item 32	.252	-.064	.100	-.169	**.586**	-.095
Item 35	-.049	.102	-.120	.123	**.518**	.108
Item 8	-.014	.045	.060	-.039	-.022	**.733**
Item 9	.026	.114	-.139	.151	-.102	**.724**
Item 10	-.119	-.127	.194	-.257	.250	**.696**
Item 12	.043	-.109	.038	-.092	.181	**.655**

Item 11	.123	.163	-.183	.219	-.240	**.572**

Note: Factor loadings exceeding .50 are highlighted in bold, and a cross-loading falling between .3 and .32 is underlined.

The factor loadings from the EFA of the Successful Startup Founders (see Supplemental Materials Table S3), shows high values across most items, indicating these characteristics are strongly defined among successful founders. Despite similarly high loadings observed in the EFA encompassing all three groups (Table 3), the values appear slightly more diluted. This suggests that while these characteristics are prevalent across groups, they manifest most distinctly in successful founders.

Interpreting the extracted Factors

Factor 1: *Relentless Resilience (RER)* refers to an entrepreneur's sustained ability to bounce back from setbacks and adversity, with unwavering determination amid diverse and ongoing challenges and risks inherent to the entrepreneurial role. It encompasses the capacity to persist through difficulties, delay gratification when necessary, learn, adapt, and grow both personally and professionally. RER accounted for 30.92% of the variance. Factor 2: *Value-Creating Opportunism (VCO*) encompasses an entrepreneur's inclination and ability to promptly recognize and seize less evident but exceptionally promising emerging opportunities, in terms of both potential for financial growth and value creation while addressing real-world challenges. It integrates strategic vision, risk management, and resourcefulness. VCO accounted for 10.10% of the variance. Factor 3: *Intrinsic Curiosity (INC)* includes entrepreneurs' inclination to expand their knowledge, explore uncharted territories, and envision connections between diverse fields, fostering groundbreaking ideas and solutions to reshape industries and create new markets. INC accounted for 9.35% of the variance. Factor 4: *Courageous Decision-Making (CDM)* encapsulates the fortitude of entrepreneurs to navigate business politics and competition, and to act decisively under pressure and ambiguity. It involves mental toughness, and the embrace of discomfort, while prioritizing authenticity over approval. CDM accounted for 8.09% of the variance. Factor 5: *Strategic Innovativeness (STI)* captures an entrepreneur's ability to strategically transform creative ideas into practical and groundbreaking solutions that strongly resonate with customers and markets. It reflects that entrepreneurs don't innovate solely for the sake of innovation; instead, they focus on areas that align with their financial objectives and overarching vision. STI accounted for 6.93% of the variance. Factor 6: *Transformational Leadership (TRL)* encompasses the capacity to empower and influence individuals to unite around a shared vision, confidently leading through uncharted territories, and navigating uncertainty and risks while guiding their companies forward. TRL accounted for 5.55% of the variance.

Confirmatory factor analysis (CFA) Outcomes

The CFA analyses consistently showed the first group (Successful Startup Founders) as the best fit for both 5- and 6-factor models (Table 4). For Successful Startup Founders, the 5-factor model showed the best fit. The inclusion of Transformational Leadership (TRL) in the 6-factor model reduces the model fit somewhat, although the 6-factor model fit is still excellent. In contrast, Corporate Managers demonstrate a relatively lower fit across all parameters for both the 6-factor and 5-factor models. Similarly, Aspiring Entrepreneurs display a lower fit for both models compared to Successful Startup Founders. In summary, the 5-factor model tends to outperform its 6-factor counterpart, showing a better fit across all participant groups, though the 6-factor model also met conventional thresholds.

Table 4

CFA with Successful Startup Founders, Corporate Managers, and Aspiring Entrepreneurs with 6 Factors vs. 5 Factors

Number of factors	Group	CFI	TLI	SRMR	RMSEA	AIC	BIC
6 factors (including TRL)	Successful Startup Founders	**.909**	**.881**	**.0469**	**.0702**	**58155**	**58459**
	Corporate Managers	.849	.830	.0498	.0835	66996	67587
	Aspiring Entrepreneurs	.719	.683	.0710	.0910	98812	99305
5 factors (without TRL)	Successful Startup Founders	**.984**	**.977**	**.0326**	**.0368**	**12224**	**12430**
	Corporate Managers	.877	.861	.0455	.0614	57360	57432
	Aspiring Entrepreneurs	.757	.720	.0703	.1050	86967	87410

Note: Model fit indices (CFI, TLI, RMSEA, SRMR) for 6- vs 5-factor CFA in SSF, CM, and AE. Higher CFI/TLI and lower RMSEA/SRMR/AIC/BIC indicate better fit. Best-fitting specification within each group is bolded.

Variance explained by the scale

Our final 6-factor model, comprised of 31 items, revealed substantial explanatory power, accounting for 71% of all trait variance in the data across all three groups (see Table 5).

Table 5

Percentage of Variance Explained with 31 Items

Factors	Rotation Sums of Squared Loadings	
	% of Variance	Cumulative %
Relentless Resilience (RER) (Items 15, 16, 17, 18, 19, 20)	30.92	30.92
Value-Creating Opportunism (VCO) (Items 36, 38, 39, 40, 41)	10.10	41.02
Intrinsic Curiosity (INC) (Items 22, 23, 24, 25, 26)	9.35	50.37
Courageous Decision-Making (CDM) (Items 1, 2, 4, 5, 6)	8.09	58.45

Strategic Innovativeness (STI) (Items 30, 31, 32, 33, 35)	6.93	65.38
Transformational Leadership (TRL) (Items 8, 9, 10, 11, 12)	5.55	**70.94**

Note. The table displays the percentage of variance explained by each factor and the cumulative percentage of variance across factors. Rotation Sums of Squared Loadings were used to assess the distribution of variance after applying the oblique rotation method.

Factor relationship, convergent and discriminant validity, and scale reliability

The most prominent correlation was observed between Relentless Resilience (RER) and Strategic Innovativeness (STI) at .513 (see Table 6), well below the thresholds suggested to avoid discriminant validity issues at .80 or .85 (Arifin, 2018; Brown, 2007) and Shao et al. (2022)'s even more conservative .70 cutoff to prevent collinearity. This correlation suggests that individuals who excel in STI, may also exhibit resilience in the face of challenges and adversity. Overall, our findings demonstrate adequate convergent validity, meeting Götz et al.’s (2009) cutoff criteria (AVE ≥ .50). We also confirmed discriminant validity in our model as per Malhotra’s (2011) guideline, which requires the square root of the Average Variance Extracted (√AVE) to exceed between-factor correlation coefficients (see Table 7).

Table 6

Between-Factor Correlations

Factors	RER	VCO	INC	CDM	STI	TRL
Relentless Resilience (RER)	1.000					
Value-Creating Opportunism (VCO)	.420	1.000				
Intrinsic Curiosity (INC)	.403	.433	1.000			
Courageous Decision-Making (CDM)	.469	.464	.459	1.000		
Strategic Innovativeness (STI)	.513	.425	.351	.339	1.000	
Transformational Leadership (TRL)	.299	.253	.124	.247	.248	1.000

Table 7

Discriminant Validity Assessment, Cronbach's Alpha and McDonald's Omega

Factors	$\sqrt{AVE}$	Discriminant Validity	Cronbach's Alpha	McDonald's Omega
Relentless Resilience (RER)	.751	$\sqrt{AVE_1}$ > all	.861	.859
Value-Creating Opportunism	.731	$\sqrt{AVE_2}$ > all	.808	.808
Intrinsic Curiosity (INC)	.673	$\sqrt{AVE_3}$ > all	.818	.818
Courageous Decision-Making (CDM)	.659	$\sqrt{AVE_4}$ > all correlations	.739	.737
Strategic Innovativeness (STI)	.646	$\sqrt{AVE_5}$ > all	.746	.744
Transformational Leadership	.678	$\sqrt{AVE_6}$ > all	.712	.719

