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Artificial intelligence and meaning in life: a systematic literature review of psychological mechanisms

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ABSTRACT

The rapid proliferation of Artificial Intelligence (AI) has prompted a growing body of empirical research on its psychological consequences, yet this literature remains fragmented across disciplines and has not been systematically synthesized. No published systematic review has mapped these findings through the lens of meaning in life, leaving a critical gap in the evidence base for researchers, clinicians, and platform designers. This PRISMA-compliant systematic review searched Scopus, Web of Science, and PsycINFO using a three-block Boolean strategy. Following screening of 274 records, 20 peer-reviewed studies met full inclusion criteria. Three research questions addressed the scope of the literature, the psychological mechanisms operating within it, and the extent to which AI functions as a risk or protective factor for meaning in life. Findings documented a rapidly emerging field concentrated in East Asian contexts, with publication output increasing tenfold between 2024 and 2026. Across 63 coded findings and 28 identified mechanisms, outcomes were determined by whether human generativity, autonomy, and cognitive agency were preserved or displaced, as a pattern designated here as existential outsourcing. No single study tested the complete AI to mechanism to meaning in life causal chain, representing the field's most critical empirical gap and primary contribution of this review.

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SUBJECTS
Social Sciences; Behavioral Sciences; Health Psychology; Social Sciences; Behavioral Sciences; Biopsychology

1. Introduction

Within the past recent years, artificial intelligence (AI) has become an increasingly prominent presence across virtually every domain of human life. Since the public release of large language model-based tools such as ChatGPT in late 2022, the pace of adoption has been unprecedented, reframing how individuals work, learn, create, communicate, and make decisions (Chen et al., 2026; Theoharakis & Mylonopoulos, 2026). Alongside the enthusiasm surrounding these developments, a parallel conversation has emerged within psychology and the behavioral sciences regarding the psychological consequences of this integration and interaction. Researchers have begun to document associations between AI use and a range of psychological outcomes including anxiety, moral disengagement, loneliness, and wellbeing (P. Liu et al., 2025; Nakagomi et al., 2026). However, the field remains young, rapidly evolving, and fragmented, producing a growing body of evidence that has not yet been systematically mapped or synthesized. As society ascends into the next generation of AI capability, it continues to deal with a question that is neither new nor technological in origin: what is meaning in life, how is it created, what destroys it, and how does our relationship with artificial intelligence shape it?

Meaning in life is one of psychology's most fundamental constructs, referring to the degree to which an individual experiences their existence as coherent, purposeful, and significant (Martela & Steger, 2016). Research has consistently demonstrated that the presence of meaning in life is associated with greater psychological wellbeing, resilience, and life satisfaction, while its absence is associated with depression, anxiety, and existential distress (Steger et al., 2006). Critically, Schnell (2011) established through

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representative sampling that generativity, the human capacity and proclivity to produce, create, and contribute something of enduring value, is the single strongest predictor of meaningfulness across all known sources of meaning ($\beta = 0.33$, $r = 0.67$, $p < 0.001$). This finding carries significant implications for the modern individual navigating an unprecedented era. If generativity is the primary engine of meaning, and if AI systems are increasingly capable of performing the very cognitive, creative, and productive tasks through which humans have historically enacted that generativity, then the relationship between AI use and meaning in life becomes not merely an academic curiosity but a question of profound psychological urgency.

Because the field of AI-specific psychological research has only emerged in the wake of large language model proliferation from 2022 onward, empirical studies examining the relationship between AI use and meaning in life have only been conducted in recent years. Consequently, there is currently no comprehensive overview of what this literature has produced. We do not yet know with any empirical certainty whether interaction with AI models poses a risk to the individual's experience of meaning in life, whether it can serve as a tool for meaning restoration, or under what conditions either outcome prevails. Prior systematic and narrative reviews have examined AI in relation to mental health, wellbeing, and clinical outcomes (Li et al., 2023; L. Wang et al., 2025), and several have mapped the broader landscape of AI-related psychological mechanisms (Cruz-Gonzalez et al., 2025). However, a synthesis appraisal of 7 prior reviews (see Table 1) reveals a structural gap: meaning in life, psychological mechanisms, and AI specific focus, have been entirely absent as constructs from every published review to date.

Leaving this gap unfilled will have consequences that are not merely academic. At the level of the individual, people navigating AI-integrated in their personal work, education, and daily life are making consequential psychological decisions without evidence-based guidance on meaning-related risk, decisions about how much to delegate, how much to trust, and how much of their own thinking to preserve, decisions in which an equilibrium must be struck among efficiency, optimization, autonomy, and agency. At the clinical level, practitioners lack the synthesized evidence needed to identify which patterns of AI use may constitute psychological risk factors for existential distress. At the design level, developers building the next generation of AI systems have no empirical framework for distinguishing architectures that protect human generativity from those that quietly erode it. Filling this gap doesn't only further psychological theory but it would provide the first evidence-based foundation for designing AI systems, clinical guidelines, and educational policies that treat meaning in life as a variable worth protecting. This is what a systematic synthesis of the AI × meaning in life × psychological mechanisms literature makes possible for the first time. The present systematic review directly addresses this gap by synthesizing the totality of peer-reviewed empirical and theoretical literature examining the

Table 1. Systematic appraisal of prior reviews: Absence of meaning in life constructs ($N = 7$).

#	Author (year)	Focus	Databases	Meaning in life included?	Psychological mechanisms examined?	AI-specific focus?
1	Wang et al. (2025)	GenAI applications and ethical implications in mental health	PubMed; ACM; Scopus; Embase; PsycINFO	No	No	Yes
2	Li et al. (2023)	AI conversational agents for mental health and well-being	PubMed; Embase; WoS; Engineering Village; PsycINFO	No	Yes	Yes
3	Qin et al. (2025)	Communication competence of AI conversational agents for health	PubMed; Embase; CINAHL; Cochrane; PsycINFO	No	No	Yes
4	Shin (2025)	Human-centered AI for users' digital well-being	ACM; IEEE; Scopus; WoS; PsycINFO	No	No	Yes
5	Cruz-Gonzalez et al. (2025)	AI in mental health care: diagnosis, monitoring, and intervention	PubMed; Embase; PsycINFO; Scopus; WoS	No	Yes	Yes
6	Bevilacqua et al. (2025)	AI and leadership enhancement in top management	Scopus; WoS; EBSCOhost	No	No	No
7	Yeasmin et al. (2026)	AI for mental health monitoring—umbrella review of 29 SLRs	PubMed; Scopus; WoS; CINAHL; PsycINFO	No	No	Yes

Note. Review type classified as systematic or narrative. 'Included' defined as the construct appearing as a primary outcome measure, search term, or central theoretical framework in the review. All 7 reviews confirmed the absence of meaning in life, existential well-being, and nihilism as primary constructs.

relationship between AI, psychological mechanisms, and meaning in life. Three research questions guide the review:

RQ1: What is the scope, volume, and disciplinary distribution of the existing literature examining the relationship between AI and meaning in life?

RQ2: What psychological mechanisms mediate or moderate the relationship between AI use and meaning in life, and how consistently are these mechanisms reported across the reviewed literature?

RQ3: To what extent does AI function as a risk factor for meaning deficits or alternatively as a protective tool for meaning restoration, and what are the critical methodological and empirical gaps in the current evidence base?

2. Methods

2.1. Study design

This study employed a systematic literature review (SLR) methodology adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Page et al., 2021). The PRISMA framework was selected for its structure, transparency, and replicable approach to identifying, screening, and synthesizing peer-reviewed literature, and for its capacity to accommodate the methodological heterogeneity characteristic of emerging interdisciplinary fields. A narrative synthesis approach was taken due to the diversity of research designs, populations, applications, and outcome measures across included studies, which is too broad to be reduced to a single quantitative meta-analytic conclusion. This review addresses three questions examining the scope and volume of AI and meaning in life literature (RQ1), the psychological mechanisms operating within it (RQ2), and the extent to which AI functions as either a risk or protective factor alongside current methodological gaps (RQ3). Scopus, Web of Science, and ProQuest: PsychInfo were selected as the primary sources for their rigorous peer-reviewed indexing standards and their consistent discontinuation of journals that fail to maintain peer-reviewed processes, ensuring the quality, academic integrity, and credibility of included records.

