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Human–AI Collaboration and Value Co-Creation in Digital Ecosystems: A Theory-Driven Systematic Review and Research Agenda

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Abstract

Purpose: This review synthesizes evidence from recent studies of human–AI collaboration in service and digital ecosystems to build and test a multi-level conceptual framework. **Design/methodology/approach:** Thirteen studies (Tier A) from 2024 to 2026 were analyzed in full text and compared with 25 qualitative and mixed-methods studies (Tier B). In total, 38 service and digital ecosystem studies were analyzed within this review. Service-Dominant (S-D) Logic and the Affect–Behavior–Cognition (ABC) model was used as the underlying theoretical framework. Narrative and thematic analysis were employed to synthesize the results from the included studies. **Findings:** Transparency, process control and outcome control have significant effects on employees in terms of cognitive and behavioral effects, while system-initiated engagement has little effect. Human–AI interaction does not, on average, perform better than the best human in each task ($g = -0.23$, $p < .001$), but does perform better than a single human in a variety of tasks ($g = 0.64$). Value is created through the integration of systems and not through technology itself. User experience, digital maturity, interoperable IT, and AI-induced technostress condition value realization. **Originality/value:** The study provides a three-stage framework, seven testable hypotheses, seven gaps in current research and an operational measurement for value creation at the employee level and for firm- and network-level value co-creation.

Keywords: Value Co-Creation, Human–AI Collaboration, Service-Dominant Logic, Technostress, Digital Maturity, Intelligence Augmentation, Systematic Review

Introduction

Value is created in modern service systems in a new and fundamentally different way. An exchange between two human beings is no longer sufficient. Today value is created in complex ecosystems consisting of many different actors who communicate via digital service platforms. Instead of being used as a mere tool, in these systems artificial intelligence (AI) is the active co-creator of value (Barile et al. 2024). Seen through the lens of Service-Dominant (S-D) Logic, value is not embedded in goods and/or services and is therefore created when actors with different resources integrate these resources (Vargo & Lusch 2004, 2008). As an operant resource AI acts upon other resources, learning from the resulting interactions and even starts new service-exchange relationships (Huang & Rust 2018; Lusch & Nambisan 2015). The analytical lens therefore must switch from a dyadic analysis of workplace interactions to the study of ecosystems that are coordinated via digital service platforms (Saxena et al. 2024).

Human Resource Management (HRM) and organizational perspective, considerable potential for both positive and negative change is currently being experienced through the introduction of AI. AI is being used in the recruitment process, performance measurement, learning and development and work force planning, to name but a few areas. Human Resource Managers perceive the potential of AI for automation, insight generation and employee and customer interaction (Davenport & Ronanki, 2018). A PRISMA-based review of 141 peer-reviewed articles on the implementation and effects of AI in work organizations found that the highest effects were reported when AI was used to augment human expertise (Benabou & Touhami, 2025). However, new forms of restriction, of recording and rating employees are introduced through algorithmic work systems, and can take away workers' autonomy (Kellogg et al., 2020). There are also several risks of improper implementation of AI, such as causing technostress, algorithmic bias and violating employees' and organizations' privacy (Gupta et al., 2024; Sapkota et al., 2025). The data also paints a different picture to that presented by management. A preregistered meta-analysis of 106 studies on human-AI collaboration was conducted by Vaccaro et al. (2024). While human-AI combinations outperformed humans working without AI ($g = 0.64$), on average, they performed worse than the best single human or AI (Hedges' $g = -0.23$, $p < .001$). The existence of large individual productivity gains for professionals using generative AI in writing tasks (Noy & Zhang, 2023) does not necessarily mean that the same gains will translate to synergy for that professional. Synergy is not inherent and depends on a host of factors including task, reliance behavior and design (Plé & Cáceres, 2010). Thus, instead of whether to use AI, the main question for both researchers and managers is under what conditions will human-AI collaboration add value as opposed to destroying value.

Three shortcomings characterize current research: (1) Fragmentation at levels of employees (trust, stress, and adherence), firms (capability building), and networks (platform coopetition): Few studies link levels of analysis; (2) A technology-contrived view of synergy that assumes that the adoption of information systems leads to synergy without modeling potential miscalibrations of users' reliance on information systems (Parasuraman & Riley, 1997; Lee & See, 2004); (3) Research of boundary conditions for the effects of information systems in isolation (e.g., user experience, digital maturity, interoperable physical and digital infrastructures, and technostress).

The new review aims at the intersection of several prior reviews. First, Benabou and Touhami (2025) reviewed applications of AI in HRM functions, whereas Sapkota et al. (2025) provided a review of stressors caused by AI systems. A structured review of the literature on value co-creation was provided by Saxena et al. (2024), and the review by Vaccaro et al. (2024) contained a meta-analytic test of synergy, as well as an examination of the organizational conditions that enhance the value created by human–AI combinations. Divergent levels and disciplines of HRM reviews were typically not linked to the research on S-D Logic, whereas the reviews on stress typically failed to link to the higher-level studies on firm value. In summary, whereas prior reviews focused on partial parts of the new review, it aims at integrating these to develop falsifiable hypotheses (Paul & Criado, 2020).

In this paper, we develop a theory-driven systematic review based on S-D Logic linked to the Affect–Behavior–Cognition (ABC) model. We highlight the function of Intelligence Augmentation as a bridging mechanism between the cognition of individual people and the results of the company. Four Research Objectives (ROs) guide this study.

RO1: To systematically and structurally review AI design features as well as (combinations of) resource-integration mechanisms aiming at value co-creation.
RO2: To summarize available empirical evidence on the affective, behavioral and cognitive (ABC) outcomes of employees involved in human–AI co-action.
RO3: What are the critical boundary conditions, failure modes and non-synergy risks within and across different service ecosystems?
RO4: A conceptual framework, testable hypotheses and adequate measurement for the quantitative study.

The paper makes four main contributions. First, it presents a transparent, tiered review of 38 studies published between 2024 and 2026, all of which were peer-reviewed. Secondly, it attempts to reconcile two apparently contradictory findings: design effects are positive at the employee level, while average synergy is negative at the task level. Thirdly, the paper sets out a three-stage framework and specifies seven hypotheses that link and test the micro-level findings of this review at the level of the firm and the network. Finally, the seven research gaps that are identified in this review are translated into a set of operational measurements and design questions that are elaborated in the remaining sections of the paper. The theoretical background to the review is presented in Section 2, the review protocol in Section 3, the synthesis of findings in Section 4, the framework and hypotheses in Section 5, the gaps in Section 6, the methodological measurements and design in Section 7, and conclusions in Sections 8 and 9.

Theoretical Background

Service-Dominant Logic and AI as an Operant Resource

S-D Logic describes the service frontier by stating that to create value, service (the application of competences for the benefit of another party) is the basic form of exchange. The value created by service is always co-created by various parties including the one who benefits from the service (Vargo & Lusch, 2008). Later axioms add that all social and economic actors are resource integrators, that value is uniquely and phenomenologically determined by the beneficiary, and that co-creation is coordinated by institutions and by the institutional arrangements (Vargo & Lusch, 2016). As far as resources are concerned, they are either

operant resources (i.e. knowledge, skills and interpretive capabilities that are used to act on other resources) or operand resources (i.e. physical means, data etc. that are acted upon by other resources (Barile et al., 2024).

