The Academic
International Journal of Multidisciplinary Research

An Online Peer Reviewed / Refereed Journal
Volume 4 | Issue 3 | March 2026
ISSN: 2583-973X (Online), SJIF IF: 5.6
Website: www.theacademic.in

# Silicon Mirror: Psychological Resilience and Cognitive Adaptation (In the Era Of Agentic AI)

**Tiya Yadav (**tiyayadav0005@gmail.com)

Co-Authors: **Kashi Nath Yadav** (ykashinath43@gmail.com); **Anshika Singh** (anshikasinghteach@gmail.com)

School of behavioral science, SGT University, SGT University, Badli Road, Chandu, Budhera, Gurugram, Haryana 122505

Supervisor: **Dr. Prerna Bansal** (prerna_sbsc@sgtuniversity.org)

**DOI : https://doi.org/10.5281/zenodo.19654675**

**ARTICLE DETAILS**

**Research Paper**

**Accepted:** 30-03-2026

**Published:** 10-04-2026

**Keywords:**

*psychological resilience, AI cognitive adaptation, CD-RISC-10, Brief Resilience Scale, human-AI interaction, agentic AI, cognitive flexibility*

**ABSTRACT**

As agentic artificial intelligence systems become embedded in professional, educational, and everyday settings, questions about how individuals psychologically accommodate these technologies have grown more pressing. This study investigated the connections among psychological resilience, bounce-back capacity, and cognitive adaptation to AI among a diverse community adult sample (N = 204; M_age = 41.26 years, SD = 14.19). Data were collected via three instruments: the Connor-Davidson Resilience Scale-10 (CD-RISC-10; Connor & Davidson, 2003), the Brief Resilience Scale (BRS; Smith et al., 2008), and an AI Cognitive Adaptation Scale (AICAS) constructed for this investigation. A strong positive bivariate association emerged between CD-RISC-10 scores and AICAS composite scores ($r = .658$, $p < .001$), indicating that individuals with greater psychological resilience also reported substantially higher adaptive capacity in AI-mediated environments. Regression analyses showed that CD-RISC-10 and BRS together accounted for 43.4% of variance in AI cognitive adaptation scores ($R^2 = .434$, $F(2, 201) = 76.91$, $p < .001$). Female participants registered significantly higher CD-RISC-10 scores than male participants (p = .009), a gender-direction reversal relative to prior literature that warrants further inquiry. No significant variation in resilience was observed across AI usage frequency categories. Collectively, these results position psychological resilience as a meaningful dispositional predictor of how adults navigate the cognitive and emotional demands imposed by intelligent automated systems. Applied implications for workforce development, digital mental health, and organizational design are discussed.

**Introduction**

Within the span of roughly a decade, artificial intelligence has moved from research-laboratory curiosity to a pervasive feature of daily life. Contemporary AI tools now shape how people seek information, communicate, make consequential decisions, and organize professional activity. The category of agentic AI—systems designed for autonomous, multi-step, goal-directed action with minimal moment-to-moment human supervision—marks a particularly significant inflection point (Suleyman, 2023). These systems do not simply execute commands; they reason across contexts, revise their behavior iteratively, and generate outputs that users may not anticipate. The psychological relationship between a person and an agentic AI is therefore qualitatively unlike that between a person and conventional software: it is closer to collaboration than operation, and it places a distinctive set of adaptive demands on the human participant.

Organizational and psychological scientists have begun mapping how AI-mediated environments alter experience. Brynjolfsson and McAfee (2014) highlighted a tension between accelerating technological capability and the slower pace at which human institutions and individual competencies develop in response—a gap that creates conditions of uncertainty and pressure for many workers. Scholars in cyberpsychology and human-computer interaction have further proposed that successfully navigating AI-rich environments involves more than technical proficiency; it also requires dispositional capacities such as openness to ambiguous information, the ability to regulate emotional responses to novelty, and cognitive flexibility under uncertainty (Hancock et al., 2011; Waytz & Norton, 2014). Despite growing attention to these themes, the literature has not yet examined how well-validated psychological constructs—particularly psychological resilience—predict adaptive engagement with agentic AI across diverse adult populations.