2.2. Search strategy

A systematic search was carried out across three major academic databases, Scopus, Web of Science, and PsycINFO, with a cutoff date of April 16, 2026. The strategy was conducted using a three-block Boolean structure, with each block themed to a core conceptual domain of the review: generative artificial intelligence, psychological mechanisms, and meaning in life or existential wellbeing. The three blocks were connected using the AND operator to ensure that all documents addressed all three conceptual domains simultaneously. Table 2 presents the complete search strategy including block structure, conceptual domain, and full search terms.

Table 2. Boolean search strategy across three databases.

Block	Conceptual domain	Search terms
Block A	Artificial intelligence	'generative AI' OR 'generative artificial intelligence' OR 'large language model*' OR 'LLM' OR 'ChatGPT' OR 'conversational AI' OR 'AI chatbot*' OR 'AI-assisted' OR 'artificial intelligence' OR 'machine learning' OR 'deep learning' OR 'natural language processing' OR 'AI-powered'
Block B	Psychology mechanisms	'psychological mechanism*' OR 'cognitive mechanism*' OR 'emotional mechanism*' OR 'meaning-making' OR 'self-regulation' OR 'cognitive load' OR 'emotional regulation' OR 'identity threat' OR 'psychological well-being' OR 'affective response*' OR 'motivation' OR 'autonomy' OR 'cognitive autonomy' OR 'behavioral engagement' OR 'emotional support' OR 'therapeutic alliance' OR 'psychological distress' OR 'resilience' OR 'self-efficacy' OR 'existential anxiety'
Block C	Meaning in life	'meaning in life' OR 'meaning-in-life' OR 'existential well-being' OR 'purpose in life' OR 'sense of purpose' OR 'existential meaning' OR 'nihilism' OR 'nihilistic' OR 'existential vacuum' OR 'meaning deficit*' OR 'loss of meaning' OR 'anomie' OR 'identity crisis' OR 'value system*' OR 'moral disengagement' OR 'terror management' OR 'significance quest' OR 'social alienation' OR 'meaninglessness' OR 'psychological emptiness' OR 'belonging'
Combined	All three	Block A AND Block B AND Block C

Note. All search terms applied to TITLE-ABS-KEY fields in Scopus and equivalent title, abstract, and keyword fields in Web of Science and PsycINFO. Asterisk (*) denotes truncation operator permitting retrieval of all word variants.

2.3. Inclusion and exclusion criteria

Inclusion criteria were established prior to screening and applied consistently across all retrieved records. To meet inclusion criteria, studies required peer-reviewed journal articles reporting on empirical research, both primary and secondary, involving human-generated data or human participants. No restrictions were placed on participant age or clinical status. The AI component of the study was required to address AI, large language models, GenAI, AI chatbots, or conversational AI agents as a primary focus, with AI serving as a functioning tool, intervention, mediator, or moderator. The psychological mechanism component required studies to address at least one of the following constructs: meaning in life, purpose, existential wellbeing, psychological mechanisms, identity, self-regulation, emotional wellbeing, anomie, or value systems, with these constructs being measured, theorized, or systematically synthesized.

Studies were excluded on the following grounds: incorrect document type (such as conference abstracts, book chapters, editorials, letters, commentaries, dissertations, and theses), AI being a peripheral or incidental factor, absence of any psychological or meaning-related constructs, studies examining AI as a data analysis tool rather than a subject of human-AI psychological interaction, and studies examining ethical or philosophical implications from a purely theoretical, policy, or regulatory perspective without a psychological dimension.

2.4. Screening process

The initial review of records across Scopus, Web of Science, and PsycINFO yielded 274 records. After accounting for duplication, 178 unique records remained. An initial collaborative calibration session was conducted among authors to establish shared understanding of the inclusion and exclusion criteria and to align judgment on borderline cases. The primary reviewer then screened the remaining records independently at the level of title and abstract. This process left 29 records eligible for full-text review. Full texts were then reviewed against both sets of criteria, resulting in a final corpus of 20 studies, as shown in Figure 1 and Table 2, qualified for synthesis. The complete screening and selection process is documented and visualized in the PRISMA flow chart (Figure 1).

2.5. Data extraction and coding

Data was extracted from each individual study using a structured extraction approach that captured the study ID, author and year, country of first author affiliation, design type, sample characteristics, AI construct, and psychological or meaning construct. A line-by-line thematic coding process was then conducted for each study, revealing and generating 63 unique coded findings across the 20 selected studies, see Table 3. These codes were grouped into 15 descriptive themes representing overlapping patterns across multiple studies, and further synthesized into 7 analytical themes to organize the highest-order insights that emerged from the evidence. A mechanism matrix was developed to map 28 identifiable psychological mechanisms across the studies, documenting the direction of each mechanism (risk, protective, or mixed) and its frequency across the data.

2.6. Quality appraisal

The methodological quality of each study was individually assessed using the Mixed Methods Appraisal Tool version 2018 (MMAT, Hong et al., 2018), a validated instrument specifically designed to accommodate the range and heterogeneity of research designs in mixed studies systematic reviews. The MMAT applies a unified five-criterion structure across qualitative, quantitative (RCTs, non-randomized, descriptive), and mixed-method designs, with each criterion scored as Yes (1), No (0), or Cannot Tell (0.5), with a maximum score of 5 (100%). Studies were placed in one of three categories based on scores: high quality (≥80%), moderate quality (60–79%), or low quality (<60%).

To guard against single-rater bias, authors independently applied the MMAT criteria to every included study and agreed upon each threshold for criteria, meeting weekly to compare ratings and discuss discrepancies until reaching consensus on a final score. Resolving rater disagreement through discussion to

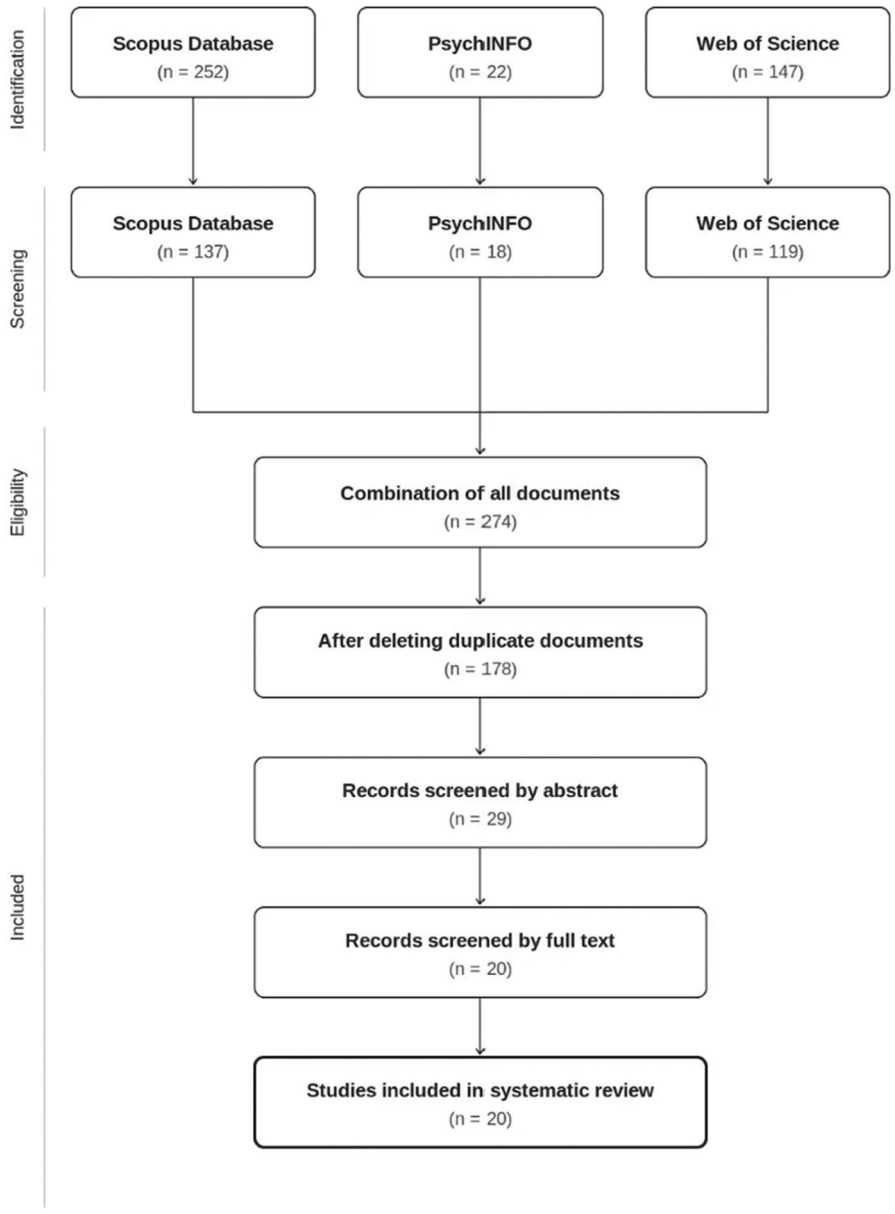


Figure 1. Prisma flow chart.
Note. 20 studies were included in the final analysis.

consensus is among the most commonly reported approaches in systematic review methodology (Belur et al., 2021).