Increasingly, AI technologies function as operant resources. They learn, they adapt and they initiate service provision within ecosystems supported by a variety of platforms. In IIoT (Industrial Internet of Things) architectures for instance, the use of AI-based operant resources is becoming more common (da Silva & Cardoso, 2024). Huang and Rust (2018) distinguish between four types of intelligence: mechanical, analytical, intuitive and empathetic. The authors claim that step by step, AI can substitute for humans. The division of labor between humans and AI-operant resources thus is dynamic. Service ecosystems are characterized by a high degree of resource liquefaction, density and platform-supported integration (Lusch & Nambisan, 2015). Co-creation of value with the help of technology depends on the way in which actors use technological resources for co-creation (Breidbach & Maglio, 2016). When, if the integration of actors fails or if they are not aligned, AI-operant resources in those circumstances wrongly allocate efforts and thus co-destroy value.

Value Co-Creation and Co-Destruction

Prahalad and Ramaswamy (2004) earlier defined co-creation in terms of joint experiences between a firm and its customers. The dialogue, access, risk and transparency between them were all seen as critical. On the other hand, the mirror concept of interactional value co-destruction describes a process where the well-being of at least one actor is decreasing because the same firm-provided resources are being misused through accident or through neglect (Plé & Cáceres, 2010). From a practice-theoretic perspective, value co-creation and value co-destruction stem from the same set of interactive practices and that it is through deviations in the actors' understandings of these practices, their procedures for putting these into practice and their respective engagements that negative value formation occurs (Echeverri & Skålén, 2011). This duality is particularly pertinent in human–AI interactions where the very same algorithmic recommendation can facilitate a better decision by a human actor or, alternatively, exacerbate errors.

Collaborative Intelligence and Intelligence Augmentation

Collaborative Intelligence (CI) design Human & AI both designed to capitalize on each other's strengths (Wilson & Daugherty, 2018). The five key structural features of CI systems, as specified by Blaurock et al. (2025) are: 1) engagement, 2) transparency, 3) process control, 4) outcome control, and 5) reciprocal strength enhancement. We identify areas in which humans can add value over AI in situations of uncertainty and equivocality and, conversely, where AI can add value over humans in situations of excessive complexity that overwhelm human information processing capacities (Jarrahi, 2018). We also emphasize that automation and human augmentation are interdependent and that overtime organizations must grapple with the tensions that arise when one is emphasized over the other (Raisch and Krakowski, 2021). In a more recent stream of research, Barile et al. (2024) introduce the concept of Intelligence Augmentation (IA) as an extension of human interpretive schemes to handle ill-structured problems. As the micro-foundation linking individual's cognitive efforts and the corresponding organizational performance, IA discerns between 'smart' systems that process fast and efficiently and 'wise' systems that not only process information but also support

human judgment regarding goals and context. Users should be aware of what a system is able to do and of its degree of efficiency and be able to correct it efficiently (Amershi et al., 2019).

The Affect–Behavior–Cognition (ABC) Model

The ABC model characterizes psychological reactions to the human AI co-worker. In terms of affect, there are threats to identity and the work's meaning. In terms of behavior, advice adherence, overriding, and reliance calibration all occur. In terms of cognition, service quality improvement and outcome responsibility perceptions are evaluated (Blaurock et al., 2025). By incorporating the S-D Logic-based ABC model, this review goes from system-level resource integration (Stage 1) through individual human psychological reactions (Stage 2) to how firm and network value is created via Intelligence Augmentation (Stage 3).

Trust, Reliance and Algorithm Aversion

Do human-AI teams perform better than either party alone in part by how much they rely on each other? Work on human factors of automation has long distinguished between four types of use of automation: misuse (over-reliance), disuse (under-reliance), and abuse (Parasuraman & Riley, 1997). Trust calibration, where trust is equal to system ability, enables appropriate reliance (Lee & See, 2004). Organizational trust can be characterized by the three components of perceived ability, benevolence, and integrity (Mayer et al., 1995). Reviews of trust in AI systems have so far distinguished between cognitive and emotional trust and identified transparency, reliability, and task characteristics as antecedents of trust in AI systems (Glikson & Woolley, 2020). Research has shown that people can reject algorithmic advice after having seen it fail on occasion (Dietvorst et al., 2015) but prefer it over human advice in other situations (Logg et al., 2019). Mechanisms to combat over-reliance such as cognitive forcing functions can be less desirable than what they achieve (Buçinca et al., 2021). Reliance behavior can be distinguished from decision quality (Schoeffer et al., 2025).

Technostress and the Job Demands–Resources Perspective

Ragu-Nathan et al. (2008) identified established technostress creators including techno-overload, techno-invasion and techno-insecurity and later work distinguished between technostress causing distress and eustress (Tarafdar et al., 2019). The Job Demands–Resources (JD-R) model views technologies in general including AI, as being able to function as job resources which support employees in achieving their goals and/or as job demands which consume employees' energy (Bakker & Demerouti, 2007). Sustained exposure to AI related stressors such as techno-unpredictability, loss of autonomy, moral conflict, social erosion and career disruption may lead to negative outcomes as identified by Sustained exposure to AI related stressors such as techno-unpredictability, loss of autonomy, moral conflict, social erosion and career disruption may lead to negative outcomes (Acemoglu & Restrepo, 2019)

Digital Maturity, Dynamic Capabilities and AI Literacy

The organizational outcomes of AI are affected by the organization's ability to integrate, build, and reconfigure competences, as described by the dynamic-capabilities perspective (Teece et al., 1997). Human–AI teaming follows a staged and capability-dependent process for achieving interoperability and trust, as described by Simón et al. (2024). The acceptance of AI at the individual level has been explained by perceived usefulness and other related variables (Davis, 1989; Venkatesh et al., 2003). The perceived usefulness of an IIoT platform increased

under high digital maturity, as reported by da Silva and Cardoso (2024). At the individual level, possible moderators of the outcomes based on design features of human–AI interaction are competences that allow people to critically evaluate AI, communicate and collaborate with it, and use it as a tool, i.e., AI literacy (Long & Magerko, 2020).

Ethics, Governance and Regulation

Several global ethics guidelines consider key principles such as transparency, justice and fairness, non-maleficence, responsibility, and privacy (Jobin et al., 2019). Explicability and autonomy are also key for a good AI society (Floridi et al., 2018). These ethics principles are codified into law within the framework of the EU's Artificial Intelligence Act, many employment-related systems and worker-management systems having been classified as high-risk and requiring human oversight (European Union, 2024). For HRM systems and design features therefore, these principles not only confer additional performance potential but also create new compliance requirements (Benabou & Touhami, 2025).