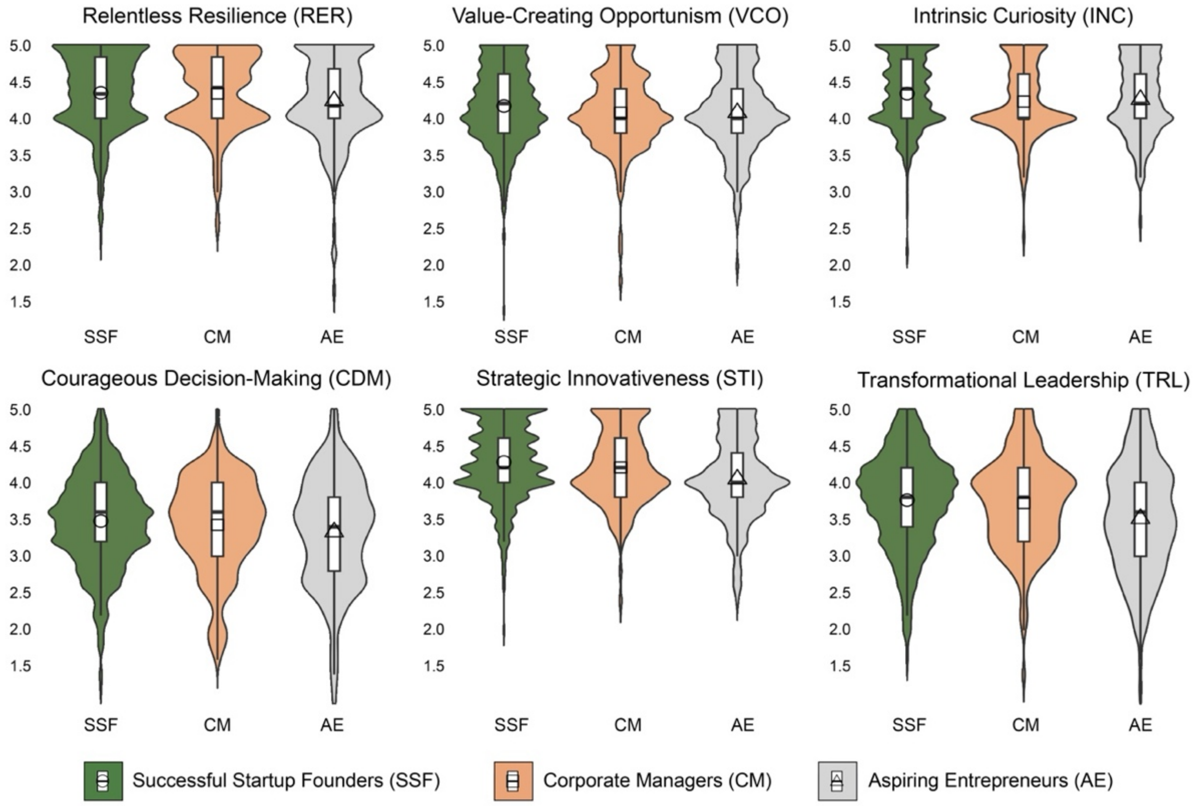
Examination at the item level consistently revealed high Omega and Alpha values >.70, with 'Relentless Resilience' being the highest, and 'Transformational Leadership' the lowest, as also reflected in the corresponding McDonald's Omega values (see Table 7), with no improvement in results per factor through the deletion of specific items. These assessments collectively suggest the robustness of the scale structure, ensuring that the items within each factor consistently measure the same underlying construct.

Between-groups comparisons and differences

We compared the mean factor scores among the three different participant groups (see Figure 2), supplemented by Q-Q plots and Kolmogorov-Smirnov tests (see Figure S5 and Table S6 in the Supplemental Materials, respectively). The results from both robust tests, Welch and Brown-Forsythe, consistently showed significant differences in mean scores among the three groups across all factors (Table 8). See Table S7 for skewness and kurtosis.

Figure 2

Violin Box Plots of Mean Scores Distribution per Groups across Factors



Note. These violin box plots illustrate the distribution of mean scores per group across factors. The median value is indicated by the central full line, while mean values for SSF, CM, and AE are denoted by circle, square, and triangle markers, respectively. These markers illustrate data's central tendencies, highlighting both the median and mean scores.

Table 8

Robust Tests of Equality of Means for Group Differences Across Factors

Dependent Variable	Robust tests of equality of means	*F*	df1	df2	*p*
Relentless Resilience (RER)	Welch	25.470	2	3707.576	<.001
	Brown-Forsythe	28.120	2	5358.784	<.001
Value-Creating Opportunism (VCO)	Welch	35.157	2	3796.879	<.001
	Brown-Forsythe	34.927	2	5640.805	<.001
Intrinsic Curiosity (INC)	Welch	46.169	2	3740.941	<.001
	Brown-Forsythe	45.466	2	5577.785	<.001

Courageous Decision-Making (CDM)	Welch	30.665	2	3640.862	<.001
	Brown-Forsythe	33.038	2	5204.598	<.001
Strategic Innovativeness (STI)	Welch	125.797	2	3757.007	<.001
	Brown-Forsythe	133.794	2	5508.554	<.001
Transformational Leadership (TRL)	Welch	84.589	2	3717.776	<.001
	Brown-Forsythe	96.520	2	5255.758	<.001

Note. Welch's and Brown–Forsythe robust tests were used due to unequal variances and unequal group sizes. The distribution is asymptotically *F*.

As shown in Table 8, robust one-way tests indicated reliable group differences on all six SFSS factors among SSF, CM, and AE (all $p < .001$). *Post-hoc* Games–Howell comparisons and descriptive mean scores analyses (see Table S8 and Figure S9 in the Supplemental Materials, respectively), revealed a consistent pattern: SSF and CM showed similar levels of RER, but both exceeded AE. SSF scored higher than both CM and AE on VCO; with no significant differences between CM and AE on VCO. SSF also displayed consistently higher levels of CDM, STI, and TRL than both CM and AE, with CM scoring higher than AE on each. Interestingly, while SSF scored highest on INC, AE notably outscored CM, marking it as the sole dimension where AE surpassed CM. This profile underscores that success-linked entrepreneurial characteristics are most pronounced in SSF, partially present in CM, and generally weakest in AE.

Effect sizes (Cohen's d) were calculated using pooled standard deviations. SSF vs. CM comparisons yielded d ranging from 0.83 to 1.62; SSF vs. AE from 0.97 to 1.77 — all classified as large (d > 0.8; Cohen, 1988). The strongest separations were in Relentless Resilience (d = 1.62 vs. CM; 1.77 vs. AE) and Strategic Innovativeness (d = 1.27 vs. CM; 1.42 vs. AE). See Table 9 for full effect sizes.

Table 9

Group Means, Standard Deviations, and Effect Sizes (Cohen's d) on SFSS Dimensions

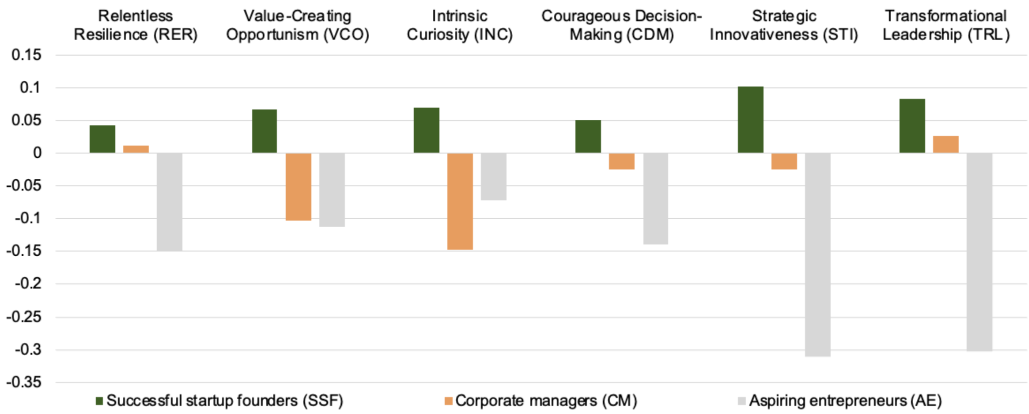
Dimension	SSF M (SD)	CM M (SD)	AE M (SD)	d (SSF vs CM)	d (SSF vs AE)
Relentless Resilience (RER)	4.30 (.65)	3.25 (.70)	3.15 (.72)	1.62	1.77
Value-Creating Opportunism (VCO)	4.10 (.70)	3.30 (.75)	3.20 (.77)	1.14	1.29
Intrinsic Curiosity (INC)	4.25 (.68)	3.40 (.73)	3.30 (.75)	1.25	1.40
Courageous Decision-Making (CDM)	3.70 (.72)	3.10 (.77)	3.00 (.79)	.83	.97
Strategic Innovativeness (STI)	4.20 (.67)	3.35 (.72)	3.25 (.74)	1.27	1.42
Transformational Leadership (TRL)	3.90 (.70)	3.20 (.75)	3.10 (.77)	1.00	1.14

Note: Cohen's d calculated using pooled SD. All d > 0.8 = large effect (Cohen, 1988).