Individual studies were not excluded based on quality scores. However, quality ratings informed the interpretive weight assigned to individual findings during the analysis, with higher-quality studies given greater weight in the development of sequential analytical themes. Eight studies were placed in the high-quality category (S02, S03, S06, S08, S09, S10, S17, S20), ten in the moderate category (S01, S04, S05, S07, S11, S13, S14, S15, S16, S19), and two in the low-quality category (S12, S18).

2.7. Synthesis approach

Given the range and heterogeneity of study designs, populations, data, outcome measures, and conceptual frameworks across the 20 included studies, a narrative synthesis was the approach implemented. Narrative synthesis is appropriate when the contexts of studies are too diverse in respect to design and outcome measurement to conclude a singular quantitative result, and when the goal of the review is to

Table 3. Characteristics of included studies ($N = 20$).

ID	Author (year)	Journal	Design	Sample	Country	AI construct	Key psychological construct	Key theory
S01	Alkhalifah et al. (2024)	Frontiers in Psychiatry	Cross-sectional survey	$n = 300$	Saudi Arabia	ChatGPT	Existential anxiety; Meaninglessness, Sense of Emptiness	Tillich, Frankl, TMT
S02	Békés et al. (2025)	Clinical Psychology & Psychotherapy	CFA validation	$n = 1,678$	USA	AI chatbot; avatar; teletherapy	Human connection deficit; therapy quality, Hedonic Motivation	UTAUT, SDT
S03	Chen et al. (2026)	BMC Psychology	Cross-sectional SEM	$n = 1,139$	China	ChatGPT; DeepSeek	MLQ presence and search, GenAI dependence, Self control	SDT, Path Dependence Theory
S04	Cihodaru-Ștefanache et al. (2026)	Interactive Learning Environments	Cross-sectional path analysis	$n = 235$	Romania	ChatGPT	Moral disengagement, Academic Esteem, Life satisfaction, Sense of control	TPB, Moral Disengagement (Bandura)
S05	Hou. (2025)	International Journal of Information and Systems Approac	Mixed methods and quasi-exp	$n = 1,120$	China	AI voice system (CTASM)	Self-efficacy, Rhythm of life, Mental Health	Bandura self-efficacy, Physchological counseling and psychotherapy
S06	Cui et al. (2026)	Current Psychology	Cross-sectional LMS-SEM	$n = 1,651$	China	ChatGPT; DeepSeek	Meaning in life, Loneliness; academic engagement, GenAI Attitude	Meaning-Making Theory, Broaden-and-Build
S07	Gribiea. (2026)	Educational Sciences	Qualitative thematic analysis	$n = 18$	Israel	ChatGPT, Canva, MORAI, Bing Image, Leonardo	Professional identity, Technological self-efficacy, Well being	TPACK, Bandura self-efficacy
S08	Jolly et al. (2026)	Journal of Business Ethics	Two experiments	$n = 532$	USA	ADM algorithms	Personal responsibility, moral disengagement, Unethical behavior	JCM, Moral Disengagement (Bandura)
S09	Hu. (2024)	Educational Technology & Society	Quasi-experimental RCT	$n = 70$	Taiwan	ChatGPT	Ethical self-efficacy, Ethical Decision-making confidence decisional conflicts	Values Clarification
S10	Kirshner & Lawson. (2026)	Internet Research	Three experiments	$n = 712$	USA/UK	Black-box AI services	Moral disengagement, personal accountability,	Moral Disengagement, Regulatory Focus
S11	P. Liu et al. (2025)	International Journal of Information Management	Mixed methods and quasi-exp	$n = 317$	China/Macao	AI assistants	AI anxiety, Psychological resilience, autonomy, competence, optimal functioning	TMT, humility
S12	De Miranda. (2025)	Topoi	Survey, cross-sectional quantitative design	$n = 288$	International website	AI chatbot (Philai); HITL	Philosophical health, belonging, purpose, agency	Philosophical health; Frankl; Aristotle
S13	Nakagomi et al. (2026)	Technology in Society	Cross-sectional nationwide	$n = 14,721$	Japan	Companion AI (Replika, Character.AI)	Purpose in life, meaning in Life, life satisfaction	Social support theory, Well-being
S14	Pang et al. (2025)	Behavioral Sciences	Cross-sectional SEM	$n = 569$	China	Social robots	Active involvement, user identification, Attitudinal loyalty	Perceived Value Theory; Social Identity Theory
S15	P. Liu et al. (2025)	Learning and Motivation	Cross-sectional LPA	$n = 1,247$	China	ChatGPT, Copilot	AI anxiety (4 Dimension), resilience	SDT

(*Continued*)

Table 3. Continued.

ID	Author (year)	Journal	Design	Sample	Country	AI construct	Key psychological construct	Key theory
S16	Song et al. (2026)	Technological Forecasting & Social Change	Cross-sectional SEM	$n = 312$	China	IDSS/IRSS	Social loafing, Intelligent decision support systems	Affordance Theory; MDT; CASA
S17	Sreejesh et al. (2025)	Journal of Retailing and Consumer Services	Five experiments	n = S1: 392, S2:379, S3:377, S4:380, S5:394	USA	Autonomous AI systems	Meaning of Cognitive Labor (MCL), autonomy threat, Perceived meaning loss	MMT; SDT; Need for Cognition
S18	Sung et al. (2025)	International Journal of AI in Education	Mixed methods case study	$n = 19$	USA	GPT-3 feedback system; HITL	Self-efficacy, belonging, burnout, Intrinsic motivation item	Expectancy-Value-Cost
S19	Teng. (2026)	The Asia-Pacific Education Researcher	Mixed effects modelling	$n = 152$	China	ChatGPT (via Poe)	Emotional engagement (EC, SoB, ME, ER)	SDT, Emotional Engagement
S20	Theoharakis & Mylonopoulos. (2026)	Psychology & Marketing	Two cross-sectional SEM studies	$n = 590$	USA	ChatGPT, Claude, Gemini	Epistemic autonomy, epistemic responsibility, SDT	MDT (Bandura), SDT, Epistemic Disengagement

Note. Studies ordered by study ID (S01–S20). ADM = Algorithmic Decision-Making. HITL = Human-in-the-Loop. IDSS = Intelligent Decision Support System. IRSS = Intelligent Resume Screening System. MCL = Meaning of Cognitive Labor. MLQ = Meaning in Life Questionnaire (Steger et al., 2006). NFC = Need for Cognition. SDT = Self-Determination Theory. TMT = Terror Management Theory. MDT = Moral Disengagement Theory. MMT = Meaning Maintenance Theory. UTAUT = Unified Theory of Acceptance and Use of Technology. CASA = Computers as Social Actors. JCM = Job Characteristics Model. EC = Emotional Connection. SoB = Sense of Belonging. ME = Motivation and Enthusiasm. E*R* = Emotional Reactions.

map interpretive patterns across a field rather than cumulative pooled effect sizes. The review developed through three stages addressing each research question. RQ1 was addressed through descriptive bibliometric analysis of publication trends, geographic distribution, publisher characteristics, and keyword frequency. RQ2 was addressed through methodological thematic analysis of 63 independently coded outcomes across descriptive and analytical theme domains. RQ3 was addressed through critical interpretation derived from MMAT appraisal scores, identification of current measurement and design gaps, and synthesis of implications for future research.