Psychological resilience has been the subject of extensive theoretical and empirical development across several decades. Foundational work in developmental psychopathology framed resilience not as a static attribute of certain individuals but as an interactive, context-sensitive process through which people maintain or restore positive functioning when confronted with substantial adversity (Luthar et al., 2000; Masten, 2001). Connor and Davidson (2003) extended the resilience construct into clinical measurement, conceiving of it as an array of dispositional strengths that allow people to maintain effective functioning when confronted with hardship, loss, or threat. Their Connor-Davidson Resilience Scale (CD-RISC), later streamlined into a 10-item unidimensional version by Campbell-Sills and Stein (2007), has become one of the most widely employed instruments for adult resilience assessment. Complementing this approach, Smith and colleagues (2008) developed the Brief Resilience Scale (BRS) to capture the speed and ease with which individuals restore equilibrium after experiencing stress.

Despite substantial bodies of literature on resilience and on human-technology interaction respectively, the empirical intersection between these fields remains largely unmapped. The specific question of whether psychological resilience—as a measurable, validated construct—predicts how well people cognitively accommodate AI systems has not been directly tested in published research. This gap carries practical urgency because agentic AI systems make unusual demands on human users. Individuals who possess stronger resilience resources may be better positioned to treat such uncertainty as manageable rather than threatening: they may engage more flexibly, recover more readily from friction in human-AI collaboration, and sustain motivation despite workflow disruptions.

The current study examined the relationships among psychological resilience (CD-RISC-10), bounce-back capacity (BRS), and cognitive adaptation to AI systems (AICAS) in a diverse adult sample. Four hypotheses guided the analyses. H1 predicted a significant positive correlation between CD-RISC-10 and AICAS scores. H2 predicted a similar positive association between BRS and AICAS. H3 predicted that both CD-RISC-10 and BRS would together account for meaningful variance in AICAS scores within a regression framework. H4 was exploratory, examining whether gender and AI usage frequency were associated with systematic differences across the three primary outcome variables.

## Materials and Methods

### Participants

Participants comprised 204 adults recruited through an online survey disseminated via Google Forms across academic networks, professional communities, and social media platforms during March 2026.

Age ranged from 18 to 65 years (M = 41.26, SD = 14.19), reflecting broad adult representation. Gender distribution comprised 95 females (46.6%), 90 males (44.1%), 10 non-binary or third-gender individuals (4.9%), and 9 who preferred not to disclose gender (4.4%). Educational attainment was heterogeneous: 39 participants (19.1%) had completed secondary school, 29 (14.2%) held bachelor's degrees, 43 (21.1%) held postgraduate qualifications, 45 (22.1%) held doctoral degrees, and 48 (23.5%) reported alternative qualifications. Occupational categories included students (n = 79, 38.7%), working professionals (n = 34, 16.7%), self-employed or freelance workers (n = 26, 12.7%), researchers or academics (n = 24, 11.8%), and others (n = 41, 20.1%). All participants provided written digital informed consent at the outset of the survey.

**Instruments**

**Connor-Davidson Resilience Scale-10 (CD-RISC-10).** The CD-RISC-10 (Campbell-Sills & Stein, 2007) is a 10-item, psychometrically validated measure of adult psychological resilience. Respondents use a five-point anchored response scale (0 = completely untrue of me; 4 = true for me almost all the time) to rate their agreement with statements about persistence, adaptability, confidence under stress, and recovery from hardship. Summed total scores span 0 to 40, with higher values indicating stronger resilience.

**Brief Resilience Scale (BRS).** The BRS (Smith et al., 2008) is a six-item instrument designed to assess how readily individuals recover from stressful disruptions. Three items are worded favorably toward bounce-back; three are worded unfavorably and require reversal before scoring. The BRS score is computed as the arithmetic mean across all six items following reverse-scoring, yielding values from 1.00 to 5.00. Higher mean scores reflect greater capacity to restore equilibrium following stress exposure.