Integrative Logic of the Review

The previous theories are employed within this paper in a layered manner. S-D Logic forms a major part of the framework by stipulating that value is created by the integration of resources of different actors within a certain ecosystem and that it can be co-created and co-destroyed (Vargo & Lusch, 2016; Plé & Cáceres, 2010). The CI features are the levers to design, which can influence the degree of human-AI co-integration (Blaurock et al., 2025). The ABC model, and the related theories on trust and reliance, explain how these levers are perceived by humans and how their perception leads to decisions (Lee & See, 2004). Intelligence Augmentation describes the transition from humans' interpretation of information to the organization's capabilities (Barile et al., 2024). The theories on dynamic capabilities, JD-R and AI literacy explain under which circumstances such a transition is effective (Teece et al., 1997; Bakker & Demerouti, 2007; Long & Magerko, 2020). The corresponding framework is described in three stages in Section 5.

Methodology and Review Protocol

Review Design

The study is a theory-driven systematic review. Such studies in management aim to generate evidence-based knowledge by employing a set of procedures that can be explicitly described and repeated (Tranfield et al., 2003). In terms of their theoretical underpinning, theory-based reviews use established theory to organize literature and to critique it (Paul & Criado, 2020). The review follows a protocol and is reported following the PRISMA 2020 reporting guideline (Page et al., 2021). The four ROs of the research are translated into four questions. First, which design features and which integration mechanisms promote co-creation (RQ1)? Second, what are the employee-level effects of co-creation in terms of ABC outcomes (RQ2)? Third, when does co-creation fail (RQ3)? Fourth, what is a suitable framework, a suitable set of hypotheses, and suitable measures to organize future research on the topic (RQ4)?

Search Strategy and Identification

Initial studies were identified through searches of Web of Science, Scopus, IEEE Xplore and ScienceDirect using the following Boolean search terms: ("human-AI collaboration" OR "AI co-creation") and ("service-dominant logic" or "resource integration") and ("technostress" or "reliance"). Studies were then reviewed against the criteria outlined in Table 1. The time

frame for the review was set from January 2024 to October 2026. This time frame captures the transition point When generative AI became business as usual and the related body of evidence for human-AI collaboration, human reliance on AI and associated stress experienced rapid growth.

Table 1
Eligibility criteria for literature ingestion

Criterion	Inclusion criteria	Exclusion criteria
Publication window	January 2024 – October 2026	Published prior to 2024
Phenomenon	Human–AI collaboration, AI value co-creation, design features, outcomes or boundary conditions	AI is treated strictly as a technical algorithm without human or organizational context
Level of analysis	Employee, organizational or network level across service, HRM, manufacturing or supply-chain sectors	No identifiable level of analysis
Source type	Peer-reviewed journal articles, systematic reviews, meta-analyses and peer-reviewed conference proceedings	Unpublished dissertations, preprints, front matter or title-only listings
Evidence tiering	Tier A: full text obtained and fully coded (13 studies) Tier B: abstract/bibliographic record verified for triangulation (25 studies)	Unverifiable records lacking abstract or bibliographic verification
Language	English-language publications	Non-English publications

Note. Tier A studies were coded in full text; Tier B studies were used for qualitative triangulation of hypotheses.

Study Selection

For our selection process we worked on three stages which are presented in Table 2. In the first stage we screened 15 records from our digital library searching for relevant information. One of the records was duplicated and thus was removed from analysis. Five of the remaining records were pre-2024 publications which were excluded from analysis because of the study restrictor. In the second stage, 12 additional potential studies were discovered and retrieved for a full-text analysis. Of these 12 studies, one was removed from potential studies for the Tier A corpus of this review because of the study's exclusion criteria. Ten of the remaining 11 studies could not be retrieved in full text by the author. As a result, only one additional study was added to the Tier A corpus in the second stage of analysis. Three additional full-text studies were added to the analysis because of Vaccaro et al. (2024) open-access meta-analysis and subsequent studies retrieved by the author in October 2026. In the third stage of analysis, 30 additional studies were assembled for qualitative analysis to provide sufficient triangulation for the qualitative data from the 38 selected studies. Five preprints, theses and studies out of scope for this review were removed from potential studies in this third stage of

analysis. As a result, 25 studies were added to the Tier B corpus, making the total number of studies used in the analysis 38 peer-reviewed studies.

Table 2
Study selection and PRISMA flow summary

Selection stage	Records evaluated	Retained records
Stage 1: Primary digital-library search	15 records	15 records
Deduplication (removal of duplicate Abanda et al., 2025)	1 duplicate	14 records
Exclusion of pre-2024 publications	5 records	9 records
Stage 2: Supplementary full-text ingestion	12 candidate records	11 records (1 screened out)
Exclusion of abstract-only or unretrievable sources	10 unretrievable	1 record
Inclusion of open-access meta-analysis (Vaccaro et al., 2024) and October 2026 retrievals	3 full-text studies	13 Tier A primary corpus
Stage 3: Tier B triangulation candidate pool	30 candidate studies	30 candidate studies
Exclusion of preprints, theses and out-of-scope papers	5 records	25 Tier B triangulation corpus

Note. Tier A (n = 13) and Tier B (n = 25) together form the 38-study analytic corpus.

Evidence Tiering, Data Extraction and Coding

The review adopted a two-tier approach to allow maximum depth and breadth to be revealed. Full studies classified as Tier A were analyzed in full of the key elements of the study (method and sample, domain and level of analysis, key design features and associated mechanisms etc., results, effect size where available, boundary conditions etc.) recorded in the review. Tier B studies were those for which an abstract or verified bibliographic record was available and were analyzed for method, context and the hypothesis or framework stage that they supported. They were used for triangulation only to reinforce claims made from Tier A studies. The distinction between Tier A and B studies is made clear in the resulting synthesis to allow the reader to assess the supporting evidence for each theme.

Analytical Approach

Gevin the studies were of very different design, level (Level 1 or Level 2) and outcome (self-report, other-report, objective), a meta-analytic pooling of effect sizes across all the studies was not feasible. Therefore, a narrative synthesis of the findings from the included studies has been combined with a thematic synthesis (Thomas & Harden, 2008) which has been used to develop a series of analytic themes through the coding of findings from the studies and the organization of these into a series of higher-order constructs (Braun & Clarke, 2006). A coding frame for the synthesis was therefore developed deductively from S-D Logic (resource integration, co-creation and co-destruction), the features of the Crisis Intervention that were studied and the three dimensions of the AcademicBEGINNERCode (ABC). The coding frame was then further refined through the process of inductive coding as several boundary

conditions became apparent. Tier A studies that reported effect sizes (e.g. as standard deviations) for the primary outcome variable of interest in each of the studies were therefore summarized using the effect size measure of Hedges' g (Hedges, 1981). Where meta-analyses had been conducted on these Tier A studies, the resultant statistics for heterogeneity, e.g. I^2 (Higgins & Thompson, 2002), have been reported as provided in the primary meta-analysis. A framework for the synthesis from within-tier description to cross-tier triangulation has been developed and hypotheses derived from the findings.