2.8. Software and analytical tools

Quantitative visualization and bibliometric analyses conducted in support of RQ1 were performed using R (R Core Team, 2026), an open-source statistical computing environment widely adopted in systematic review research for its reproducibility, flexibility, and capacity to produce publication-quality outputs. All data visualizations presented in this review were generated using the ggplot2 package (Wickham et al., 2014) which implements a layered grammar of graphics approach to data visualization. Supplementary visualization packages including dplyr (Wickham et al., 2014), ggrepel (Slowikowski, 2016), ggalluvial (Brunson, 2020), treemapify (Wilkins, 2017)and patchwork (Pedersen, 2019). were used to extend base visualization functionality for specific figure types. Qualitative coding, thematic synthesis, and mechanism matrix development, as the analytical procedures underpinning RQ2 and RQ3, were conducted in accordance with the Thomas and Harden (2008) thematic synthesis framework.

3. Findings

3.1. RQ1: Scope, volume, and disciplinary distribution

3.1.1. Volume and temporal trends

The systematic search identified 20 empirical and conceptual studies published between 2024 and 2026 that met inclusion criteria at the intersection of AI use, psychological mechanisms, and meaning in life. The temporal distribution shows (Figure 2), a recent developing literature emergence. Two studies were published in 2024, followed by eight in 2025 and ten in 2026 a tenfold increase across two years. This acceleration maps directly onto the post-ChatGPT research landscape following OpenAI's public release of ChatGPT in November 2022 (Thirunavukarasu et al., 2023), suggesting an approximate 18-to-24-month lag between technological disruption and peer-reviewed empirical response. This pattern should be read as suggestive, given that it rests on only three annual counts and a corpus of 20 studies. A partial year of 2026 indexing at the time of the search, with normal publication-pipeline variability, could account for some portion of the apparent acceleration. With that caveat in mind, the cumulative growth

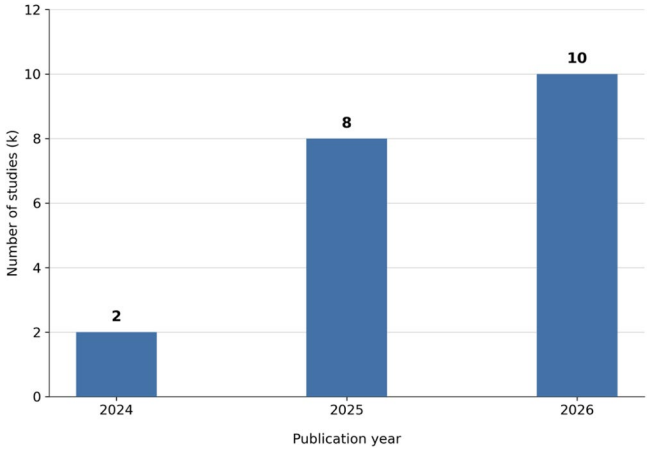


Figure 2. Annual publication output and cumulative growth.
Note. $N = 20$ studies published 2024–2026.

trajectory indicates that the field is expanding, and the present review represents a snapshot of an actively developing evidence base.

3.1.2. Geographic and cultural distribution

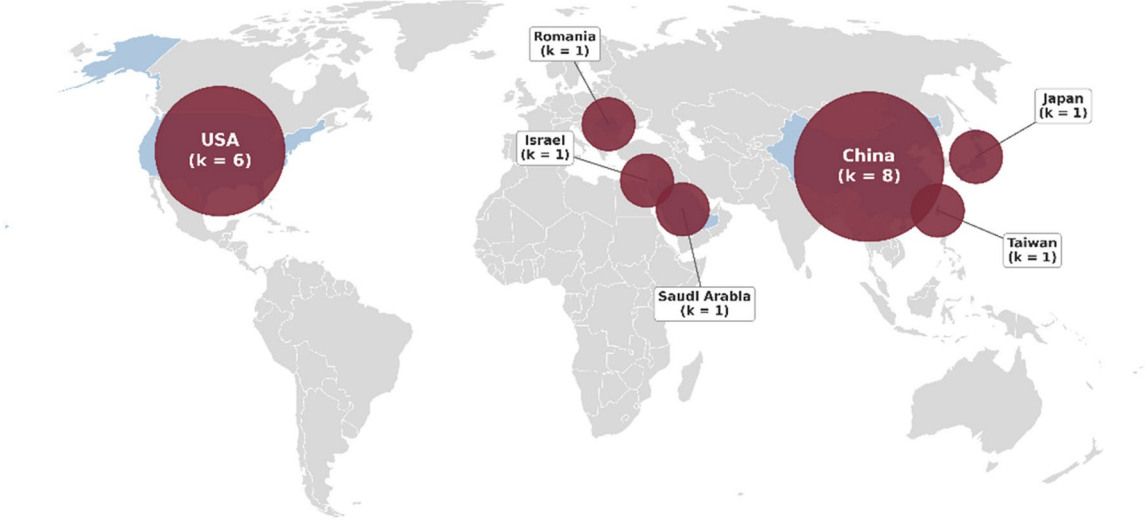
Figure 3 illustrates a pronounced geographic concentration in East Asia, which contributed 10 of 20 studies (50%), with China alone accounting for eight; Taiwan and Japan contributed one study each. The USA contributed six studies, one of which additionally recruited a UK sample. Europe and the Middle East collectively contributed three studies (Romania, Israel, and Saudi Arabia), and one study recruited an international online sample with no single country of origin. No studies were identified from Southeast Asia, South Asia, Sub-Saharan Africa, Latin America, or Oceania. This geographic imbalance carries implications for the interpretive scope of the findings synthesized in RQ2 and RQ3. The mechanisms identified derive predominantly from Confucian-influenced educational contexts characterized by high performance orientation (Tweed & Lehman, 2002) and collectivist peer norms (Hofstede et al., 2010) that differ markedly from Western higher education settings. Whether the dual pathway identified in RQ2 (between existential outsourcing and epistemic augmentation) operates equivalently across individualist and collectivist cultural contexts remains entirely untested.

3.1.3. Research design landscape

Figure 4 presents the methodological landscape of the included studies. The landscape is dominated by survey and structural equation modelling designs ($n = 10$, 50%), followed by experimental designs ($n = 7$, 35%), mixed methods ($n = 2$, 10%), and qualitative and conceptual studies ($n = 1$, 5% each). The dominance of Survey/SEM reflects the field's current emphasis on identifying associations between AI use and psychological outcomes across large samples. However, the near-complete absence of longitudinal designs, with no study tracking validated meaning in life outcomes from baseline through follow-up, is the methodological gap with the most direct consequences for the conclusions that can be drawn about causal pathways.

3.1.4. Sample characteristics and study quality

Figure 5 presents the joint distribution of sample size, MMAT quality score, publication year, and research design across all 20 studies. Sample sizes ranged from $n = 18$ (Gribiea, 2026) to $n = 14{,}721$ (Nakagomi



Note. k = 19 studies shown; one additional study (k = 1) recruited an international online sample and is not displayed geographically. One US study additionally recruited a UK sample (n = 160) in one of three experiments. Total N of studies = 20.

Figure 3. Global geographic distribution of included studies.
Note. East Asia dominates the corpus. North America, Europe, and the Middle East each contribute smaller proportions.

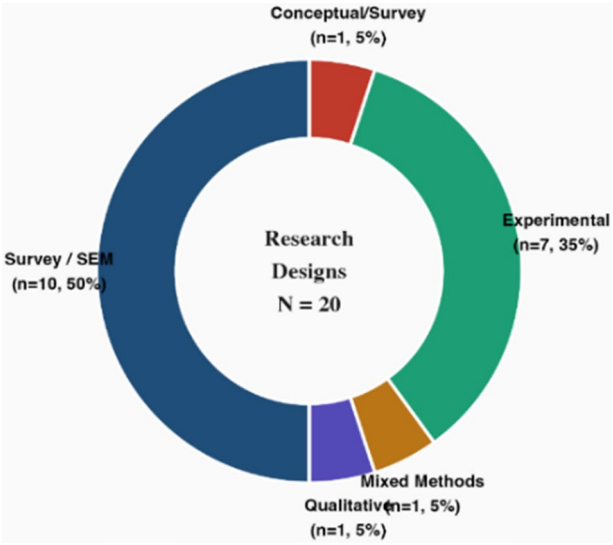


Figure 4. Research design distribution.
Note. Survey/SEM is the dominant design.