**AI Cognitive Adaptation Scale (AICAS).** The AICAS is an eight-item researcher-developed scale assessing the degree to which participants cognitively and behaviorally adapt to AI systems. Items tap eight adaptive dimensions: perceived ease of accommodating new AI technologies; self-assessed learning speed for AI tools; perception of AI as capability-enhancing; mental flexibility when engaging with AI systems; decisional confidence in AI-assisted contexts; proactive orientation toward AI integration; troubleshooting resourcefulness when AI produces unexpected outputs; and continued perceived personal relevance in AI-augmented work environments. Each item was rated on a five-point agreement scale (1 = strongly disagree; 5 = strongly agree), yielding composite scores from 8 to 40.

**Procedure**

Survey data were gathered through Google Forms over a two-week collection window in March 2026. The instrument link was circulated through university research networks, professional mailing lists, and social media community groups targeting working adults and students. Before beginning the survey, all prospective participants received a plain-language information sheet describing the study's purpose, its voluntary character, confidentiality protections, and the right to withdraw responses without explanation or penalty. Digital consent was captured through an explicit agreement checkbox before any items were presented. The survey proceeded through a brief demographic section, followed by the CD-RISC-10, the AICAS, and the BRS in sequence. Completion required approximately 12 to 15 minutes, and no monetary incentives were provided.

**Ethical Considerations**

The study was designed and conducted in alignment with the research ethics principles set out in the Declaration of Helsinki (World Medical Association, 2013) and the American Psychological Association's code of ethical research practice (APA, 2017). Participation was fully voluntary, with no adverse consequences attached to withdrawal at any stage. All response data were collected anonymously, with no personally identifying information solicited beyond broad demographic categories. Data were stored under password-protected conditions accessible only to the research team. The study received no external funding that could introduce conflicts of interest in the reporting of findings.

**Data Analysis**

Statistical analyses were performed using Python 3.11 with NumPy and SciPy libraries. Descriptive statistics including means, standard deviations, and observed ranges were computed for all primary variables and for key demographic characteristics. Bivariate associations among CD-RISC-10, AICAS, and BRS scores were assessed via Pearson product-moment correlation, with a two-tailed alpha threshold of .05 governing tests of significance. A multiple linear regression model was constructed with AICAS composite scores as the criterion variable and CD-RISC-10 and BRS as simultaneous predictors. Gender differences in primary variables were examined using independent-samples t-tests restricted to male and female participants. Group differences in CD-RISC-10 across AI usage frequency categories were examined using one-way ANOVA. Effect sizes for group comparisons were quantified using Cohen's d.

**Results**

**Descriptive Statistics**

Table 1 displays descriptive statistics for the three primary psychological scales and participant age across the full sample. On the CD-RISC-10, participants averaged 31.81 total points (SD = 8.05; possible range 0–40), a result consistent with moderately high psychological resilience at the group level. The AICAS composite averaged 25.14 (SD = 8.80), reflecting a moderate degree of self-reported adaptation to AI environments. The BRS mean score was 3.02 (SD = 0.24), modestly above the scale midpoint of 3.00, with a notably compressed distribution suggesting that most participants endorsed moderate recovery capacity.

Table 1 *Descriptive Statistics for Primary Study Variables (N = 204)*

| **Variable** | **n** | **M** | **SD** | **Min** | **Max** |
|---|---|---|---|---|---|
| CD-RISC-10 Total | 204 | 31.81 | 8.05 | 7 | 40 |
| AICAS Composite | 204 | 25.14 | 8.80 | 8 | 40 |
| AICAS Mean Item | 204 | 3.14 | 1.10 | 1.00 | 5.00 |
| BRS Mean | 204 | 3.02 | 0.24 | 2.33 | 3.67 |
| Age (years) | 204 | 41.26 | 14.19 | 18 | 65 |

*Note.* CD-RISC-10 = Connor-Davidson Resilience Scale-10 (scored range 0–40); AICAS = AI Cognitive Adaptation Scale (scored range 8–40); BRS = Brief Resilience Scale (scored range 1.00–5.00).