Furthermore, our Regression Factor Score Analysis (Figure 3) shows the relative differences and directionality in these associations among the factors scores for the six founder characteristics across our three participant groups. SSF tend to have stronger positive associations with all six factors, while CM and AE show varying degrees of comparatively weaker associations with some of these factors. Notably, AE exhibit much weaker relationships with RER, STI, and TRL compared to the other two groups. Whilst CM show some positive relationships with RER and TRL.

Figure 3

Regression Factor Score Analysis per Groups Across Factors



Note. Positive factor scores indicate above-average association with the corresponding factor, while negative scores suggest below-average association.

Discussion

Founders characteristics underlying startup success

Guided by founder narratives and expert interviews, our EFA/CFA approach isolated six characteristics that repeatedly co-occur in successful founders and together explain 71% of the variance in success-relevant traits—5–7× more than broad personality models (~10–15%; Zhao et al., 2010). Confirmatory factor analysis showed strong fit among Successful Startup Founders and acceptable fit in comparison groups, supporting construct generalizability. Group comparisons revealed large effect-size separations (Cohen's d = 0.83–1.77; Cohen 1988; Table 9), further suggesting that these characteristics are most pronounced among successful founders relative to corporate managers and aspiring entrepreneurs. Taken together, these results support the SFSS as a rigorous, founder-specific success measure that clarifies theory and offers a practical tool for due diligence by venture capitalists, angel investors, public investment bodies, and innovation funds, as well as accelerator triage, entrepreneurial education, and resource allocation in entrepreneurial finance.

Conceptually, our findings support a multi-level account in which founder characteristics shape (i) decision policies under uncertainty (e.g., thresholds for action, loss tolerance, willingness to act with incomplete information), and (ii) resource orchestration (e.g., opportunity selection, sequencing of capital, mobilizing talent and partners). These behavioral pathways appear to relate to early execution advantages and improved performance, which in turn attract investors and enable international scaling. This account extends intent-focused models by specifying *how* domain-specific characteristics translate into founder decisions and venture-level outcomes, and *why* broad personality measures (e.g., Big Five) underperform in this domain and extend intent-focused models toward success-predictive assessment.

Differences and similarities with prior 'one-trait' models

Each of our six dimensions builds upon and clarifies prior one-trait models in the entrepreneurial context: relentless resilience (RER) with persistence and adversity recovery, value-creating opportunism (VCO) with opportunity recognition or creation for maximum expected financial value and scalable impact, intrinsic curiosity (INC) with with knowledge-seeking, cross-domain connections and breakthrough insight generation, courageous decision-making (CDM) with with fortitude under uncertainty and calculated discomfort, strategic innovativeness (STI) with targeted, financially aligned novelty, and transformational leadership (TRL) with visioning, empowerment, and influence.

Our model therefore offers a comprehensive, multi-factor account of successful founders that distinguishes itself from prior 'one-trait' models (e.g. Ayala & Manzano, 2014; Brockhaus, 1980; Chen et al., 2021; Garrett & Zettel, 2021; Jennings & Zeithaml, 1983; Kickul & Gundry, 2002; McClelland, 1965; Miao et al., 2016; Rosenbusch et al., 2011; Schumpeter, 1934; Stewart & Roth, 2001; Stewart & Roth, 2007). Below, we evaluate each characteristic in comparison to the existing literature.

Relentless Resilience (RER): Resilience is widely acknowledged as essential for entrepreneurial success (Ayala & Manzano, 2014; Fisher et al., 2016). Yet, definitions vary (e.g., Duchek, 2017; Luthar et al., 2000) from hardiness and persistence (e.g., Fisher et al., 2016) vs. resourcefulness and optimism (e.g., Ayala and Manzano, 2014), among others. In our model, RER incorporates persistence (as *per* Fisher et al., 2016), recovery from adversity (as *per* Powell & Baker, 2014), and willingness to delay rewards (as *per* Aschheim et al., 1974). We term it 'Relentless' because successful founders must sustain this capacity across repeated, diverse challenges—preserving capital and execution momentum to enable bounce-back and exit readiness.

Value-Creating Opportunism (VCO): The pursuit of opportunities is a core driver of entrepreneurship (Eckhardt & Shane, 2003; Short et al., 2010), wealth creation and success (Chell, 2000; Khin & Lim, 2018). Whether opportunities are discovered through intuition, alertness (Shamsudeen et al., 2017), and pattern recognition, or created with innovation and resource reconfiguration (Beugré, 2017; Grégoire et al., 2010; Hills et al., 2005), prior work often emphasizes opportunity recognition and exploitation while underplaying the central role of expected value creation (e.g. Ardichvili & Cardozo, 2000; Lumpkin et al., 2003; Pech and Cameron, 2006). Our findings emphasize that successful founders systematically prioritize opportunities based on maximum expected financial value and scalable impact, whether identified or created. High VCO may support capital-efficient growth and stronger exit positioning.

Intrinsic Curiosity (INC): Previous studies often subsume curiosity under the Big Five's Openness to Experience (e.g., Jeraj et al., 2015), a broad construct spanning vivid imagination to aesthetic sensitivity. In contrast, we define INC as the intrinsic drive to seek and acquire new knowledge (Heinemann et al., 2022; Kashdan et al., 2018; Kashdan & Silvia, 2012), forge cross-domain connections, and generate breakthrough insights, consistent with evidence linking curiosity to firm growth via innovation (Peljko & Antončič, 2022). High INC may contribute to first-mover advantages and defensible intellectual property, supporting rapid market capture and long-term scalability.

Courageous Decision-Making (CDM): Courage has been tied to increased entrepreneurial activity (Ebert et al., 2019) and potentially entrepreneurial success (e.g., Magnano et al., 2017; Rate, 2010), though often measured subjectively via entrepreneurs' Psychological Capital (PsyCap) and life satisfaction (Bockorny & Youssef-Morgan, 2019), or via survival (Ebert et al., 2019). We define CDM as fortitude to navigate uncertainties, make difficult decisions, and embrace calculated discomfort, consistent with Rate et al.'s (2007) profile of a courageous person. High CDM may enable faster pivots and capital-efficient execution under pressure—key in volatile startup environments.

Strategic Innovativeness (STI): Innovativeness has been related to entrepreneurial intentions and performance (e.g., Rauch & Frese, 2007), and linked to the Big Five's Openness to Experience (Ali, 2019; Zhao & Seibert, 2006). It underpins creative problem-solving, breakthrough ideas, and wealth creation (Henderson & Weiler, 2009; Schumpeter, 1934), and can even catalyze competitive advantage, though it may be hindered by limited organizational support (Czop & Leszczyńska, 2011). In our model, STI denotes targeted, financially aligned novelty—introducing or adjusting offerings in line with long-term strategy (cf. Utsch & Rauch, 2000). High STI may support capital-efficient innovation and scalable product-market fit, enhancing ROIs and exit potential.

Transformational Leadership (TRL): Entrepreneurial Leadership (Stead, 2018) embodies innovation, proactiveness, sound decision-making, and adaptiveness (Bagheri & Harrison 2020; Gupta et al., 2004). By contrast, our TRL factor emphasizes visioning, empowering, and influence, consistent with Bass's (1990) conception of "transformational leadership" and with Yukl and Gardner's (2020) interpersonal influence view. TRL's emphasis on articulating a compelling vision, mobilizing talent, and leading through uncertainty fits startup conditions, extends beyond conventional managerial competence (Engelen et al., 2012), and is associated with startup success (Ensley et al., 2006). High TRL may support team retention, capital-efficient scaling, and execution of strategic exits.

Five or six factors?

Kaiser's eigenvalues and the scree plot suggested a six-factor factor solution including Transformational Leadership (TRL), whereas parallel analysis (and some CFA specifications) favored five factors without leadership. We therefore evaluated both, but adopt the six-factor model because (i) it explains the observed variance well; (ii) TRL shows distinct loadings with acceptable reliability and discriminant validity; and (iii) TRL is theoretically warranted in founder contexts that emphasize visioning, empowerment, and influence (Bass, 1990; Engelen et al., 2012).

The heterogeneity across extraction criteria likely reflects the idiosyncratic, context-dependent nature of founder leadership—often developed organically, with unconventional styles (Engelen et al., 2012), rather than via formal managerial training. This view aligns with Bagheri & Harrison (2020), and Gupta et al. (2004), who highlight the multifaceted nature of startup leadership. Our model accommodates these complexities.