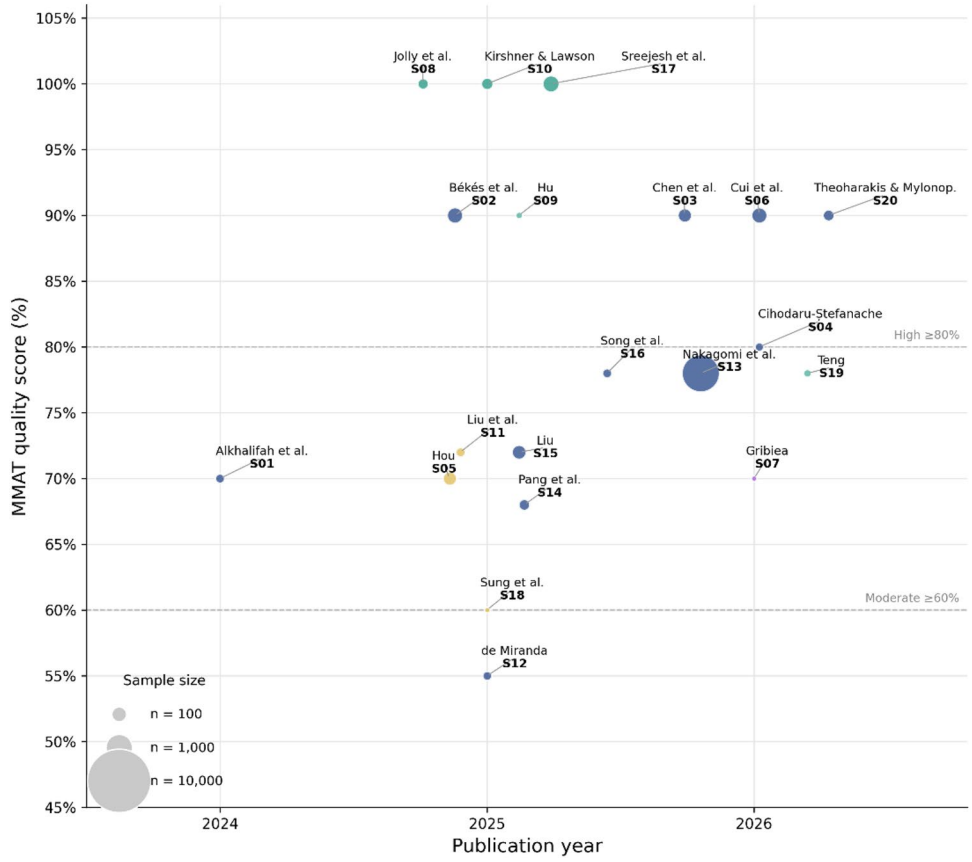


Figure 5. Study quality, sample size, and temporal distribution.
Note. $N = 20$ studies. S13 (Nakagomi et al., 2026) has the largest sample ($n = 14{,}721$).

et al., 2026), a more than 800-fold range reflecting the methodological heterogeneity of the corpus. University students constituted the dominant population ($n = 14$, 70%), followed by workers and consumers ($n = 4$, 20%) and general population samples ($n = 2$, 10%). MMAT quality scores ranged from 55% (De Miranda, 2025) to 100% (Jolly et al., 2026; Kirshner & Lawson, 2026; Sreejesh et al., 2025), with a corpus mean of 77.5%. Consistent with standard SLR practice in psychology (Hong et al., 2018), studies were not

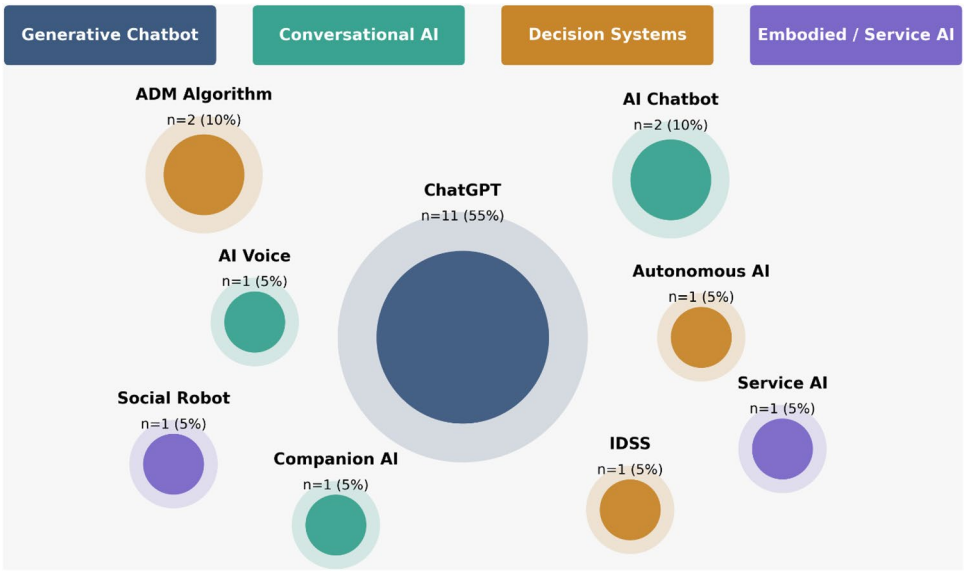


Figure 6. AI tools and systems studied across the corpus ($N = 20$ Studies).
Note. Each bubble represents one AI tool/system category.

excluded on the basis of quality scores, but quality ratings informed the interpretive weight assigned to individual findings in the thematic synthesis.

3.1.5. AI tools and theoretical frameworks

Figure 6 illustrates the distribution of AI tools and systems studied across the corpus. ChatGPT and its variants, including GPT-3, GPT-3.5, and DeepSeek, dominated the literature ($n = 11$, 55%), reflecting its status as the most widely adopted generative AI platform globally during the 2024–2026 publication window. Algorithmic decision-making systems were the second most studied category ($n = 2$, 10%), followed by companion AI, social robots, IDSS, autonomous AI systems, AI chatbots, AI voice systems, and service AI ($n = 1$ each, 5%). The theoretical landscape was correspondingly diverse. Self-Determination Theory (Ryan & Deci, 2023) was the most frequently invoked framework ($n = 8$ studies), followed by Moral Disengagement Theory (Bandura, 1999; $n = 6$), Meaning Maintenance Theory (Heine et al., 2006; $n = 3$), and Terror Management Theory (Pyszczynski et al., 1999; $n = 2$). Three studies introduced newly validated constructs, Meaning of Cognitive Labor (Sreejesh et al., 2025) AI Epistemic Disengagement, and AI Epistemic Substitution (Theoharakis & Mylonopoulos, 2026), that extend existing theoretical traditions into the AI domain for the first time.

3.2. RQ2: Psychological mechanisms linking GenAI use to meaning in life

3.2.1. Overview of the mechanism landscape

Across 20 included studies, 63 individual findings were coded, yielding 28 identifiable psychological mechanisms through which AI use appears to influence an individual's experience of meaning in life, see Table 4. Mechanisms spanned five broad categories: existential ($n = 10$), cognitive ($n = 9$), behavioral ($n = 6$), affective ($n = 2$), and mixed ($n = 1$). These mechanisms uncover a fundamental tension within the AI–meaning relationship: the same technology, used in different ways and under different conditions, produces divergent outcomes for meaning. To interpret this pattern, the present review draws on Schnell (2011) empirical finding that generativity is the single strongest predictor of meaningfulness across 26 identified sources of meaning in a representative adult sample ($\beta = 0.33$, $r = 0.67$, $p < 0.001$, $N = 603$). Generativity provides a theoretically coherent lens through which the identified mechanisms become interpretable: where AI use preserves the individual's generative role, meaning-related outcomes tend to be protected or enhanced; where it displaces that role, meaning-related outcomes tend to decline.

Table 4. Psychological mechanisms linking GenAI use to meaning in life.