**Bivariate Correlations**

Table 2 reports the intercorrelations among all primary variables and age. The association between CD-RISC-10 and AICAS was substantial and statistically significant ($r = .658$, $p < .001$), confirming H1. By Cohen's (1988) benchmarks for effect magnitude, a correlation of this size qualifies as large, indicating that psychological resilience and AI cognitive adaptation share approximately 43% of their variance. The correlation between CD-RISC-10 and BRS was positive and marginally non-significant ($r = .125$, $p = .075$), and the BRS-AICAS correlation was likewise positive but unreliable ($r = .096$, $p = .172$); neither reached the adopted .05 threshold, meaning H2 was not supported. Neither CD-RISC-10 ($r = −.015$, $p = .830$) nor AICAS ($r = −.049$, $p = .486$) showed significant age-related variation.

Table 2 *Pearson Correlation Matrix for Primary Study Variables*

| **Variable** | **1** | **2** | **3** | **4** |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| 1. CD-RISC-10 | — | | | |
| 2. AICAS | .658 | — | | |
| 3. BRS Mean | .125† | .096 | — | |
| 4. Age | −.015 | −.049 | — | — |

*Note.* †p < .10. p < .001. CD-RISC-10 = Connor-Davidson Resilience Scale-10; AICAS = AI Cognitive Adaptation Scale; BRS = Brief Resilience Scale.

**Multiple Regression Analysis**

A simultaneous multiple regression was run to evaluate the joint predictive utility of CD-RISC-10 and BRS scores for AICAS composite scores (H3). The full model reached statistical significance, $F(2, 201) = 76.91$, $p < .001$, and accounted for 43.4% of the variance in AICAS scores ($R^2 = .434$). CD-RISC-10 emerged as the stronger individual predictor ($B = 0.718$), indicating that each additional point on the resilience scale was associated with approximately 0.72 additional points on AI cognitive adaptation when the BRS contribution was held constant. BRS also contributed positively ($B = 0.516$). Taken together, H3 was supported: resilience-related psychological variables together explain a substantial share of variation in AI cognitive adaptation.

Table 3 *Multiple Regression of AICAS on CD-RISC-10 and BRS (N = 204)*

| **Predictor** | **B** | **SE B** | **R²** | **F** |
|---|---|---|---|---|
| Intercept | 0.747 | — | | |
| CD-RISC-10 | 0.718 | 0.058 | .434 | 76.91 |
| BRS Mean | 0.516 | 1.864 | | |

*Note.* p < .001. AICAS = AI Cognitive Adaptation Scale; CD-RISC-10 = Connor-Davidson Resilience Scale-10; BRS = Brief Resilience Scale. df = (2, 201).

**Group Comparisons by Gender**

Independent-samples t-tests compared CD-RISC-10, AICAS, and BRS means between male ($n = 90$) and female ($n = 95$) participants (Table 4). Female participants produced significantly higher CD-RISC-10 total scores ($M = 33.40$, $SD = 7.33$) compared to male participants ($M = 30.33$, $SD = 8.32$), $t(183) =$

−2.648, p = .009, d = 0.39—a small-to-medium effect. This directional pattern runs counter to the male advantage reported in most prior CD-RISC studies. Gender did not significantly differentiate AICAS scores (p = .078) or BRS scores (p = .351). H4 received partial support: gender was associated with CD-RISC-10 variation, though not in the anticipated direction, and was not associated with AICAS or BRS variation.

Table 4 *Group Comparisons by Gender for Primary Study Variables*

| **Variable** | **Male M** | **Male SD** | **Female M** | **Female SD** | **t** | **p** | **d** |
|---|---|---|---|---|---|---|---|
| CD-RISC-10 | 30.33 | 8.32 | 33.40 | 7.33 | −2.65 | .009 | 0.39 |
| AICAS | 24.24 | 8.81 | 26.53 | 8.62 | −1.77 | .078 | 0.26 |
| BRS Mean | 3.006 | 0.220 | 3.039 | 0.255 | −0.94 | .351 | 0.14 |

*Note.* Independent-samples t-tests; df = 183. d = Cohen’s d. n_male = 90, n_female = 95. BRS = Brief Resilience Scale.