Transparency and Trustworthiness of the Synthesis

Our synthesis of findings within Section 4 has been designed to enable readers to trace the basis for each analytic claim back to the individual study in question (and where appropriate, the study's Tier). For studies where primary authors have reported effect sizes for key relationships, these have been reported within the synthesis. In contrast, the reviewers of this synthesis did not calculate or impute any effect sizes. All aspects of the study selection, coding and analysis processes have been rendered transparent through the provision of the coding frame within Tables 3–6. In addition to these procedural matters, all included studies have been selected on an intentional, theory-focused rather than exhaustive basis (Paul & Criado, 2020) with the consequent prime objective of contributing to the extant theoretical literature (Tranfield et al., 2003; Page et al., 2021).

Synthesis of Findings

Characteristics of the Corpus

The corpus is relatively recent and is methodologically very diverse (see Table 3). The studies in Tier A are spread evenly over the three years, with one study from 2026. The Tier B studies are mostly from 2026 (as opposed to the Tier A studies, which are mostly from 2024 and 2025), reflecting the very recent rise of qualitative studies on generative AI at work. The studies in Tier A are mostly reviews and/or bibliometric analyses (seven out of 13 studies), including one study that was preregistered as a meta-analysis. There are also three experimental studies, two mixed-method studies, and two design-science studies, as well as two conceptual studies. The 19 studies in Tier B are 11 qualitative interview studies / grounded-theory studies and 3 qualitative case studies. Of the 5 mixed-method studies, 2 include quantitative surveys. There are also 6 quantitative surveys, experiments, or multilevel studies. Note that while there is strong causal evidence from the few experiments, as well as from one of the meta-analyses, the documentation of the mechanisms and the contexts in which generative AI is used at work is mostly qualitative

Table 3

Descriptive characteristics of the analytic corpus (N = 38)

Characteristic	Category	Tier A (n = 13)	Tier B (n = 25)
Publication year	2024	6	2
	2025	6	10
	2026	1	13
Study design	Systematic (PRISMA) reviews	4	–
	Bibliometric / scientometric analyses	3	–
	Meta-analysis	1	–
	Conceptual / framework papers	2	–
	Experimental, mixed-method or design-science	3	–
	Qualitative (interviews, grounded theory, phenomenology)	–	11
	Case studies	–	3
	Mixed methods	–	5
	Quantitative (survey, experiment, multilevel)	–	6
Primary level of analysis (Tier A)	Employee	2	–
	Task / decision	2	–
	Firm / organization	3	–
	System, network or field	4	–
	Sectoral technology (digital twins)	2	–

Note. Categories are derived from the coding in Tables 4 and 5. A dash indicates that the category was not applied to that tier.

Primary Evidence (Tier A)

Table 4 lists the 13 Tier A studies that provided evidence on employees (Blaurock et al., 2025; stressors, taxonomy: Sapkota et al., 2025; Vaccaro et al., 2024, meta-analysis; Vaccaro et al., 2024; Schoeffer et al., 2025, formal framework for reliance on HRM technology). There is also evidence at the firm-level (reviews on AI in HRM and digital innovation: Benabou & Touhami, 2025; Aldoseri et al., 2024; Gupta et al., 2024) as well as at the network-level (technology-specific: IIoT platforms, digital twins and blockchain-enabled supply chain management: da Silva & Cardoso, 2024; Abanda et al., 2025; Hasan & Crawford, 2025; Pittri et al., 2026). The two principal conceptual and bibliometric studies on S-D Logic are Barile et al. (2024) and Saxena et al. (2024).

Table 4

Synthesis of primary Tier A full-text studies (N = 13)

Study & citation	Method & sample	Domain & level	Core findings & effect sizes
Blaurock et al. (2025)	Review (47 articles); 14 interviews; 2 experiments (N = 309, N = 345)	Financial services; employee level	Defines CI systems; transparency, process control and outcome control drive perceived service quality and adherence; reciprocal strength enhancement mitigates threat.
Barile et al. (2024)	Conceptual framework	Service systems; system level	Formalizes Intelligence Augmentation (IA); differentiates "smart" from "wise" systems; highlights co-destruction risks when resource integration fails.
Gupta et al. (2024)	Bibliometric and content analysis (73 articles)	HRM; firm level	Links AI-driven digital transformation to work–life balance and performance; identifies core techno stressors.
da Silva & Cardoso (2024)	Design science research (24 SMEs, 2-firm pilot)	Industrial IoT; network level	IIoT platform for coopetition; perceived usefulness rose from 1.2 to 5.0 under high digital maturity; on-time delivery improved to 77.5%.
Abanda et al. (2025)	Systematic review (227 articles)	Digital twins; manufacturing & construction	Establishes that construction lags manufacturing; highlights hardware, data-protection and interoperability constraints.
Hasan & Crawford (2025)	Systematic review (222 articles)	Digital twins; cross-industry	Identifies core architecture (ML, edge computing, blockchain); prioritizes security and interoperable data standards.
Saxena et al. (2024)	Bibliometric analysis (3,431 articles)	Value co-creation; field level	Maps the paradigm shift from dyadic customer interactions to multi-actor platform-ecosystem co-creation.
Aldoseri et al. (2024)	Conceptual synthesis	AI innovation; firm level	Outlines five structural pillars of AI innovation; establishes privacy and data quality as boundary limits.
Pittri et al. (2026)	Scientometric analysis (145 articles, 40 coded)	Blockchain supply chains; network level	Demonstrates transparency gains in construction; flags barriers in interoperability, cost, privacy and regulatory compliance.
Vaccaro et al. (2024)	Preregistered meta-analysis (106 experiments, N = 5,126)	Human–AI decision and creation tasks	Hybrid synergy $g = -0.23$ ($p < .001$, 95% CI [−0.36, −0.09]); augmentation vs. human alone $g = 0.64$; decision tasks $g = -0.27$; creation tasks $g = 0.19$; $I^2 = 97.7\%$.
Sapkota et al. (2025)	PRISMA systematic review (66 articles)	AI workplace stress; employee level	Identifies six amplified techno stressors and five AI-specific stressors (unpredictability, loss of autonomy, moral conflict, social erosion, career disruption).

Study & citation	Method & sample	Domain & level	Core findings & effect sizes
Benabou & Touhami (2025)	PRISMA systematic review (141 articles)	AI in HRM; organizational level	AI improves efficiency and reduces bias; emphasizes augmentation over replacement; highlights EU AI Act high-risk compliance requirements.
Schoeffer et al. (2025)	Formal framework and 3 experiments	AI-assisted decisions; task level	Separates reliance from decision quality; shows accuracy is maximized when advice adherence matches AI accuracy; details under- and over-reliance dynamics.

Note. CI = collaborative intelligence; IA = intelligence augmentation; IIoT = Industrial Internet of Things; g = Hedges' g.

Supplementary Evidence (Tier B)

These 25 Tier B studies (Table 5) expand on the evidence base provided in Tier A for healthcare, recruitment, advertising, gig economy, smart manufacturing and enterprise ecosystems. They are utilized to check for the presence of said patterns in other domains as well as provide additional evidence for the corresponding mechanisms. Studies are referenced as S1–S25 and the last column indicates the hypothesis, stage or the corresponding research gap that the respective study addresses.