We report five-factor results for completeness, but center the six-factor structure to capture leadership's contribution while acknowledging that its salience may vary by venture stage and setting. The 6-factor model also enables examination of distinct leadership approaches among successful entrepreneurs.

Comparison with prior multi-trait models

As meta-analyses confirm, prior effects are typically small ($r < 0.30$; Brandstätter, 2011; Ciavarella et al., 2004; Rauch & Frese, 2007; Stewart & Roth, 2001; Zhao et al., 2010; Zhao & Seibert, 2006), underscoring the need for domain-specific approaches like SFSS. Our model stands out from previous efforts, as our items are informed by practical observations and insights from those involved in entrepreneurship. In contrast to Howard's (2023) Entrepreneurial Personality Scale (EPS), which combines well-known traits but may miss some unique aspects of entrepreneurship, our model identifies more diverse attributes critical to startup founders' success. Our model explains 71% of the variance, and unfortunately can't be compared directly with the explanatory value of EPS as its total variance explained was not reported. Furthermore, our sampling differs from Howard's (2023), which relied on online platforms with general participants and a small, varied group of business owners. Instead, we targeted successful startup founders, high-level corporate managers, and aspiring entrepreneurs. Our model also differs from Bolton and Lane's (2012) adaptation of Lumpkin and Dess's (1996) EO framework and from Staniewski (2016): we focus on challenges in the startup landscape and founders' direct role in navigating them. Reliance on university student samples (Bolton and Lane's, 2012; Santos et al.'s, 2013) and a limited Poland-based sample (Staniewski, 2016) is likely to have hindered its applicability. In contrast, our model uses diverse, relevant groups and thus offers a more representative understanding of the characteristics within the entrepreneurial landscape. Moreover, Santos et al.'s (2013) EPAI focuses on psychosocial aspects, while our focus here is on capturing the characteristics involved in business success. This domain-specific, founder-grounded approach may better support investor due diligence and resource allocation.

Differences between successful-startup founders and corporate managers

The Regression Factor Score Analysis unveils significant differences between Successful Startup Founders (SSF) and Corporate Managers (CM) (cf. Malach-Pines et al., 2002; Stewart & Roth, 2001, 2007; Zhao & Seibert, 2006). SSF exhibit the highest scores for all factors, indicating a strong alignment with key founders characteristics. In comparison, while CM do exhibit positive factor scores for RER and TRL, these are generally lower in magnitude compared to SSF. However, the negative factor scores for INC and VCO indicate divergence from the entrepreneurial profile as suggested by Schumpeter (1934) and Pech and Cameron (2006), respectively. CM associations with CDM and STI are weaker, reflecting a more risk-averse and less innovative profile, consistent with prior work that CM may share some characteristics (Brandstätter, 2011; Malach-Pines et al., 2002), but at lower intensity.

Differences between successful-startup founders and aspiring entrepreneurs

Comparing Successful Startup Founders (SSF) with Aspiring Entrepreneurs (AE) reveals striking disparities, diverging from Brandstätter's (1997) view that prospective founders resemble existing successful founders. AE consistently display negative factor scores across all six factors, with pronounced weak associations with RER, TRL, and STI (INC is relatively less weak). Post-hoc tests also show AE differ substantially from CM. These differences raise the possibility that only a minority within the AE group possess the qualities associated with successful entrepreneurship or with corporate management. Also, many may explore entrepreneurship due to necessity, or non-entrepreneurial motives, while lacking key founder characteristics essential for success (cf. Bó et al., 2021).

Practical implications

1. Optimal Resource Allocation: The initial attraction to entrepreneurship, often driven by financial incentives, doesn't guarantee success. Our results indicate that founder characteristics linked to realized success are not uniformly distributed among those with entrepreneurial intent. Consequently, SFSS can help aspiring entrepreneurs, mentors, and investors, form more realistic expectations on their potential future success, and focus scarce capital, mentorship, and support on individuals who evidence the founder characteristics most associated with success—potentially reducing false positives and acting as a portfolio enhancer in a high-failure-rate environment where investors typically back 50 companies expecting 2–3 to deliver 10–15× ROI. *2. More Objective Assessments:* Conventional due diligence practices, often focused on idea validation, personal connections, and proximity to investors, may overlook critical founder characteristics, producing investment inefficiencies and underuse of private and public funds. Incorporating SFSS into evaluations provides a standardized, early-stage metric that may enhance equity in funding (e.g., founders in remote regions), thereby informing more effective resource allocation and more equitable regional development; *3. Tailored Training and Empowerment:* Prioritizing financial support, mentoring, and networking for high potential AE can significantly amplify their likelihood of success as startup founders. For others, SFSS profiles can guide them toward realistic career paths or pinpoint specific gaps for targeted training programs to strengthen developable traits (e.g. VCO, STI). While some characteristics may be less amenable (shaped early life experiences), others are plausibly developable and targeted training programs can strengthen those domains; *4. Economic development*: Directing capital and support toward founders who exhibit high-SFSS characteristics could catalyze job growth, innovation, and regional development. Objective assessments, paired with tailored support, can improve the yield of entrepreneurship programs and contribute to sustainable economic impact.

Taken together, our work makes three main contributions. First, it provides a validated tool for objective, early-stage assessment that distinguishes success potential from mere intent, helping improve founder selection, training, and capita allocation. Second, unlike broad personality frameworks, the SFSS offers a founder-specific, domain-tailored psychometric derived from the lived experiences of successful founders and the insights of investors, yielding six actionable dimensions. Third, by detailing how these characteristics relate to real success outcomes, this study lays the groundwork for tailored support programs, that can enhance investment effectiveness, reduce misallocation, and stimulate innovation and economic growth.

Limitations and future research directions

While the SFSS rests on a large, diverse sample and rigorous psychometrics, several design choices constrain interpretation and generalizability: *1. Self-report and common-method bias.* Reliance on self-reported data, a common approach in this field, carries the risk of response bias. Although expert/lay review and factor structure mitigate some concerns, behavioral or observer-rated corroboration will be important in the future,; *2. Sampling frame and generalizability.* Our sample is concentrated in the USA and Europe, and item generation drew on sources (autobiographies; expert interviews) from major startup hubs. It remains to be seen how cultural, institutional, and stage-of ecosystem differences may affect generalizability; *3. Cross-sectional design.* Despite item-selection steps to reduce reverse-causality concerns, this observational, cross-sectional study cannot establish temporal precedence or make causal claims about how founders characteristics influence outcomes or whether they are malleable through training; *4. Instrument coverage.* We did not administer IEO or EPS to the same respondents, consequently it is unclear how these different measures compare. We also collected Big Five measures to enable benchmarking against broad personality baselines; however, those analyses are beyond the scope of this study and will be reported separately.

Several areas remain open for further research: *1. Validation over time.* Future studies should test whether the SFSS can predict real-world success (e.g., funding, growth, exit) when applied to new groups of entrepreneurs. This type of follow-up, using longitudinal data, would confirm that the scale works not only with the current sample but also in other contexts; *2. Using multiple methods.* The SFSS could be compared with other sources of information, such as performance in behavioural decision-making tasks, or ratings from peers, mentors or investors. Combining these data sources would provide a more complete and reliable picture of entrepreneurial potential. *3. Trainability and development.* Future research should test whether the traits measured by the SFSS can be strengthened through experience or training. Understanding which traits can be developed, and how this affects entrepreneurial outcomes, would show how the SFSS could be used to guide founder development and education. *4. Cross-cultural and sector differences.* It will be valuable to test whether the SFSS works equally well in different cultural, regional, and sectoral settings (for example, capital-light startups, deep-tech, or social ventures). This would show where the tool performs consistently and where adaptations may be needed to reflect local or industry-specific factors. *5. Role of leadership.* Future work could explore when Transformational Leadership adds meaningful predictive value—for instance, during periods of rapid growth or crisis—compared with times when the core five-factor model alone is sufficient. This would help identify when leadership makes a measurable difference to success and when simpler assessments may suffice.