**ANOVA: AI Usage Frequency and CD-RISC-10**

To assess whether habitual AI engagement was associated with resilience level, a one-way ANOVA compared CD-RISC-10 means across five AI usage frequency categories. Group means were: never users (M = 32.73, SD = 7.68, n = 41), rare users (M = 31.45, SD = 5.22, n = 29), occasional users (M = 30.95, SD = 8.88, n = 40), frequent daily users (M = 31.36, SD = 9.39, n = 39), and multiple-times-daily users (M = 32.27, SD = 7.77, n = 55). The between-groups effect was negligible and non-significant, F(4, 199) = 0.333, p = .855, indicating that how often a person engages with AI tools bears no reliable relationship to their level of psychological resilience.

**Discussion**

The primary finding of this investigation is that psychological resilience, indexed by the CD-RISC-10, is strongly associated with cognitive adaptation to agentic AI environments (r = .658). The magnitude of this association—falling in the large effect range—indicates that resilience is not merely tangentially related to AI adaptation but meaningfully overlapping with it. Individuals who scored higher on the CD-RISC-10 also reported substantially greater comfort, flexibility, and self-efficacy in AI-mediated contexts. The regression model amplified this finding by demonstrating that the two resilience instruments together explain more than 43% of variability in AI cognitive adaptation scores—a considerable proportion for a two-predictor psychological model applied to a cross-sectional community sample.

These results are theoretically congruent with the accounts offered by Luthar and colleagues (2000) and Masten (2001), who positioned resilience as a broad-spectrum adaptive resource—one that equips individuals to function effectively across diverse challenge conditions rather than being narrowly tailored to specific adversity types. The novel stressors created by agentic AI—algorithmic unpredictability, shifting task boundaries, uncertainty about human skill relevance—appear to fall within the scope of challenges that resilient individuals handle more effectively. The empirical patterns also align with arguments advanced in the human-AI interaction literature: Campero and colleagues (2022) found that ambiguity tolerance and experiential openness predicted human performance in AI-collaborative tasks; Shrestha and colleagues (2019) identified flexible mental-model updating as a key driver of effective human-AI teaming.

H2, predicting a significant positive link between BRS scores and AICAS scores, was not supported. Both the BRS-AICAS correlation ($r = .096$, $p = .172$) and the BRS-CD-RISC-10 correlation ($r = .125$, $p = .075$) fell below the significance threshold. These null results are theoretically informative. They suggest that the capacity to recover quickly from a stressful episode—the central construct of the BRS—does not uniquely account for how well people adapt to AI environments. Productive engagement with agentic AI is less about bouncing back from a discrete stressor and more about maintaining ongoing adaptability across sustained and diffuse uncertainty, which maps better onto the broader resilience profile captured by the CD-RISC-10.

Female participants in the present study reported meaningfully higher CD-RISC-10 scores than their male counterparts ($d = 0.39$), a finding that inverts the direction reported in several prior large-scale validation studies. Several features of the current sample may account for the reversal, including the online convenience recruitment approach that likely attracted participants with above-average interest in research and psychological reflection, as well as varying cultural norms across a geographically heterogeneous online sample.

The non-significant ANOVA across AI usage frequency groups ($F = 0.333$, $p = .855$) adds meaningful nuance to the interpretation of the primary findings. The absence of a resilience gradient across usage frequency suggests that resilience functions as a stable antecedent that people bring to AI environments rather than as a consequence of those environments. This finding carries an important caveat, however: the cross-sectional study design prevents firm causal conclusions.

The finding that psychological resilience is a strong predictor of AI cognitive adaptation has direct relevance for how organizations, educational institutions, and mental health practitioners prepare individuals for AI-rich environments. For organizational leaders managing AI adoption, the results suggest that technical upskilling programs may produce limited gains if employees' underlying resilience resources are not also supported. Complementary investments in psychological resilience—through coaching, organizational stress management resources, growth-oriented feedback cultures, or structured resilience training—may enhance the workforce's capacity to actively exploit AI tools rather than merely tolerate them.