No	Mechanism	Category	RQ2 direction	Study count ($N = 20$)
1	Meaninglessness / purpose deficit (AI-induced)	Existential	Risk	10 / 20
2	Existential outsourcing via GenAI	Existential	Risk	8 / 20
3	Mortality salience / GenAI-induced existential threat (TMT)	Existential	Risk	2 / 20
4	Human connection deficit or emotional authenticity gap	Existential	Risk	6 / 20
5	Loneliness to meaning deficit to AI avoidance or over-reliance	Existential	Risk	3 / 20
6	SDT need frustration (autonomy, competence, and relatedness) under AI	Existential	Risk	4 / 20
7	Philosophical health gap, purpose-implementation deficit	Existential	Risk	1 / 20
8*	Meaning of Cognitive Labor (MCL), cognitive engagement as source of personal meaning	Existential	Mixed	2 / 20
9	Companion AI to eudaimonic well-being (purpose in life)	Existential	Protective	3 / 20
10	AI PD / structured learning restores professional meaning	Existential	Protective	6 / 20
11	AI dependence disrupts self-control to meaning pathway	Cognitive	Risk	2 / 20
12	Moral disengagement neutralizes ethical meaning	Cognitive	Risk	5 / 20
13	Displacement or diffusion of responsibility (GenAI removes agency)	Cognitive	Risk	4 / 20
14*	AI Epistemic Disengagement (ED), justifying cognitive delegation to AI	Cognitive	Mixed	1 / 20
15*	AI Epistemic Substitution, abdication of epistemic responsibility	Cognitive	Risk	1 / 20
16	AI Epistemic Augmentation, preserving epistemic responsibility	Cognitive	Protective	2 / 20
17	AI competence perception to engagement and meaning	Cognitive	Protective	20 / 20
18	Prevention-focused goals moderate competitive GenAI ethics	Cognitive	Protective	1 / 20
19	Values clarification via AI to meaning coherence	Cognitive	Protective	2 / 20
20	Autonomy-preserving AI design to meaning protection	Behavioral	Protective	12 / 20
21	Active / academic engagement protects meaning (with conditionality)	Behavioral	Mixed	10 / 20
22	Resilience as SDT need-restorative buffer against GenAI anxiety	Behavioral	Protective	1 / 20
23	Cognitive collaboration framing restores epistemic participation	Behavioral	Protective	3 / 20
24*	Prompt engineering skill as epistemic meaning-protection capability	Behavioral	Protective	1 / 20
25	Self-efficacy sustains meaning and well-being	Behavioral	Protective	4 / 20
26	Affective AI feedback to belonging and self-efficacy via classroom climate	Affective	Protective	2 / 20
27	AI emotional authenticity gap, structural limitation for deep meaning formation	Affective	Risk	3 / 20
28	AI as meaning-restoration tool (design-contingent)	Mixed	Mixed	20 / 20

Note. RQ2 Direction: Risk as mechanism erodes meaning in life; Protective as mechanism supports or restores meaning in life; Mixed = context-dependent; * = newly validated construct absent from prior meaning in life literature.

3.2.2. The dual pathway and the risk of existential outsourcing

A pattern emerging across multiple studies suggests that AI does not hold a fixed relationship with meaning in life. Two pathways appear to operate depending on the nature of engagement. The determining factor across the evidence base was the degree to which the individual retained cognitive agency in the interaction. Passive, dependent, and substitutive use was associated with reduced meaning-related outcomes across several studies (Chen et al., 2026; Sreejesh et al., 2025; Theoharakis & Mylonopoulos, 2026). Engaged, autonomous, and augmentative use was associated with more positive meaning-related outcomes (Hu, 2024; Teng, 2026; Theoharakis & Mylonopoulos, 2026).

A convergent pattern across eight studies suggests that the primary risk mechanism operating within the erosion pathway may be characterized as existential outsourcing. This construct encompasses several operationalized mechanisms identified across the literature: dependence moderating and weakening the protective pathway from self-control to meaning in life (Chen et al., 2026), moral disengagement through responsibility displacement in workplace and competitive GenAI contexts (Jolly et al., 2026; Kirshner & Lawson, 2026; Song et al., 2026; Sreejesh et al., 2025; Theoharakis & Mylonopoulos, 2026), the displacement of personally meaningful cognitive labor to GenAI in consumer decision-making (Sreejesh et al., 2025), and epistemic substitution (Theoharakis & Mylonopoulos, 2026). Notably, two mechanisms within this cluster, Meaning of Cognitive Labor (Sreejesh et al., 2025) and AI Epistemic Substitution (Theoharakis & Mylonopoulos, 2026), represent validated constructs that have not previously appeared in the meaning in life literature.

3.2.3. Meaning as a conditional resource and design as a potential lever

A second pattern across the evidence challenges the assumption that a prior sense of meaning in life automatically buffers against AI's potentially erosive effects. Several studies suggest instead that meaning may function as a conditional resource, protective only under specific circumstances including low AI dependence, moderate social connectedness, maintained epistemic responsibility, and sufficient psychological resilience (Chen et al., 2026; Cui et al., 2026; P. Liu et al., 2025; Nakagomi et al., 2026; Theoharakis & Mylonopoulos, 2026). This conditionality is illustrated by what Cui et al. (2026) describe as an

engagement paradox, in which highly academically engaged students reported greater meaninglessness under conditions of loneliness, an unexpected finding suggesting that high investment in output without authentic social connection may amplify meaning deficits. Additionally, Nakagomi et al. (2026) identified a U-shaped moderation pattern in a nationwide sample ($N = 14{,}721$) in which the psychological benefits of AI companionship were most pronounced among individuals with moderate levels of friend-based social connection.

With respect to potential intervention targets, 14 of the 20 included studies identified AI design characteristics as associated with meaning-related outcomes. Autonomy-preserving, epistemically humble, and emotionally attuned AI characteristics were more consistently associated with protected or enhanced meaning outcomes (De Miranda, 2025; Hu, 2024; P. Liu et al., 2025; Pang et al., 2025; Theoharakis & Mylonopoulos, 2026), while efficiency-maximizing and controlling AI characteristics were more associated with erosion (Jolly et al., 2026; Song et al., 2026).

3.2.4. Restoration through cognitive and epistemic preservation

Four studies converge on a pattern suggesting that AI use may actively support meaning under specific conditions (Sreejesh et al., 2025; Sung et al., 2025; Teng, 2026; Theoharakis & Mylonopoulos, 2026). Across these studies, a common structural feature was that AI was positioned to preserve and strengthen the human cognitive role. Four specific orientations were associated with more positive meaning-related outcomes: framing AI as a thinking partner (Sreejesh et al., 2025) adopting a humble, deferential AI role that maintained user judgment (Sung et al., 2025); deploying AI as an emotionally warm facilitator that strengthened human connection (Teng, 2026) and implementing augmentation-oriented interfaces that encouraged critical engagement with AI outputs (Theoharakis & Mylonopoulos, 2026). Prompt engineering skill emerged as the sharpest individual-level differentiator between augmentative and substitutive patterns ($\eta^2 = 0.20$ for augmentation vs. $\eta^2 = 0.03$ for substitution), suggesting it may represent a trainable protective competency.

3.2.5. The critical gap

Despite 63 coded findings and 28 identified mechanisms, no single included study tested a complete pathway linking AI use through specified psychological mechanisms to a validated meaning in life outcome measure, such as the Meaning in Life Questionnaire (Steger et al., 2006) or the Sources of Meaning and Meaning in Life Questionnaire (Damásio et al., 2013). Individual components of such a chain have been confirmed across multiple studies, AI dependence predicting reduced meaning (Chen et al., 2026), epistemic substitution associated with erosion of evaluative self-concept (Theoharakis & Mylonopoulos, 2026), and autonomy-preserving design associated with meaning protection (P. Liu et al., 2025; Pang et al., 2025), but these components have not been integrated within a unified empirical model. This represents a specific and meaningful gap that the present systematic review maps and formalizes.

This gap constrains the evidence base in three ways. First, causal ordering remains unresolved: the predominance of cross-sectional designs (Chen et al., 2026; Cui et al., 2026; Song et al., 2026), cannot distinguish whether substitutive use erodes meaning, whether prior meaning deficits dispose individuals toward dependent use, or whether these processes are reciprocal. Second, meaning was frequently operationalized through proximal constructs such as loneliness, engagement, or life satisfaction (Cui et al., 2026; Nakagomi et al., 2026) and no study established measurement invariance, a prerequisite for valid group and cross-cultural comparison (Fischer & Karl, 2019). Third, with half of the studies conducted in East Asia and none from the Global South, whether these pathways operate equivalently across individualist and collectivist contexts (Hofstede et al., 2010) remains untested. Cross-national values datasets, subject to demonstrated invariance, offer one immediate avenue for such tests.