Table 5

Supplementary Tier B qualitative and triangulation corpus (N = 25)

ID & reference	Method & sample	Domain & context	Framework positioning & relevance
S1: Zhao et al. (2026)	Qualitative Gioia (30 interviews)	Smart manufacturing	Staged movement toward alignment; informs **H_6** and Stage 3.
S2: Jia et al. (2026)	Grounded theory (27 nurses)	Healthcare / nursing	Co-creation vs. co-destruction mechanisms; informs **H_1, H_3, H_7**.
S3: Int. J. Advertising (2026)	Qualitative (34 interviews)	Advertising / creative work	Human oversight and expertise balance; informs **H_1, H_4**.
S4: Heimburg et al. (2025)	Case study (44 interviews)	GenAI platform ecosystem	Four co-creation mechanisms (curation, instruction, revision); informs **H_1, H_6**.
S5: Simón et al. (2024)	Longitudinal case study	AI recruitment teaming	Interoperability and trust building; informs **H_3, H_6**.
S6: Bui et al. (2025)	Mixed methods	Travel & customer experience	Co-destruction through frustration and AI error; informs **H_7**.
S7: Su et al. (2025)	Case study (Baidu)	Enterprise ecosystem	Resource integration and intelligence empowerment; informs Stage 3.
S8: Tech. in Society (2025)	Quantitative study	GenAI robot assistants	Psychological co-creation mechanisms; informs Stage 2.

ID & reference	Method & sample	Domain & context	Framework positioning & relevance
S9: Ind. 5.0 Review (2026)	Expert interviews	Manufacturing / Industry 5.0	Socio-technical design principles; informs **H_1, H_6**.
S10: Eur. J. Innov. Mgmt. (2025)	Open-ended qualitative	Knowledge work (copilot)	AI as assistant vs. teammate; informs **H_2**.
S11: J. Workplace Learn. (2025)	Qualitative (357 responses)	MNC knowledge sharing	Workplace learning and skill gains; informs **H_3, H_5**
S12: J. Managerial Psych. (2026)	Interviews (19 employees)	Cross-industry work	Affordances and work-design conditions; informs **H1, H_7**.
S13: Kyambade & Namatovu (2026)	Phenomenology (12 HR officers)	Public healthcare HR	Recruitment in resource-constrained environments; informs Gap 5.
S14: Front. Psychology (2025)	Mixed methods (50 participants)	User preferences	Perceived usefulness and partner selection; informs Stage 2.
S15: J. Operations Mgmt. (2025)	Field experiment (N = 114)	Healthcare service network	GenAI boundary-spanning intervention; informs Gap 4.
S16: Personnel Review (2026)	Multilevel quantitative	Employee–AI performance	Cognitive flexibility and empowerment moderators; informs **H_3, H_6**.
S17: CHB: Artificial Humans (2026)	Survey (N = 1,001)	Early-adoption workplaces	GenAI literacy moderation effects; informs **H_5.**
S18: Pinho et al. (2026)	Empirical survey	Work–life balance	Job demands–resources balance under AI; informs **H_7**.
S19: Ala-Luopa et al. (2024)	Interviews (15 experts)	Recruitment work	Expertise evaluation of AI outputs; informs **H_1, H_4**.
S20: Keirmov et al. (2025)	Qualitative study	Gig delivery work (UAE)	Organizational support and worker well-being; informs **H_7**.
S21: Tech. in Society (2026)	Interviews (26 managers)	Industry 5.0 manufacturing	Managerial agency and worker knowledge; informs **H_6**.
S22: Hum. Soc. Sci. Comm. (2026)	Grounded theory and empirical	Employee interaction	Interaction mechanisms and task performance; informs **H_3**.
S23: Inf. Process. Mgmt. (2025)	Mixed methods	GenAI symbiotic agency	Domain knowledge combined with AI memory; informs **H_1, H_4**.
S24: J. Ind. Inf. Integr. (2026)	Mixed methods (14 interviews)	Industry 5.0 manufacturing	Information integration and human expertise; informs **H_6**.
S25: Front. Psychology (2026)	Quantitative survey	Workplace engagement	Dual psychological pathways to engagement; informs Stage 2.

Note. S = supplementary study. H = hypothesis (Section 5). Entries are identified by journal source where the bibliographic record was verified at abstract level.

Thematic Analysis across the Corpus

Our analysis of the coded data resulted in five themes. Themes 1 and 2 detail how the different integration mechanisms and design options can support co-creation (RO1) and provide evidence from employee level data regarding ABC outcomes (RO2). The subsequent

Themes 3 to 5 explain where collaboration succeeds or fails and why this is the case for whom. The themes, in turn, address RO3 (where, why and for whom collaboration succeeds or fails). RO4 is addressed in Sections 5 to 7. Tier A studies in each theme state the core claim, whereas Tier B studies are referred to by identifier where they support the core claim of Tier A studies or add further details.

Theme 1: Integration, not deployment, creates value (RO1)

Technology deployment does not bring any value across different service systems. Value is created when the AI operant resources are integrated into the socio-technical decision-making processes (Barile et al., 2024; Benabou & Touhami, 2025). In terms of subtasks allocation, the highest level of task-specific capability between humans and AI is the key to achieve synergy (Vaccaro et al., 2024). Also, at the level of the ecosystem, studies of Tier B research papers have identified curation, instruction and revision as the main forms of co-creation on generative AI platforms (Heimburg et al., 2025), while the value co-creation on Baidu takes place through resources integration (Su et al., 2025). In Service-Dominant logic terms, integration is the unit of value creation. A deployed AI system that is not integrated into the existing decision-making processes and service delivery of a company is an unused operand resource. What is needed is a matching investment in the models and in the licenses to re-design the workflows and clarify the roles of all stakeholders involved, and to set up the adequate data pipelines that allow to actually make use of the operant resources in order to serve customers and make decisions.

Theme 2: Human oversight is the most reliable design lever (RO1, RO2)

Blaurock et al. (2025) found in experimental studies that transparency, process control and outcome control were able to significantly increase service quality perceptions, perception of responsibility and advice compliance whereas system-initiated engagement did not show any significant added value. For creative work and for recruitment work, experts judge AI output in comparison with their own expertise. They clearly state their expectations for human AI collaboration (Ala-Luopa et al., 2024). As already mentioned before, these findings coincide with the EU AI Act's requirements for human oversight in high-risk HR systems (Benabou & Touhami, 2025; European Union, 2024). Moreover, they underpin a system's function which supports users in efficient correction (Amershi et al., 2019). This also coincides with Service-Dominant (S-D) Logic's notion of beneficiaries as co-creators not receivers of value (Vargo & Lusch, 2014).

Theme 3: Synergy is highly conditional (RO3)

Previous meta-analytic work found that human-AI hybrids are most accurate when users engage in calibrated reliance on the hybrid (Schoeffer et al., 2025; Vaccaro et al., 2024). Users who rely too heavily on hybrids run the risk of accepting errors generated by the AI, whereas users who rely too little on hybrids forgo potentially great value in machine analytical capabilities. This work can be viewed through the classic lens of automation misuse and disuse (Parasuraman & Riley, 1997). Results from the present set of studies were found to vary considerably by task (very high heterogeneity, $I^2 = 97.7\%$), with negative synergy in decision-making tasks ($g = -0.27$) and small positive synergy in creative tasks ($g = 0.19$). When compared against the human-alone mean ($g = 0.64$), medium-to-large, the sum of human and AI performance is only slightly less than the best single party (Cohen, 1988). Thus, while augmenting humans to form human-AI hybrids can add considerable value above and beyond

what can accomplish in isolation, doing so does not yield great benefit in exceeding the single best performer.