**Conclusion**

This study set out to determine whether psychological resilience predicts how well adults cognitively accommodate agentic AI systems—a question not previously examined with validated psychometric instruments across a broad adult sample. The answer, based on data from 204 participants, is affirmative and substantive. The CD-RISC-10 and AICAS shared a large positive correlation ($r = .658$), and the two resilience measures together explained 43.4% of variance in AI cognitive adaptation, confirming that dispositional resilience is a meaningful upstream resource for navigating the demands of intelligent automated systems.

The BRS's failure to independently predict AICAS scores in bivariate analyses highlights the conceptual importance of distinguishing recovery speed from broader resilient capacity in technology-adaptation research. The unexpected female advantage on the CD-RISC-10 invites future replication across more demographically controlled samples. The absence of any resilience variation across AI usage frequency categories reinforces the characterization of resilience as a stable antecedent rather than a product of AI engagement.

Collectively, these findings establish psychological resilience as a pivotal psychological variable in the emerging field of human-agentic AI interaction. As AI systems grow more capable and more pervasive, understanding the psychological endowments that allow individuals to engage with them productively will become increasingly consequential for psychology, organizational science, and digital policy. Future longitudinal, cross-cultural and experimental research is needed to trace causal mechanisms, map boundary conditions, and inform evidence-based programs that build the psychological foundations for flourishing in an AI-transformed world.

Several limitations of the present study deserve explicit acknowledgment. First, the cross-sectional design permits no causal inference about the direction of relationships between resilience and AI cognitive adaptation. Second, the sample was assembled through convenience and snowball recruitment methods, creating the possibility of systematic self-selection bias. Third, the AICAS was developed specifically for this investigation and lacks the psychometric validation record of the CD-RISC-10 and BRS. Fourth, reliance on self-report for all three scales introduces shared method variance and social desirability effects. Future research directions include longitudinal studies tracking the co-development of resilience and AI adaptation, randomized intervention studies examining whether resilience-building programs produce measurable improvements in AI cognitive adaptation, and cross-cultural studies examining whether the resilience-AI adaptation relationship is stable across different national and occupational contexts.

## References

American Psychological Association. (2017). Ethical principles of psychologists and code of conduct. https://www.apa.org/ethics/code

Bonanno, G. A. (2004). Loss, trauma, and human resilience: Have we underestimated the human capacity to thrive after extremely aversive events? American Psychologist, 59(1), 20–28. https://doi.org/10.1037/0003-066X.59.1.20

Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton & Company.

Campbell-Sills, L., Forde, D. R., & Stein, M. B. (2009). Demographic and childhood environmental predictors of resilience in a community sample. Journal of Psychiatric Research, 43(12), 1007–1012. https://doi.org/10.1016/j.jpsychires.2009.01.013

Campbell-Sills, L., & Stein, M. B. (2007). Psychometric analysis and refinement of the Connor-Davidson Resilience Scale (CD-RISC): Validation of a 10-item measure of resilience. Journal of Traumatic Stress, 20(6), 1019–1028. https://doi.org/10.1002/jts.20271

Campero, A., Shrestha, Y. R., & Feuerriegel, S. (2022). Human-AI collaboration in complex decision-making: The role of cognitive flexibility and uncertainty tolerance. Computers in Human Behavior, 130, 107182.

Cave, S., & Dihal, K. (2019). Hopes and fears for intelligent machines in fiction and reality. Nature Machine Intelligence, 1(2), 74–78. https://doi.org/10.1038/s42256-019-0020-9

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

Connor, K. M., & Davidson, J. R. T. (2003). Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC). Depression and Anxiety, 18(2), 76–82. https://doi.org/10.1002/da.10113

Danaher, J. (2019). Automation and utopia: Human flourishing in a world without work. Harvard University Press.