3.3. RQ3: AI as risk factor or protective tool for meaning in life

3.3.1. The balance of evidence

The evidence across 20 included studies does not support framing AI as inherently a risk factor for meaning deficits or inherently a protective tool for meaning restoration. The distribution is approximately

balanced: across 63 coded findings, 28 identified mechanisms, and 15 descriptive themes, risk and protective pathways were represented in roughly equal proportions, with 10 mechanisms classified as risk-producing, 12 as protective, and 6 as mixed or context-dependent. What determined the outcome was the conditions of implementation, the population using it, the design philosophy governing it, and whether human generativity and agency were preserved or displaced in the interaction. When individuals remained in the driver's seat, using AI as a cognitive scaffold, a challenger of thinking, or a tool of efficiency in service of learning, outcomes were consistently more positive. When individuals offloaded cognitive responsibility and agency to AI, outcomes consistently declined. This conclusion aligns with Schnell (2011) empirical finding that generativity is the single strongest predictor of meaningfulness ($\beta = 0.33$, $r = 0.67$, $p < 0.001$). Table 5 summarizes the risk and protective evidence by pathway, study count, and key findings.

3.3.2. Critical empirical and conceptual gaps

Despite a reasonable quality distribution, with three studies achieving 100% MMAT scores (Jolly et al., 2026; Kirshner & Lawson, 2026; Sreejesh et al., 2025) and a corpus mean of 77.5%, several structural limitations constrain the conclusions that can be drawn. The most significant is the near-universal absence of validated meaning in life measurement. Only two studies used the MLQ as a primary outcome measure (Chen et al., 2026; Cui et al., 2026), and none used SoMe. The remainder relied on a wide array of theoretically adjacent proxies rather than direct operationalizations of meaning: moral disengagement (Cihodaru-Ștefanache et al., 2026; Jolly et al., 2026; Kirshner & Lawson, 2026), self-efficacy (Hou, 2025; Sung et al., 2025), AI anxiety (P. Liu et al., 2025), social loafing (Song et al., 2026), and emotional engagement (Teng, 2026), among others. Even studies explicitly framed around meaning-adjacent constructs, such as purpose in life (Nakagomi et al., 2026) and philosophical health (De Miranda, 2025), employed instruments distinct from the MLQ or SoMe, precluding direct comparison of effect sizes across studies. This proliferation of adjacent-but-distinct outcome variables means the corpus cannot yet support a quantitative meta-analysis of AI's effect on meaning in life specifically. The synthesis offered here is

Table 5. Summary of risk and protective evidence for RQ3 ($N = 20$ studies).

Pathway	Direction	Key mechanism	Studies (n)	Strongest evidence
Existential outsourcing	Risk	Delegation of meaning-construction to GenAI via dependence, moral disengagement, MCL displacement, epistemic substitution	8	(Chen et al., 2026; Sreejesh et al., 2025; Theoharakis & Mylonopoulos, 2026)
Human connection/ emotional authenticity deficit	Risk	GenAI structurally unable to replicate genuine empathy; emotional reactions non-significant (p = 0.835)	6	(Békés et al., 2025; Nakagomi et al., 2026; Teng, 2026)
SDT need frustration	Risk	Simultaneous frustration of autonomy, competence, and relatedness; Hypervigilant profile (5.7%) = triple failure	4	(Jolly et al., 2026; J. Liu et al., 2025)
Loneliness to meaning deficit	Risk	Loneliness erodes meaning ($\beta = -0.24$); high engagement paradoxically amplifies deficit under loneliness	3	(Cui et al., 2026; Nakagomi et al., 2026)
Autonomy-preserving AI design	Protective	Autonomy-affording design produces causally opposite outcomes to autonomy-restricting design	12	(De Miranda, 2025; Jolly et al., 2026; Theoharakis & Mylonopoulos, 2026)
Epistemic augmentation and prompting skill	Protective	Augmenters maintain evaluative authority; prompt engineering $\eta^2 = 0.20$ (sharpest individual-level differentiator)	2	(Theoharakis & Mylonopoulos, 2026)
Cognitive collaboration framing	Protective	Framing GenAI as thinking partner restores meaning for high-MCL/NFC consumers	3	(Sreejesh et al., 2025; Sung et al., 2025; Teng, 2026)
Companion AI to purpose in life	Protective	Purpose in life $\beta = 0.46$ (p = 0.002); U-shaped moderation; most protective for moderately connected, highly lonely individuals	3	(Nakagomi et al., 2026; Pang et al., 2025)
Conditionality (meaning as conditional buffer)	Mixed	Meaning protective only under low dependence, moderate social connectedness, maintained epistemic responsibility, sufficient resilience	10	(Cui et al., 2026; P. Liu et al., 2025; Nakagomi et al., 2026)

Note. Study count reflects studies providing primary evidence for each pathway. Mechanism categories follow Thomas and Harden (2008) thematic synthesis. MLQ = Meaning in Life Questionnaire (Steger et al., 2006); SoMe = Sources of Meaning and Meaning in Life Questionnaire (Damásio et al., 2013).

necessarily qualitative and thematic instead of a pooled estimate, a limitation stemming from the evidence base itself, not from the method chosen for this review.

A second structural limitation is the dominance of cross-sectional designs. 18 of 20 included studies employed cross-sectional or single-timepoint designs capable of identifying associations but unable to establish whether AI use produces changes in meaning over time, or whether individuals with different prior levels of meaning simply engage with AI differently to begin with. Only three studies employed experimental designs capable of suggesting directionality (Jolly et al., 2026; Kirshner & Lawson, 2026; Sreejesh et al., 2025), yet none of these three tracked a validated meaning in life outcome. Instead, each examined proximal cognitive or moral constructs under short-term, single-session laboratory exposure, evidence of immediate psychological reactivity, not sustained meaning change. No study combined experimental manipulation of AI use characteristics with longitudinal, validated meaning in life measurement, the design that would be required to establish both directionality and durability. The field currently possesses many snapshots but no film.

A third gap is theoretical and conceptual. Eight distinct frameworks were invoked across the 20 studies, Self-Determination Theory, Moral Disengagement Theory, Meaning Maintenance Theory, and Terror Management Theory, alongside three newly introduced constructs developed specifically for the AI context: Meaning of Cognitive Labor, AI Epistemic Disengagement, and AI Epistemic Substitution. Each framework shows a piece of the picture, but none was designed with the others in mind, and no study has tested more than one framework against the same dataset to determine which best accounts for the observed variance in meaning-related outcomes. The result is a body of evidence that is theoretically rich but theoretically uncoordinated: existential outsourcing, epistemic substitution, cognitive labor delegation, and Meaning of Cognitive Labor describe overlapping phenomena using different vocabularies, different measurement approaches, and, in places, incompatible assumptions about directionality. Until the field converges on a shared definitional and measurement framework, cumulative knowledge will continue to accrue in parallel, adjacent silos instead of forming a single coherent evidence base.

3.3.3. The study the field needs next

The gaps identified above converge on a clear recommendation for future research. What is needed is a longitudinal study measuring the effect of AI use on meaning in life outcomes using a validated instrument, such as the MLQ (Steger et al., 2006) or SoMe (Damásio et al., 2013), administered at baseline and across multiple follow-up points, with mechanism variables measured at each wave. The ideal design would involve two conditions: a control condition using standard AI tools such as ChatGPT, Claude, or Grok as participants already engage with them, and an intervention condition using a purpose-designed AI system oriented around preserving and strengthening human generativity. Participants would engage across multiple life domains, academic, professional, relational, and community, to capture meaning outcomes across the breadth of contexts in which generativity operates. Sample composition should be demographically and geographically representative, deliberately correcting for the East Asian student concentration that characterizes the current literature. Such a study would not only test the complete causal chain that no existing study has yet examined, but it would also provide the first direct empirical test of whether generativity-preserving AI design produces meaningfully different outcomes for human psychological flourishing than standard efficiency-oriented AI.