Theme 4: Contextual moderation by experience and maturity (RO3)

Previous meta-analytic work found that human-AI hybrids are most accurate when users engage in calibrated reliance on the hybrid (Schoeffer et al., 2025; Vaccaro et al., 2024). Users who rely too heavily on the hybrid run the risk of accepting errors generated by AI, whereas users who rely too little on the hybrid forgo potentially great value in machine analytical capabilities. This work can be viewed through the classic lens of automation misuse and disuse (Parasuraman & Riley, 1997). Results from the present set of studies were found to vary considerably by task (very high heterogeneity, $I^2 = 97.7\%$), with negative synergy in decision-making tasks ($g = -0.27$) and small positive synergy in creative tasks ($g = 0.19$). When compared against the human-alone mean ($g = 0.64$), medium-to-large, the sum of human and AI performance is only slightly less than the best single party (Cohen, 1988). Thus, while augmenting humans to form human-AI hybrids can add considerable value above and beyond what can accomplish in isolation, doing so does not yield great benefit in exceeding the single best performer.

Theme 5: Well-being risks and AI techno stressors (RO3)

AI integration brings 11 new workplace stressors to the jobs of employees. 6 of these stressors are new amplifications of 'traditional' techno stressors (e.g. IT assurance, technical change support), and 5 are novel 'AI-specific' stressors (e.g. techno-unpredictability, loss of autonomy, moral conflict, social erosion and career disruption) (Gupta et al., 2024; Sapkota et al., 2025). Tier B evidence shows how these new stressors operate in practice. There are accounts of the ways in which generative AI supports and hinders nurses (S2), 'co-destruction' (S6) describes the negative frustration experienced by consumers through interactions with AI which fail in various ways, and a review of work on work–life balance including some survey and interview data describes the impact of organizational support on those who work in gig economy type delivery work (S18, S20). These findings are consistent with the Job Demands and Resources model of employee well-being which regards technology as either a demand or a resource (Bakker & Demerouti, 2007), and with design of technology producing either distress or eustress (Tarafdar et al., 2019).

Cross-Level and Cross-Sector Patterns

Reading a corpus by level reveals a consistent, yet not equally supported picture. At the employee level, the design features and answers to questions are best represented (Blaurock et al., 2025). Stress at work is represented in a catalog, so far, however, not even measured with validated instruments (Sapkota et al., 2025). At the firm level, the evidence concerning the capabilities and readiness to change refers above all to digital maturity, the data quality and the privacy (Aldoseri et al., 2024; Gupta et al., 2024). At the network level, the evidence is concentrated on the interoperability, the security and the trust in platform-mediated coopetition (da Silva & Cardoso, 2024; Hasan & Crawford, 2025). The levels are hardly ever empirically connected, which is the starting point for Gap 1. By domain, we found the strongest evidence for design features in financial services (Blaurock et al., 2025), expertise, trust building, and compliance in studies of HRM and recruitment (Ala-Luopa et al., 2024; Benabou & Touhami, 2025; Simón et al., 2024). Studies in healthcare (S2: grounded theory, S15: field experiment, S13: phenomenological analysis of HR officers in public hospitals)

emphasized that value and risk are primarily determined by the professional and resources in that domain. In manufacturing and Industry 5.0 (S1, S9, S21, S24), the main themes were socio-technical alignment and the role of management. Given the state of the art in digital-twin and blockchain applications in construction, it is not yet ready to match manufacturing in terms of extent of adoption, mostly due to the nature of data in construction (fragmented) and related interoperability challenges (Abanda et al., 2025; Pittri et al., 2026). Creative, travel, and gig-work contexts (S3, S6, S20) are very different from each other but all underscore the significance of oversight, error tolerance, and organization support for human–AI collaboration. We find it significant that the same boundary conditions keep recurring in so different sectors.

Failure Modes and Co-Destruction Pathways

Therefore, to address RO3 we first need to understand how collaboration fails, in other words how failure pathways in human-AI collaboration occur. Based on the reviewed studies we found six failure pathways that kept re-occurring. The failure pathway of over-reliance (Schoeffer et al., 2025; Parasuraman & Riley, 1997) occurs when employees mistakenly rely on wrong AI output. The failure pathway of under-reliance (Dietvorst et al., 2015) is reversed, namely employees fail to use valuable machine-based analysis, even when AI errors have become obvious. The failure pathway of interactional co-destruction (S6) of user experiences by AI errors, also occurring in the context of generative AI travel services (S5; Plé & Cáceres, 2010), was a further failure pathway identified. The failure pathway of loss of control and AI opacity (Blaurock et al., 2025; European Union, 2024) threatens organizations with potential regulatory violations because employees no longer can understand what happens in their organization. Human-AI collaboration also gives rise to specific types of strain (Sapkota et al., 2025), i.e. stressors that negatively affect employees' well-being and work. Finally, the collaboration can also fail due to infrastructural and governance failures (Abanda et al., 2025; Pittri et al., 2026), e.g. because of insufficient interoperability, lacking security or even inadequate data governance so that in the end no integration at all of the provided resources is possible.

Evidence Mapping to Hypotheses

Table 6 cross-references the evidence in S7-S25 with the 7 hypotheses, listed in order in Section 5, and reports in Table 6 the Tier B counts of studies where each hypothesis was said to have been informed by the study's results. While seven studies support H1 and H6, only few corroborations for H2 and H5 is available, hence these two hypotheses need to be tested in a confirmatory design first. As for the Stage 3 mechanisms, S7 and S1 need further testing;

for the Stage 2 content, S8, S14 and S25 are relevant, and for Gaps 5 and 4, S13 and S15 respectively.

Table 6
Evidence mapping of Tier A anchors and Tier B triangulation to hypotheses

H	Tier A anchor studies	Tier B corroborating studies	Tier B (n)	Evidence profile
H_1	Blaurock et al. (2025); Benabou & Touhami (2025)	S2, S3, S4, S9, S12, S19, S23	7	Experimental plus broad qualitative convergence
H_2	Blaurock et al. (2025); Barile et al. (2024)	S10	1	Experimental; thin corroboration
H_3	Barile et al. (2024); Blaurock et al. (2025)	S2, S5, S11, S16, S22	5	Conceptual and qualitative; mediation untested
H_4	Schoeffer et al. (2025); Vaccaro et al. (2024)	S3, S19, S23	3	Formal, experimental and meta-analytic
H_5	Blaurock et al. (2025)	S11, S17	2	Experimental; limited corroboration
H_6	da Silva & Cardoso (2024); Abanda et al. (2025); Hasan & Crawford (2025); Pittri et al. (2026); Aldoseri et al. (2024)	S1, S4, S5, S9, S16, S21, S24	7	Design-science and reviews; broad qualitative support
H_7	Sapkota et al. (2025); Gupta et al. (2024)	S2, S6, S12, S18, S20	5	Review-based taxonomy; no validated scale

Note. Tier B counts are taken from the “informs” coding in Table 5.