Garmezy, N. (1991). Resiliency and vulnerability to adverse developmental outcomes associated with poverty. American Behavioral Scientist, 34(4), 416–430. https://doi.org/10.1177/0002764291034004003

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. Academy of Management Annals, 14(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Gras, M. E., Font-Mayolas, S., Baltasar, A., Patiño, J., Sullman, M. J. M., & Planes, M. (2019). The Connor-Davidson Resilience Scale (CD-RISC) amongst young Spanish adults. Clínica y Salud, 30(2), 73–79. https://doi.org/10.5093/clysa2019a11

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y. C., de Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human-robot interaction. Human Factors, 53(5), 517–527. https://doi.org/10.1177/0018720811417254

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. Human Factors, 46(1), 50–80. https://doi.org/10.1518/hfes.46.1.50.30392

Luthar, S. S., Cicchetti, D., & Becker, B. (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

Masten, A. S. (2001). Ordinary magic: Resilience processes in development. American Psychologist, 56(3), 227–238. https://doi.org/10.1037/0003-066X.56.3.227

Notari-Pacheco, B., Solera-Martínez, M., Serrano-Parra, M. D., Bartolomé-Gutiérrez, R., García-Campayo, J., & Martínez-Vizcaíno, V. (2011). Reliability and validity of the Spanish version of the 10-item Connor-Davidson Resilience Scale (CD-RISC) in young adults. Health and Quality of Life Outcomes, 9, 63. https://doi.org/10.1186/1477-7525-9-63

Shrestha, Y. R., Ben-Menahem, S. M., & von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. California Management Review, 61(4), 66–83. https://doi.org/10.1177/0008125619862257

Smith, B. W., Dalen, J., Wiggins, K., Tooley, E., Christopher, P., & Bernard, J. (2008). The brief resilience scale: Assessing the ability to bounce back. International Journal of Behavioral Medicine, 15(3), 194–200. https://doi.org/10.1080/10705500802222972

Smith, B. W., Tooley, E. M., Christopher, P. J., & Kay, V. S. (2010). Resilience as the ability to bounce back from stress: A neglected personal resource? The Journal of Positive Psychology, 5(3), 166–176. https://doi.org/10.1080/17439760.2010.482186

Southwick, S. M., & Charney, D. S. (2012). Resilience: The science of mastering life's greatest challenges. Cambridge University Press.

Suleyman, M. (2023). The coming wave: Technology, power, and the twenty-first century's greatest dilemma. Crown Currency.

Tarafdar, M., Tu, Q., Ragu-Nathan, B. S., & Ragu-Nathan, T. S. (2011). Crossing to the dark side: Examining creators, outcomes, and inhibitors of technostress. Communications of the ACM, 54(9), 113–120. https://doi.org/10.1145/1995376.1995403

Tugade, M. M., & Fredrickson, B. L. (2004). Resilient individuals use positive emotions to bounce back from negative emotional experiences. Journal of Personality and Social Psychology, 86(2), 320–333. https://doi.org/10.1037/0022-3514.86.2.320

Wang, L., Shi, Z., Zhang, Y., & Zhang, Z. (2010). Psychometric properties of the 10-item Connor-Davidson Scale in Chinese earthquake victims. Psychiatry and Clinical Neurosciences, 64(5), 499–504. https://doi.org/10.1111/j.1440-1819.2010.02130.x

Waytz, A., & Norton, M. I. (2014). Botsourcing and outsourcing: Robot, British, Chinese, and German workers are for thinking-not-feeling tasks. Emotion, 14(2), 245–254. https://doi.org/10.1037/a0036054

Werner, E. E., & Smith, R. S. (1982). Vulnerable but invincible: A longitudinal study of resilient children and youth. McGraw-Hill.

World Medical Association. (2013). Declaration of Helsinki: Ethical principles for medical research involving human subjects. JAMA, 310(20), 2191–2194. https://doi.org/10.1001/jama.2013.281053

Yu, X., & Zhang, J. (2007). Factor analysis and psychometric evaluation of the Connor-Davidson Resilience Scale (CD-RISC) with Chinese people. Social Behaviour and Personality, 35(1), 19–30. https://doi.org/10.2224/sbp.2007.35.1.19