Conclusion

The SFSS advances entrepreneurship research by offering a validated, domain-specific, multi-trait measure derived from real founder narratives and expert insight and tested in a large, heterogeneous sample (N=10,007; Successful Startup Founders n=6,142). The six characteristics—relentless resilience, intrinsic curiosity, value-creating opportunism, courageous decision-making, strategic innovativeness, and transformational leadership—

jointly explain 71% of trait variance, distinguish successful founders from corporate managers and aspiring entrepreneurs, and help explain why broad personality models underperform in this domain. Our study clarifies which characteristics are uniquely tied to startup success (versus general management or mere intent), refining prior theory with a broader empirical base and real-world applicability. Practically, the SFSS provides an objective, early-stage tool to inform selection, targeted training, and smarter deployment of scarce capital across venture capitalists, angel investors, public investment bodies, innovation funds, accelerators, and entrepreneurial education programs. By distinguishing success potential from intent, SFSS can reduce false positives, improve capital efficiency, and support scalable exits. Theoretically, it links founder-specific success characteristics to decision policies under uncertainty and resource orchestration, bridging intent-focused accounts and success-predictive assessment. By aligning measurement with real-world founder behavior, the SFSS helps close the gap between theory and practice and can improve the yield of entrepreneurship programs and investment processes, enabling stakeholders to identify high-potential founders earlier, енханце key traits through training, and support them more effectively, potentially transforming how we cultivate future business leaders and contributing to a more sustainable, innovative, and dynamic entrepreneurial landscape.

Resource availability

De-identified datasets analyzed during the current study are available from the corresponding author on reasonable request.

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Author contributions

Conceptualization: ICD, NEB; Methodology: ICD, NEB, MK, CP; Investigation/Data curation: ICD; Formal analysis: ICD; Writing—original draft: ICD, NEB; Writing—review & editing: ICD, NEB, MK; Supervision: NEB, MK, CP; Project administration: ICD.

Declaration of interests

The authors declare no competing interests.

References

Ahmad, N., & Hoffman, A. (2008). A framework for addressing and measuring entrepreneurship. In *OECD Statistics Working Papers*. https://doi.org/10.1787/243160627270

Ali, I. (2019). Personality traits, individual innovativeness and satisfaction with life. *Journal of Innovation & Knowledge*, *4*(1), 38–46. https://doi.org/10.1016/j.jik.2017.11.002

Aminova, M., & Marchi, E. (2021). The Role of Innovation on Start-Up Failure vs. its Success. *The International Journal of Business Ethics and Governance*, 41–72. https://doi.org/10.51325/ijbeg.v4i1.60

Ardichvili, A., & Cardozo, R. N. (2000). A Model of the Entrepreneurial Opportunity Recognition Process. *Journal of Enterprising Culture*, *08*(02), 103–119. https://doi.org/10.1142/s0218495800000073

Arifin, W. N. (2018). A web-based sample size calculator for reliability studies. *Education in Medicine Journal*, *10*(3), 67–76. https://doi.org/10.21315/eimj2018.10.3.8

Aschheim, J., Tanzi, V., & White, R. K. (1974). Time preference: A psychological concept in economics. *Journal of Behavioral Economics*, *3*, 111–125. https://doi.org/10.1016/0090-5720(74)90006-0

Astebro, T. B., Herz, H., Nanda, R., & Weber, R. A. (2014). Seeking the Roots of Entrepreneurship: Insights from Behavioral Economics. *Journal of Economic Perspectives*, *28*(3), 49–70. https://doi.org/10.1257/jep.28.3.49

Ayala, J., & Manzano, G. (2014). The resilience of the entrepreneur. Influence on the success of the business. A longitudinal analysis. *Journal of Economic Psychology*, *42*, 126–135. https://doi.org/10.1016/j.joep.2014.02.004

Ayre, C., & Scally, A. J. (2014). Critical values for Lawshe's Content Validity ratio. *Measurement and Evaluation in Counseling and Development*, *47*(1), 79–86. https://doi.org/10.1177/0748175613513808

Bagheri, A., & Harrison, C. (2020). Entrepreneurial Leadership Measurement: A Multi-Dimensional Construct. *Journal of Small Business and Enterprise Development*, *27*(4), 659–679. https://doi.org/10.1108/jsbed-01-2019-0027

Bass, B. M. (1990). From transactional to transformational leadership: Learning to share the vision. *Organizational Dynamics*, *18*(3), 19–31. https://doi.org/

10.1016/0090-2616(90)90061-s

Berre, M., & Pendeven, B. L. (2022). Business-Cycles and Cash-on-Market: Pre-money startup valuation in the macroeconomic environment. *Social Science Research Network*. https://doi.org/10.2139/ssrn.4286910

Beugré, C. D. (2017). A neurocognitive model of entrepreneurial opportunity. In *Routledge eBooks* (pp. 17–42). https://doi.org/10.4324/9780203788394-2

Bó, M. P., López-Muñoz, J. F., & Novejarque-Civera, J. (2021). The ever-changing socioeconomic conditions for entrepreneurship. *International Entrepreneurship and Management Journal*, *17*(3), 1335–1355. https://doi.org/10.1007/s11365-020-00737-z

Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H., & Young, S. L. (2018). Best Practices for developing and Validating scales for health, Social, and Behavioral Research: A primer. *Frontiers in Public Health*, *6*. https://doi.org/10.3389/fpubh.2018.00149

Bockorny, K. M., & Youssef-Morgan, C. M. (2019). Entrepreneurs' courage, psychological capital, and life satisfaction. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.00789

Bolton, D. L., & Lane, M. D. (2012). Individual entrepreneurial orientation: development of a measurement instrument. *Journal of Education and Training*, *54*(2/3), 219–233. https://doi.org/10.1108/00400911211210314

Brandstätter, H. (1997). Becoming an entrepreneur — A question of personality structure? *Journal of Economic Psychology*, *18*(2–3), 157–177. https://doi.org/10.1016/s0167-4870(97)00003-2

Brandstätter, H. (2011). Personality aspects of entrepreneurship: A look at five meta-analyses. *Personality and Individual Differences*, *51*(3), 222–230. https://doi.org/10.1016/j.paid.2010.07.007

Brockhaus, R. H. (1980). Risk taking propensity of entrepreneurs. *Academy of Management Journal*, *23*(3), 509–520. https://doi.org/10.2307/255515

Brown, M. B., & Forsythe, A. B. (1974). The small sample behavior of some statistics which test the equality of several means. *Technometrics*, *16*(1), 129–132. https://doi.org/10.1080/00401706.1974.10489158

Brown, T. A. (2007). Confirmatory factor analysis for applied research. *Choice Reviews*

Online, *44*(05), 44–2769. https://doi.org/10.5860/choice.44-2769

Burton, L., & Mazerolle, S. M. (2011). Survey Instrument Validity Part I: Principles of survey instrument development and validation in Athletic Training Education research. *Athletic Training Education Journal*, *6*(1), 27–35. https://doi.org/10.4085/1947-380x-6.1.27

Cattell, R. B. (1966). The scientific analysis of personality. *American Sociological Review*, *31*(1), 127. https://doi.org/10.2307/2091310

Chapman, M. J. (2010). When the entrepreneur sneezes, the organization catches a cold: A practitioner's perspective on the state of the art in research on the entrepreneurial personality and the entrepreneurial process. *European Journal of Work and Organizational Psychology*, *9*(1), 97–101. https://doi.org/10.1080/135943200398102

Chell, E. (2000). Towards researching the "'opportunistic entrepreneur'": A social constructionist approach and research agenda. *European Journal of Work and Organizational Psychology*, *9*(1), 63–80. https://doi.org/10.1080/135943200398067

Chen, J., Liu, L., & Chen, Q. (2021). The effectiveness of effectuation: a meta-analysis on contextual factors. *International Journal of Entrepreneurial Behaviour & Research*, *27*(3), 777–798. https://doi.org/10.1108/ijebr-02-2020-0050

Ciavarella, M. A., Buchholtz, A. K., Riordan, C. M., Gatewood, R. D., & Stokes, G. S. (2004). The Big Five and venture survival: Is there a linkage? *Journal of Business Venturing*, *19*(4), 465–483. https://doi.org/10.1016/j.jbusvent.2003.03.001

Clinch, J., & Keselman, H. J. (1982). Parametric alternatives to the analysis of variance. *Journal of Educational Statistics*, *7*(3), 207–214. https://doi.org/10.3102/10769986007003207

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences. In *Routledge eBooks* (2nd ed.). L. Erlbaum Associates. https://doi.org/10.4324/9780203771587

Cohen, R. J., & Swerdlik, M. E. (2017). *Psychological testing and assessment*. McGraw-Hill Education.