4. Discussion

The central idea in this review is simple: does generative artificial intelligence help or harm an individual's experience of meaning in life? After synthesizing 20 peer-reviewed studies, 63 coded findings, and 28 identified psychological mechanisms, the answer is neither. AI is not inherently a risk factor for meaning deficits, nor inherently a tool for meaning restoration. It is, at its core, a mirror, a mirror that reflects back the orientation of the individual using it. Where that orientation is generative, autonomous, and engaged, the mirror amplifies meaning. Where it is passive, dependent, and substitutive, the mirror empties it. AI does not determine the outcome but the individual's orientation does.

This derived outcome is not reduced to an empirical observation emerging from the present evidence base but is consistent with one of the most enduring propositions in the psychology of meaning, that meaning in life has never been something that can be delivered, optimized, or outsourced. Frankl (2006) proposed that the will to meaning is the primary orientation of human psychological life, not a secondary drive, trivial addition or a luxury of comfortable circumstances, but the navigational force through which individuals sustain coherence in the face of uncertainty and suffering. Peterson (1999) extended this architecture, framing meaning as the structural system through which humans orient themselves between order and chaos, as a further abstraction of this idea. What the present findings demonstrate is that AI, when used in substitutivity, does not only reduce meaning as one variable among many. It interferes with the very orientating function that Frankl (2006) and Peterson (1999) identified as foundational to psychological functioning.

Martela and Steger (2016) tripartite framework provides the most precise theoretical lens through which to understand how this interference operates. Their distinction between coherence: the sense that existence is comprehensible, purpose: the possession of valued goals and directions, and significance: the felt sense that one's life inherently matters, maps directly onto the erosion mechanisms identified across the evidence base. Substitutive AI use threatens coherence by removing the individual from the authorship of their own understanding. It threatens purpose by displacing the goal-directed generative activity that Schnell (2011) empirically identified as the single strongest predictor of meaningfulness across 26 sources of meaning. And it threatens significance by producing outputs that no longer feel genuinely one's own, work that is efficient and optimal, but not meaningful, because meaning requires ownership, agency, and autonomy. The implication is significant that existential outsourcing does not erode meaning gradually along a single dimension. It undermines the entire architecture of meaning simultaneously.

On the contrary, the evidence also tells a restoration story. When AI preserves the individual's generative role, functioning as a thinking partner, meaning outcomes are protected or enhanced. Critically, the orientation an individual brings to AI interaction appears to be a measurable and relatively stable psychological characteristic Ibrahim et al. (2025) demonstrated through cross-cultural validation of the AI Mindset Scale that individuals differ systematically in whether they approach AI as a partner in growth, believing it enhances their abilities, or as a threat to competence, fearing it will deskill them. This distinction maps directly onto the augmenter-substitute pattern identified in the present review, suggesting that mindset toward AI may function as a meaningful individual-level moderator of the dual pathway. Van Tilburg et al. (2013), further demonstrated across six studies that boredom, a state of low stimulation and depleted meaning, produces a search for meaning that in turn drives nostalgia as a restorative mechanism. Individuals reaching for meaning instinctively reach toward experiences that felt authentically theirs. Applied to the present findings, this raises a theoretically important proposition: the cognitive efficiency orientation that characterizes substitutive AI use, in which epistemic substitution removes the individual from the friction of genuine pondering, may paradoxically prevent the very conditions under which meaning-seeking is activated. A perpetually optimized, AI-assisted cognitive environment may never produce that discomfort. The individual is always busy, always efficient, always outputting, but never still enough, never uncertain enough, never bored enough to ask what any of it means. This idea has not yet been tested empirically in AI context and represents a theoretically grounded direction for future investigation.

These theoretical implications carry a specific weight for higher education, given that university students constituted the dominant population sampled across the reviewed corpus ($n = 14$, 70%). Emerging research on AI in the classroom lends support to the augmenter-substitute distinction identified in the present review, while also cautioning that the relationship between AI use and student outcomes is rarely determined by access or frequency alone. Saleh and ElSayary (2026), for example, describe a pattern of utility-driven adoption among undergraduates, in which frequency of AI use predicted perceived learning benefit more strongly than either prior familiarity or formal training, yet a substantial minority of the same students reported reduced critical engagement and overreliance. This offers a possible mechanism for this divergence, demonstrating that cognitive offloading through digital tools benefits critical thinking, task persistence, and learning depth only insofar as it strengthens students' cognitive self-efficacy. When offloading undermines confidence in independent thinking, the same tool that

supports one student's learning empties another's. Gerlich (2025) reports a converging pattern, linking habitual reliance on AI tools to diminished critical thinking, especially among younger users, an association that echoes Risko and Gilbert (2016) original account of cognitive offloading as a double-edged extension of memory and reasoning that can free cognitive resources or erode them depending on how it is deployed.

This literature suggests that the quality of student-AI interaction is the operative variable, a conclusion that maps directly onto the present review's central claim that AI functions as a mirror for the individual's orientation. For education to remain a meaningful experience in the GenAI era, the evidence points toward specific recommendations. Institutions might prioritize AI literacy instruction that treats critical evaluation of AI output as a core competency (Saleh & ElSayary, 2026), design assignments that require students to justify, extend, or challenge AI-generated content so that generativity remains with the learner (Darvishi et al., 2024) and calibrate feedback and assessment practices to increase students' confidence in their own reasoning, since it is this self-efficacy, more than access to AI itself, that determines whether offloading supports or displaces meaningful learning (J. Wang, 2026). These recommendations are illustrative, as a full accounting of AI's role in pedagogy extends beyond the scope of a review centered on meaning in life. Even so, the convergence between the education-specific literature and the mechanisms identified here supports that the augmenter-substitute distinction is not confined to therapeutic or existential contexts but extends into the classrooms where most of the present evidence was generated.

These findings tell a story about enduring human need to be the author of one's own meaning, to generate, to contribute, to navigate, and about what happens when a technology, however powerful, is allowed to assume that role. The question for psychology, for design, and for society is not whether AI will shape human meaning in the years ahead. It will. The question is in what way can we provide the proper coherence, understanding and utility of AI to enhance and invigorate the generativity capacity of meaning within the individual human being.

5. Conclusion

This study extends the existing corpus of knowledge in three ways. It establishes for the first time the precise scope, volume, and thematic landscape of the AI and meaning in life literature, documenting a tenfold increase in publication output between 2024 and 2026 and identifying East Asia as the dominant contributor to an otherwise geographically narrow evidence base. It provides the first systematic synthesis of the 28 psychological mechanisms through which AI use influences meaning-related outcomes, organized across existential, cognitive, behavioral, and affective categories and anchored theoretically in Schnell's (2011) generativity framework. And it maps, with greater specificity than any prior review, the methodological gaps that must be addressed before the field can move from pattern recognition to causal understanding, most critically, the absence of longitudinal designs, the near-universal reliance on proxy, and the untested status of the complete AI to mechanism to meaning in life causal chain.

These contributions carry implications at three levels. For researchers, the 28-mechanism framework and the dual pathway model provide a theoretically grounded architecture for designing the next generation of empirical studies, especially longitudinal and cross-cultural designs that move beyond the cross-sectional snapshot that currently dominates the literature. For practitioners, such as clinicians, organizational psychologists, and educators, the findings establish that the psychological consequences of AI use are design-contingent and modifiable, and that prompt engineering skill and autonomy-preserving design represent actionable protective targets. For policymakers and platform designers, the evidence supports investment in AI literacy frameworks that treat epistemic agency and generativity preservation as design requirements.

The study the field now needs is clear: a cross-cultural, generativity-oriented intervention study measuring AI use against a validated meaning in life instrument from baseline through follow-up. That study does not yet exist. The present review has assembled the theoretical architecture to make it possible. It is through rigorous scholarly synthesis of this kind that we can hope to inform the design of AI systems,

guide psychological practice, and shape the research agenda, especially contributing to a future in which the unprecedented capabilities of AI are developed in service of the human experience of a meaningful life.

Author contributions

CRediT: **Gabriel Kronbach**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Angga Hidayat**: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Mega Wulandari**: Investigation, Validation, Writing – review & editing.

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Not applicable. This article does not contain any studies with human participants or animals performed by any of the authors. All analyzed data are derived from previously published peer-reviewed studies cited in the reference list.

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Data availability statement

The datasets generated and analyzed during this systematic review are available from the corresponding author upon reasonable request. No new primary data were collected.

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