Conceptual Framework and Formal Hypotheses

Framework Overview

Figure 1 presents a multi-level framework comprising three sequential stages. In the first stage, System Design and Integration Features, the structural features of AI applications that enable human interaction with AI systems are described. In the second stage, Employee Micro-Foundations and Intelligence Augmentation, the affective, behavioral and cognitive responses that are translated into individual-based interpretation augmentation and decision quality are described. In the third stage, Firm and Network Value Co-Creation, individual-based augmentation is transformed into organizational and ecosystem-level value through the integration of resources. Three sets of boundary conditions (AI literacy and experience, digital maturity and infrastructure, and AI technostress) are introduced to test the conditions under which the paths described between the antecedents and consequences converge. S-D Logic is treated as the macro-logic of resource integration, the ABC model is treated as the micro-level structure that generates responses, and IA is treated as the mechanism that links the two.

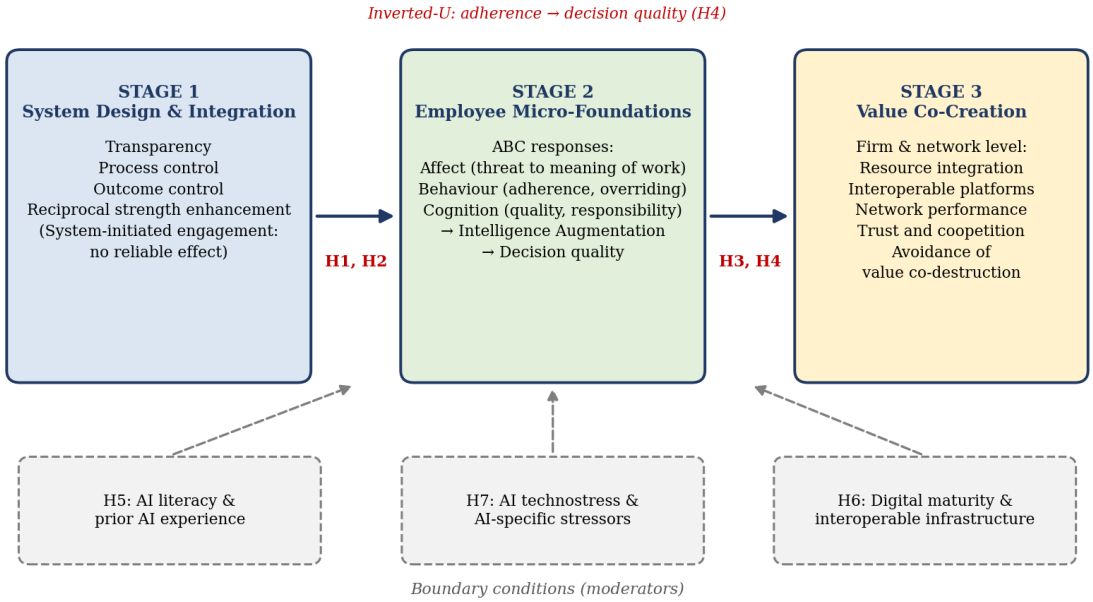

Figure 1. Three-stage conceptual framework of human–AI collaboration and value co-creation, with hypothesized paths (H1–H4) and boundary conditions (H5–H7).

Stage 1: Design Features and Employee Response

Prahalad and Ramaswamy (2004) identified transparency as one of the major characteristics of co-creation. Transparency of how a recommendation is generated and what happens to it afterwards, as well as process and outcome control, are three features that have been found to increase perceived service quality, sense of responsibility and adherence by employees more than any other feature (Blaurock et al., 2025). These features allow employees to have visibility into and influence on the process of generating recommendations, which is at the core of human-centered design and efficient correction (Amershi et al., 2019). Unlike algorithmic management, which takes away workers' discretion (Kellogg et al., 2020), these features grant workers a sense of agency over their work. Each of these features affects a different strain in work that is fully algorithmically managed and thus is expected to influence cognitive, behavioral and affective responses at work jointly. In contrast to system-initiated engagement, these features provide no protection for employees and thus are not expected to have similar effects (Blaurock et al., 2025).

> **Hypothesis 1 (Stage 1 design features → employee response).** H1: Structural features of AI applications, specifically transparency, process control and outcome control, positively influence employees' perceived service-quality improvement, perceived outcome responsibility and advice adherence, while reducing affective threat to the meaning of work.

While control is not the only consideration for collaboration between humans and AI, also important is the question of whether both parties' strengths are being enhanced by their collaboration. Reciprocal strength enhancement (RSE) of AI and humans describes a system where each learns from the other's strengths, to be mutually enhanced (Blaurock et al., 2025). Such systems of collaboration are exemplified by Intelligence Augmentation (IA) that increases the interpretive schemes of both human and AI without replacing the human (Barile et al., 2024). The ability of such systems to mitigate perceived threats of substitution by

humans, is greater than when humans perceive that AI is replacing them (Acemoglu & Restrepo, 2019; Wilson & Daugherty, 2018). Work that clearly distinguishes between using AI as an assistant and using AI as a teammate (S10), highlights the significance of the quality of such reciprocal collaboration to achieve desired outcomes. It is precisely this type of collaboration that, according to the ABC logic, leads to higher levels of cognitive and behavioral outcomes without a corresponding increase in affective threat, precisely because the focus is on how the worker's strengths are enhanced by AI, as complement. The issue of whether increased efficiency will come at the cost of identity and meaning at work, is at the core of the current automation debate (Raisch & Krakowski, 2021).

> **Hypothesis 2 (Stage 1 reciprocal design → employee response).** H2: Reciprocal strength enhancement between humans and AI positively influences employee cognitive and behavioral outcomes (perceived service improvement, responsibility and adherence), without increasing affective threat to work identity.

Stage 2: Intelligence Augmentation and Reliance Calibration

Barile et al. (2024) position IA as the microfoundations of the link between employees' cognition and the firm's performance. By positively responding in terms of both cognition and behavior, employees are likely to incorporate AI input into their interpretive schemes to translate design features into higher-quality co-created decisions. Consistent with the hypothesis, Tier B studies investigate workplace learning, interaction mechanisms and psychological co-creation (S11, S22, S8). However, none of them provides any empirical evidence that supports the mediating role hypothesized here. Thus, mediation is proposed as a hypothesis rather than a proven result. In terms of methodology, testing the claim requires a specific temporal sequence, namely design features that precede employees' responses and the latter that preceded augmented interpretation. To test the proposed hypothesis, therefore, an independent assessment of decision quality is required instead of a single survey wave, i.e. separate measurement occasions are needed.

> **Hypothesis 3 (Stage 2 employee response → Intelligence Augmentation).** H3: Positive employee cognitive and behavioral responses mediate the relationship between AI design features and Intelligence Augmentation (IA), leading to higher quality co-created decision outcomes.