Comrey, A. L., & Lee, H. B. (2013a). A first course in factor analysis. In *Psychology Press eBooks*. https://doi.org/10.4324/9781315827506

Comrey, A. L., & Lee, H. B. (2013b). A first course in factor analysis. In *Psychology Press eBooks*. https://doi.org/10.4324/9781315827506

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis. *Practical Assessment, Research and Evaluation*, *10*(1), 1–9. https://doi.org/10.7275/jyj1-4868

Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. *Psychometrika*, *16*(3), 297–334. https://doi.org/10.1007/bf02310555

Czop, K., & Leszczyńska, A. (2011). Entrepreneurship and innovativeness: in search of the interrelationships. *International Journal of Innovation and Learning*, *10*(2), 156. https://doi.org/10.1504/ijil.2011.041795

De Luce, I. (2020, November 10). These fraudulent founders were once hailed as 'the next Steve Jobs' of their now-disgraced startups. *The Business of Business*. https://www.businessofbusiness.com/articles/startup-founders-fraud-theranos-wework-nikola/

De Winter, J., & Dodou, D. (2012). Factor recovery by principal axis factoring and maximum likelihood factor analysis as a function of factor pattern and sample size. *Journal of Applied Statistics*, *39*(4), 695–710. https://doi.org/10.1080/02664763.2011.610445

DeVellis, R. F. (2016). *Scale development: Theory and Applications*. SAGE Publications.

Digman, J. M. (1990). Personality Structure: Emergence of the Five-Factor Model. *Annual Review of Psychology*, *41*(1), 417–440. https://doi.org/10.1146/annurev.ps.41.020190.002221

Dinno, A. (2009). Implementing Horn's parallel analysis for principal component analysis and factor analysis. *The Stata Journal*, *9*(2), 291–298. https://doi.org/10.1177/1536867x0900900207

Duchek, S. (2017). Entrepreneurial resilience: a biographical analysis of successful entrepreneurs. *International Entrepreneurship and Management Journal*, *14*(2), 429–455. https://doi.org/10.1007/s11365-017-0467-2

Ebert, T., Götz, F. M., Obschonka, M., Zmigrod, L., & Rentfrow, P. J. (2019). Regional variation in courage and entrepreneurship: The contrasting role of courage for the emergence and survival of start-ups in the United States. *Journal of Personality*, *87*(5), 1039–1055. https://doi.org/10.1111/jopy.12454

Eckhardt, J., & Shane, S. (2003). Opportunities and entrepreneurship. *Journal of Management*, *29*(3), 333–349. https://doi.org/10.1177/014920630302900304

Engelen, A., Gupta, V. K., Strenger, L. S., & Brettel, M. (2012). Entrepreneurial orientation, firm performance, and the moderating role of transformational leadership behaviors. *Journal of Management*, *41*(4), 1069–1097. https://doi.org/10.1177/0149206312455244

Ensley, M. D., Pearce, C. L., & Hmieleski, K. M. (2006). The moderating effect of environmental dynamism on the relationship between entrepreneur leadership behavior and new venture performance. *Journal of Business Venturing*, *21*(2), 243–263. https://doi.org/10.1016/j.jbusvent.2005.04.006

Field, A. (2018). *Discovering statistics using IBM SPSS Statistics*. SAGE Publications Limited.

Fisher, R., Maritz, A., & Lobo, A. (2016). Does individual resilience influence entrepreneurial success. *Academy of Entrepreneurship Journal*, *22*(2), 39. https://www.researchgate.net/publication/311259544_Does_individual_resilience_influence_entrepreneurial_success

Freiberg, B., & Matz, S. (2023). Founder personality and entrepreneurial outcomes: A large-scale field study of technology startups. *Proceedings of the National Academy of Sciences of the United States of America*, *120*(19). https://doi.org/10.1073/pnas.2215829120

Garrett, R. G., & Zettel, L. (2021). Entrepreneurial resilience. *Oxford Research Encyclopedia of Business and Management*. https://doi.org/10.1093/acrefore/9780190224851.013.314

Glorfeld, L. W. (1995). An improvement on Horn's parallel analysis methodology for selecting the correct number of factors to retain. *Educational and Psychological Measurement*, *55*(3), 377–393. https://doi.org/10.1177/0013164495055003002

Götz, O., Liehr-Gobbers, K., & Krafft, M. (2009). Evaluation of structural equation models using the partial Least squares (PLS) approach. In *Springer eBooks* (pp. 691–711). https://doi.org/10.1007/978-3-540-32827-8_30

Grégoire, D. A., Barr, P. S., & Shepherd, D. A. (2010). Cognitive Processes of Opportunity Recognition: the role of Structural alignment. *Organization Science*, *21*(2), 413–431. https://doi.org/10.1287/orsc.1090.0462

Gupta, V., MacMillan, I. C., & De Surie, G. S. (2004). Entrepreneurial leadership: developing and measuring a cross-cultural construct. *Journal of Business Venturing*, *19*(2), 241–260. https://doi.org/10.1016/s0883-9026(03)00040-5

Hair, J. F. (2010). *Multivariate data analysis*. Pearson.

Heinemann, H., Mussel, P., & Schäpers, P. (2022). Curious enough to start up? How epistemic curiosity and entrepreneurial alertness influence entrepreneurship orientation and intention. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.1003866

Henderson, J., & Weiler, S. (2009). Entrepreneurs and job Growth: Probing the boundaries of time and space. *Economic Development Quarterly*, *24*(1), 23–32. https://doi.org/10.1177/0891242409350917

Hills, G. E., Hansen, D. J., & Hultman, C. M. (2005). A value creation view of opportunity recognition processes. *International Journal of Entrepreneurship and Small Business*, *2*(4), 404. https://doi.org/10.1504/ijesb.2005.007089

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179–185. https://doi.org/10.1007/bf02289447

Howard, M. C. (2015). A review of exploratory factor analysis decisions and overview of current practices: what we are doing and how can we improve? *International Journal of Human-Computer Interaction*, *32*(1), 51–62. https://doi.org/10.1080/10447318.2015.1087664

Howard, M. C. (2023). Creation of the entrepreneurial personality scale: Removing conceptual and empirical barriers from the study of personality and entrepreneurship. *Journal of Business Venturing Insights*, *20*, e00398. https://doi.org/10.1016/j.jbvi.2023.e00398

Howard, M. C., & Boudreaux, M. M. (2021). A Systematic Literature Review and Meta-Analysis of Entrepreneurial Personality. *Entrepreneurship Research Journal*, *0*(0). https://doi.org/10.1515/erj-2021-0322

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: a review of four recent studies. *Strategic Management Journal*, *20*(2), 195–204. https://doi.org/10.1002/(sici)1097-0266(199902)20:2

Hurst, E., & Pugsley, B. W. (2011). What Do Small Businesses Do? *Brookings Papers on Economic Activity*, *2011*(2), 73–118. https://doi.org/10.1353/eca.2011.0017

Jennings, D. E., & Zeithaml, C. P. (1983). Locus of Control: A review and Directions for Entrepreneurial Research. *Proceedings - Academy of Management*, *1983*(1), 417–421. https://doi.org/10.5465/ambpp.1983.4976387

Jeraj, M., Marič, M., Todorović, I., Čudanov, M., & Komazec, S. (2015). *The role of openness and entrepreneurial curiosity in company's growth*. http://hdl.handle.net/10419/168922

Kahn, J. H. (2006). Factor analysis in counseling psychology research, training, and practice. *The Counseling Psychologist*, *34*(5), 684–718. https://doi.org/10.1177/0011000006286347

Kaiser, H. F. (1960). The application of electronic computers to factor analysis. *Educational and Psychological Measurement*, *20*(1), 141–151. https://doi.org/10.1177/001316446002000116

Kaiser, H. F. (1981). A revised measure of sampling adequacy for Factor-Analytic data matrices. *Educational and Psychological Measurement*, *41*(2), 379–381. https://doi.org/10.1177/001316448104100216

Kaiser, H. F., & Rice, J. R. (1974). Little Jiffy, Mark IV. *Educational and Psychological Measurement*, *34*(1), 111–117. https://doi.org/10.1177/001316447403400115

Kane, T. (2010). The importance of startups in job creation and job destruction. *Social Science Research Network*. https://doi.org/10.2139/ssrn.1646934

Kang, W., Guzman, K. L., & Malvaso, A. (2023). Big Five personality traits in the workplace: Investigating personality differences between employees, supervisors, managers, and entrepreneurs. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.976022

Kashdan, T. B., & Silvia, P. J. (2012). Curiosity and Interest: The Benefits of Thriving on Novelty and Challenge. In *The Oxford Handbook of Positive Psychology* (2nd ed., pp. 366–374). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195187243.013.0034

Kashdan, T. B., Stiksma, M. C., Disabato, D. J., McKnight, P. E., Bekier, J., Kaji, J., & Lazarus, R. C. (2018). The five-dimensional curiosity scale: Capturing the bandwidth of curiosity and identifying four unique subgroups of curious people. *Journal of Research in Personality*, *73*, 130–149. https://doi.org/10.1016/j.jrp.2017.11.011

Kerr, S. P., Kerr, W. R., & Xu, T. (2018). Personality Traits of Entrepreneurs: A Review of Recent literature. *Foundations and Trends® in Entrepreneurship*, *14*(3), 279–356. https://doi.org/10.1561/0300000080

Khan, R. (2023, February 12). The new face of fraud- marquee education and privileged access. *Forbes*. https://www.forbes.com/sites/roomykhan/2023/02/06/the-new-face-of-fraudmarquee-education-and-privileged-access/?sh=422fe28537d6

Khin, S., & Lim, T. H. (2018). Entrepreneurial Opportunity recognition, exploitation and new venture success: Moderating role of prior market and technology knowledge. *International Journal of Entrepreneurship*, *22*(4), 1. https://abacademies.org/articles/entrepreneurial-opportunity-recognition-exploitation-and-new-venture-success-moderating-role-of-prior-market-and-technology-knowle-7793.html

Kickul, J., & Gundry, L. K. (2002). Prospecting for strategic advantage: the proactive entrepreneurial personality and small firm innovation. *Journal of Small Business Management*, *40*(2), 85–97. https://doi.org/10.1111/1540-627x.00042

Korpysa, J. (2020). Neuroentrepreneurship a new paradigm in the management science. *Procedia Computer Science*, *176*, 2605–2614. https://doi.org/10.1016/j.procs.2020.09.309

Lawshe, C. H. (1975). A quantitative approach to content validity. *Personnel Psychology*, *28*(4), 563–575. https://doi.org/10.1111/j.1744-6570.1975.tb01393.x

Levine, R., & Rubinstein, Y. (2016). Smart and illicit: Who becomes an entrepreneur and do they earn more? *The Quarterly Journal of Economics*, *132*(2), 963–1018. https://doi.org/10.1093/qje/qjw044

Liu, Y., Li, Y., Hao, X., & Zhang, Y. (2019). Narcissism and learning from entrepreneurial failure. *Journal of Business Venturing*, *34*(3), 496–512. https://doi.org/10.1016/j.jbusvent.2019.01.003

Lix, L. M., Keselman, J. C., & Keselman, H. J. (1996). Consequences of assumption violations revisited: A quantitative review of alternatives to the One-Way analysis of variance F test. *Review of Educational Research*, *66*(4), 579–619. https://doi.org/10.3102/00346543066004579

Lumpkin, G. T., & Dess, G. G. (1996). Clarifying the entrepreneurial orientation construct and linking it to performance. *Academy of Management Review*, *21*(1), 135. https://doi.org/10.2307/258632

Lumpkin, G. T., Hills, G. E., & Shrader, R. C. (2003). Entrepreneurial Processes: Opportunity recognition. In *Entrepreneurship: The Way Ahead* (1st ed., pp. 73–90). Routledge. https://doi.org/10.4324/9780203356821

Luthar, S. S., Cicchetti, D., & Becker, B. E. (2000). The Construct of Resilience: a critical evaluation and guidelines for future work. *Child Development*, *71*(3), 543–562. https://doi.org/10.1111/1467-8624.00164

Magnano, P., Paolillo, A., Platania, S., & Santisi, G. (2017). Courage as a potential mediator between personality and coping. *Personality and Individual Differences*, *111*, 13–18. https://doi.org/10.1016/j.paid.2017.01.047

Malach-Pines, A., Sadeh, A., Dvir, D., & Yofe-Yanai, O. (2002). Entrepreneurs and Managers: Similar Yet Different. *International Journal of Organizational Analysis*, *10*(2), 172–190. https://doi.org/10.1108/eb028949

Malhotra, N. K. (2010). *Marketing research: An Applied Orientation*.

McClelland, D. C. (1965). Achievement and Entrepreneurship: A longitudinal study. *Journal of Personality and Social Psychology*, *1*(4), 389–392. https://doi.org/10.1037/h0021956

McCoach, D. B., Gable, R. K., & Madura, J. P. (2013). Instrument development in the affective domain. In *Springer eBooks*. https://doi.org/10.1007/978-1-4614-7135-6

McDonald, R. P. (2013). Test theory. In *Psychology Press eBooks*. https://doi.org/10.4324/9781410601087

Miao, C., Qian, S., & Ma, D. (2016). The Relationship between Entrepreneurial Self-Efficacy and Firm Performance: A Meta-Analysis of Main and Moderator Effects. *Journal of Small Business Management*, *55*(1), 87–107. https://doi.org/10.1111/jsbm.12240

Montanelli, R. G., & Humphreys, L. G. (1976). Latent roots of random data correlation matrices with squared multiple correlations on the diagonal: A monte carlo study. *Psychometrika*, *41*(3), 341–348. https://doi.org/10.1007/bf02293559

Morgeson, F. P., Campion, M. A., Dipboye, R. L., Hollenbeck, J. R., Murphy, K. R., & Schmitt, N. (2007). Reconsidering the use of personality tests in personnel selection contexts. *Personnel Psychology*, *60*(3), 683–729. https://doi.org/10.1111/

j.1744-6570.2007.00089.x

Mubarak, A., Irham, Jangkung, H. M., & Hartono, S. (2019). The influence of entrepreneurship characteristics and competencies on farmers' entrepreneurial intentions in the border region of North Borneo. *IOP Conference Series: Earth and Environmental Science*, *250*, 012109. https://doi.org/10.1088/1755-1315/250/1/012109

Pech, R. J., & Cameron, A. (2006). An entrepreneurial decision process model describing opportunity recognition. *European Journal of Innovation Management*, *9*(1), 61–78. https://doi.org/10.1108/14601060610640023

Peljko, Ž., & Antončič, J. A. (2022). Entrepreneurial curiosity, innovativeness of the entrepreneur, and company growth. *Behavioral Sciences*, *12*(11), 424. https://doi.org/10.3390/bs12110424

Powell, E. E., & Baker, T. (2014). It's what you make of it: founder identity and enacting strategic responses to adversity. *Academy of Management Journal*, *57*(5), 1406–1433. https://doi.org/10.5465/amj.2012.0454

Preacher, K. J., & MacCallum, R. C. (2003). Repairing Tom Swift's electric factor analysis machine. *Understanding Statistics*, *2*(1), 13–43. https://doi.org/10.1207/s15328031us0201_02

Presenza, A., Abbate, T., Meleddu, M., & Sheehan, L. (2019). Start-up entrepreneurs' personality traits. An exploratory analysis of the Italian tourism industry. *Current Issues in Tourism*, *23*(17), 2146–2164. https://doi.org/10.1080/13683500.2019.1677572

Quas, A., Alperovych, Y., & Pendeven, B. L. (2024). The role of personality traits in entrepreneurial finance. *Venture Capital*, *26*(2), 101–107. https://doi.org/10.1080/13691066.2024.2319359

Rate, C. R. (2010). Defining the features of courage: A search for meaning. In *American Psychological Association eBooks* (pp. 47–66). https://doi.org/10.1037/12168-003

Rate, C. R., Clarke, J. A., Lindsay, D., & Sternberg, R. J. (2007). Implicit theories of courage. *The Journal of Positive Psychology*, *2*(2), 80–98. https://doi.org/10.1080/17439760701228755

Rauch, A., & Fresé, M. (2007). Let's put the person back into entrepreneurship research: A meta-analysis on the relationship between business owners' personality traits, business creation, and success. *European Journal of Work and Organizational Psychology*, *16*(4), 353–385. https://doi.org/10.1080/13594320701595438

Rauch, A., Wiklund, J., Lumpkin, G. T., & Fresé, M. (2009). Entrepreneurial Orientation and Business Performance: An Assessment of Past Research and Suggestions for the Future. *Entrepreneurship Theory and Practice*, *33*(3), 761–787. https://doi.org/10.1111/j.1540-6520.2009.00308.x

Razmus, W., & Łaguna, M. (2018). Dimensions of Entrepreneurial Success: A Multilevel study on stakeholders of Micro-Enterprises. *Frontiers in Psychology*, *9*. https://doi.org/10.3389/fpsyg.2018.00791

Roberts, E. B. (1989). The personality and motivations of technological entrepreneurs. *Journal of Engineering and Technology Management*, *6*(1), 5–23. https://doi.org/10.1016/0923-4748(89)90012-x

Roebianto, A., Savitri, S. I., Aulia, I. S., Sriyanto, A. S., & Mubarokah, L. (2023). Content validity: Definition and procedure of content validation in psychological research. *TPM - Testing*, *30*(1). https://www.researchgate.net/publication/369171317_Content_validity_Definition_and_procedure_of_content_validation_in_psychological_research

Rosenbusch, N., Brinckmann, J., & Bausch, A. (2011). Is innovation always beneficial? A meta-analysis of the relationship between innovation and performance in SMEs. *Journal of Business Venturing*, *26*(4), 441–457. https://doi.org/10.1016/j.jbusvent.2009.12.002

Rubio, D. M., Berg-Weger, M., Tebb, S., Lee, E. S., & Rauch, S. (2003). Objectifying content validity: Conducting a content validity study in social work research. *Social Work Research*, *27*(2), 94–104. https://doi.org/10.1093/swr/27.2.94

Ruscio, J., & Roche, B. (2012). Determining the number of factors to retain in an exploratory factor analysis using comparison data of known factorial structure. *Psychological Assessment*, *24*(2), 282–292. https://doi.org/10.1037/a0025697

Salmony, F. U., & Kanbach, D. K. (2021). Personality trait differences across types of entrepreneurs: a systematic literature review. *Review of Managerial Science*, *16*(3), 713–749. https://doi.org/10.1007/s11846-021-00466-9

Santos, S. C., Caetano, A., & Curral, L. (2013). Psychosocial aspects of entrepreneurial potential. *Journal of Small Business and Entrepreneurship*, *26*(6), 661–685. https://doi.org/10.1080/08276331.2014.892313

Sauder, D., & DeMars, C. E. (2019). An updated recommendation for multiple comparisons. *Advances in Methods and Practices in Psychological Science*, *2*(1), 26–44. https://doi.org/10.1177/2515245918808784

Schmitt, T. A. (2011). Current methodological considerations in exploratory and confirmatory factor analysis. *Journal of Psychoeducational Assessment*, *29*(4), 304–321. https://doi.org/10.1177/0734282911406653

Schumpeter, J. A. (1934). The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle. *Social Science Research Network*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1496199

Shamsudeen, K., Keat, O. Y., & Hassan, H. (2017). Entrepreneurial Success within the Process of Opportunity Recognition and Exploitation: An Expansion of Entrepreneurial Opportunity Recognition Model. *DOAJ (DOAJ: Directory of Open Access Journals)*. https://doaj.org/article/1567023ae2634b4b98b96874c9fd1ad0

Shao, K., Shirvan, M. E., & Alamer, A. (2022). How accurate is your correlation? Different methods derive different results and different interpretations. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.901412

Short, J. C., Ketchen, D. J., Shook, C. L., & Ireland, R. D. (2009). The concept of "Opportunity" in Entrepreneurship Research: past accomplishments and future challenges. *Journal of Management*, *36*(1), 40–65. https://doi.org/10.1177/0149206309342746

Sireci, S. G., & Faulkner-Bond, M. (2014). Validity evidence based on test content. *PubMed*, *26*(1), 100–107. https://doi.org/10.7334/psicothema2013.256

Slaney, K. L. (2017). Validating psychological constructs. In *Palgrave Macmillan UK eBooks*. https://doi.org/10.1057/978-1-137-38523-9

Staniewski, M. W. (2016). The contribution of business experience and knowledge to successful entrepreneurship. *Journal of Business Research*, *69*(11), 5147–5152. https://doi.org/10.1016/j.jbusres.2016.04.095

Startup Genome. (2020). *The Global Startup Ecosystem Report 2020 (GSER2020)*. Startup

Genome. https://startupgenome.com/article/state-of-the-global-startup-economy

Startup Genome. (2022). *The Global Startup Ecosystem Report 2022 (GSER2022)*. https://startupgenome.com/article/the-state-of-the-global-startup-economy

Statista. (2023, November 3). *U.S. jobs created by start-ups 1994-2022*. https://www.statista.com/statistics/235515/jobs-created-by-start-ups-in-the-us/

Stead, V. (2018). Using critical methodologies to examine entrepreneurial leadership. In E. Hamilton (Ed.), *Research Handbook on Entrepreneurship and Leadership* (pp. 87–105). Edward Elgar Publishing. https://doi.org/10.4337/9781783473762.00010

Stewart, W. H., & Roth, P. L. (2001). Risk propensity differences between entrepreneurs and managers: A meta-analytic review. *Journal of Applied Psychology*, *86*(1), 145–153. https://doi.org/10.1037/0021-9010.86.1.145

Stewart, W. H., & Roth, P. L. (2007). A Meta-Analysis of Achievement Motivation Differences between Entrepreneurs and Managers. *Journal of Small Business Management*, *45*(4), 401–421. https://doi.org/10.1111/j.1540-627x.2007.00220.x

Stewart, W. H., Watson, W. E., Carland, J. C., & Carland, J. W. (1999). A proclivity for entrepreneurship. *Journal of Business Venturing*, *14*(2), 189–214. https://doi.org/10.1016/s0883-9026(97)00070-0

Tabachnick, B. G., & Fidell, L. S. (2007). *Using multivariate statistics*. Allyn & Bacon.

Teare, G. (2024, January 10). *Global startup funding in 2023 clocks in at lowest level in 5 years*. Crunchbase News. https://news.crunchbase.com/venture/global-funding-data-analysis-ai-eoy-2023/

Thode, H. C. (2011). Normality tests. In *Springer eBooks* (pp. 999–1000). https://doi.org/10.1007/978-3-642-04898-2_423

Thompson, B., & Daniel, L. G. (1996). Factor analytic evidence for the construct Validity of scores: a historical overview and some guidelines. *Educational and Psychological Measurement*, *56*(2), 197–208. https://doi.org/10.1177/0013164496056002001

Thornberry, N. (2001). Corporate entrepreneurship: *European Management Journal*, *19*(5), 526–533. https://doi.org/10.1016/s0263-2373(01)00066-4

Thurstone, L. L. (1934). The vectors of mind. *Psychological Review*, *41*(1), 1–32. https://doi.org/10.1037/h0075959

Timmons, J. A. (1994). *New venture creation: Entrepreneurship for the 21st Century*. Irwin

Professional Publishing.

Turner, N. E. (1998). The effect of common variance and structure pattern on random data Eigenvalues: Implications for the accuracy of parallel analysis. *Educational and Psychological Measurement*, *58*(4), 541–568. https://doi.org/10.1177/0013164498058004001

Utsch, A., & Rauch, A. (2000). Innovativeness and initiative as mediators between achievement orientation and venture performance. *European Journal of Work and Organizational Psychology*, *9*(1), 45–62. https://doi.org/10.1080/135943200398058

Velicer, W. F., Eaton, C. A., & Fava, J. L. (2000). Construct Explication through Factor or Component Analysis: A Review and Evaluation of Alternative Procedures for Determining the Number of Factors or Components. In *Springer eBooks* (pp. 41–71). https://doi.org/10.1007/978-1-4615-4397-8_3

Welch, B. L. (1951). On the Comparison of Several Mean Values: An Alternative Approach. *Biometrika*, *38*(3/4), 330. https://doi.org/10.2307/2332579

Willmer, M., Jacobson, J. W., & Lindberg, M. (2019). Exploratory and confirmatory factor analysis of the 9-Item Utrecht Work Engagement Scale in a Multi-Occupational female sample: a Cross-Sectional study. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.02771

Yukl, G. A., & Gardner, W. L. (2020). *Leadership in organizations*.

Zamanzadeh, V., Ghahramanian, A., Rassouli, M., Abbaszadeh, A., Alavimajd, H., & Nikanfar, A. (2015). Design and Implementation Content Validity Study: Development of an instrument for measuring Patient-Centered Communication. *Journal of Caring Sciences*, *4*(2), 165–178. https://doi.org/10.15171/jcs.2015.017

Zhao, H., & Seibert, S. E. (2006). The Big Five personality dimensions and entrepreneurial status: A meta-analytical review. *Journal of Applied Psychology*, *91*(2), 259–271. https://doi.org/10.1037/0021-9010.91.2.259

Zhao, H., Seibert, S. E., & Lumpkin, G. T. (2010). The Relationship of Personality to Entrepreneurial Intentions and Performance: A Meta-Analytic Review. *Journal of Management*, *36*(2), 381–404. https://doi.org/10.1177/0149206309335187

Zoski, K., & Jurs, S. G. (1990). Priority Determination in Surveys: An Application of the

Scree Test. *Evaluation Review*, *14*(2), 214–219. https://doi.org/10.1177/0193841x9001400208

Zwick, W. R., & Velicer, W. F. (1986). Comparison of five rules for determining the number of components to retain. *Psychological Bulletin*, *99*(3), 432–442. https://doi.org/10.1037/0033-2909.99.3.432