A further problem that Vaccaro et al. (2024) encountered in their study is the negative average synergy between human and AI system performance and employees' self-reported ratings of their systems. However, this problem disappears when considering the reliance employees place on the systems. Schoeffer et al. (2025) prove that human decision making is maximized when the degree of advice adherence to AI recommendations is equal to the AI's accuracy. Thus, less than optimal levels of adherence result in the squandering of potential system capability, whereas levels of adherence greater than optimal lead to the decisions being corrupted by errors in the system's output. A curvilinear relationship between a given variable of interest and decision making is hypothesized and graphically represented by an inverted-U. Notably, the peak level of decision making for a given variable of interest would occur at a specific level of calibrated reliance, rather than at some higher-than-optimal level of adherence for instance. Moreover, there are several managerial policies designed to

improve human-AI system performance that would lead to decreased levels of system-based decision making. For instance, a policy encouraging employees to rely on a system as much as possible would likely perform worse than a policy that urged employees to rely on the system to the degree of calibration, rather than misuse or(disuse) of system capability. Note that the optimal degree of reliance would vary with AI system accuracy. Thus, rather than specifying a particular level of reliance (e.g., always), the present hypothesis is stated in terms of the variable of calibration.

> **Hypothesis 4 (Stage 2 reliance calibration → decision quality).** H4: Advice adherence exhibits an inverted-U curvilinear relationship with decision quality, such that calibrated adherence yields optimal accuracy, whereas under-reliance or over-reliance diminishes collaborative quality.

Boundary Conditions

The evidence from two sources supports that AI literacy and experience are moderators. On the one hand, Blaurock et al. (2025) reports a higher design-feature effect for novices, whereas S17 reports a moderation effect from survey evidence on GenAI literacy in early adopting workplaces. In terms of concept, AI literacy comprises several competencies for evaluating, collaborating with and using AI (Long & Magerko, 2020). People who lack these competencies mostly rely on interface cues to adjust their trust. In contrast, experienced users form calibrated expectations based on their prior experience and therefore perceive additional controls as a burden. Hence, the moderation effect is expected to be asymmetric: for novices design features can substitute for lack of experience, whereas for experts the same features would merely duplicate existing knowledge and add friction. Thus, a one-size-fits-all interface would be suboptimal and deserves to be evaluated for adaptive interfaces that adjust the degree of control to the user's level of expertise. Finally, cognitive forcing evidence shows that the benefits of interventions are uneven across users (Buçinca et al., 2021).

> **Hypothesis 5 (contextual moderation: AI literacy).** H5: Employees' AI literacy and prior AI experience moderate the impact of system design features, such that transparency and control features exert stronger positive effects on AI novices than on experienced users.

Looking at the firm and network level, according to the dynamic-capabilities perspective value can only be created by technology integration, building of resources, and reconfiguration of existing ones (Teece et al., 1997). For IIoT coopetition (da Silva & Cardoso, 2024), digital-twin adoption (Abanda et al., 2025; Hasan & Crawford, 2025), blockchain-based supply chains (Pittri et al., 2026), and AI innovation (Aldoseri et al., 2024) secure and interoperable infrastructure and sufficient digital maturity of firms are preconditions. Longitudinal case studies on recruitment teams for AI (Simón et al., 2024) even demonstrate how over time interoperability and trust are developed. At the two levels of infrastructure, i) technical interoperability must be in place so that data and decisions can be moved across organizational boundaries and ii) digital maturity in the organization has to be sufficient so that what is moved can also be properly interpreted and acted upon. Without the first, network co-creation is not possible; without the second it will not last.

Hypothesis 6 (contextual moderation: digital maturity and infrastructure). H6: Organizational digital maturity and secure, interoperable platform infrastructure positively moderate the relationship between AI collaboration platforms and firm- and network-level value co-creation.

Boundary condition 3 is strain. If the demands of using AI at work are increased by unpredictability, loss of control, moral dilemma, social split or career threat (Sapkota et al., 2025) then the benefits of collaboration at work could be nullified and even reversed and lead to excessive stress and disengagement at work (Bakker & Demerouti, 2007; Ragu-Nathan et al., 2008). Stress at work with technology can be either bad or good depending on how technology is designed (Tarafdar et al., 2019). Therefore, in this study, stress is modeled as a moderator which decreases the size of the relationship between collaboration at work and both performance and well-being at work. The effect of stress on this relationship is expected to be both direct (depletes energy) and indirect (deteriorates cognitive and affective appraisal in Stage 2). Future studies may also test whether stress moderates the relationships between collaboration, performance and well-being at work depicted in paths H1-H3.

Hypothesis 7 (contextual moderation: AI technostress). H7: AI-induced workplace stress (technostressors and AI-specific stressors) negatively moderates the relationship between human–AI collaboration and employee performance and well-being.

Table 7
Summary of hypotheses, theoretical grounding and expected effects

H	Relationship	Theoretical grounding	Expected effect
H1	Transparency, process control, outcome control → perceived quality, responsibility, adherence; ↓ threat	CI features; ABC; S-D principle of beneficiary co-creation	Positive (cognitive, behavioral); negative on threat
H2	Reciprocal strength enhancement → cognitive and behavioral outcomes	CI; Intelligence Augmentation	Positive; no increase in threat
H3	Design features → employee response → IA → decision quality	S-D resource integration; IA; ABC	Mediation (positive)
H4	Advice adherence → decision quality	Reliance calibration; trust in automation	Inverted-U (curvilinear)
H5	AI literacy / experience × design features	AI literacy; trust calibration	Stronger for novices
H6	Digital maturity and infrastructure × platforms → firm/network value	Dynamic capabilities; S-D ecosystems	Positive moderation
H7	AI technostress × collaboration → performance, well-being	JD-R; technostress	Negative moderation

Note. CI = collaborative intelligence; IA = intelligence augmentation; JD-R = job demands–resources.

Discussion and Research Gaps

Interpretation of the Evidence

A key result of the synthesis of findings is the solution of a seemingly contradictory set of results from employee-level studies and a meta-analysis. The former indicated that designing for transparency, for control of process and for control of outcome of human work with AI increased perceptions of the quality of work, of human responsibility for work, and of employees' adherence to process. The latter, however, reported that, on average, human–AI systems did not outperform their best human counterparts. The reason for this apparent contradiction is that the two sets of findings address different links in a chain. Employees' perceptions and behavior in work with AI are affected by features of design that facilitate their work with technology. However, the designs that cause positive perceptions to arise are not sufficient to ensure that those perceptions will lead to better decisions by employees. Whether employees' reliance on a particular human or on an AI will lead to good decisions is affected by several factors including the extent to which employees' reliance is calibrated, and the degree to which the tasks that employees do with the technology are ones in which humans and AI have complementary strengths rather than working to oppose each other. As such, positive perceptions are necessary but not sufficient for the kind of synergy described here. Adherence to process, for example, can be both good and bad.

The review also addresses technology-centric views on the value created by AI. The mere adoption of technology does not generate value; its integration within an organization does (Barile et al., 2024). Therefore, the S-D Logic perspective views organizations as integrators of resources, and value is generated by the beneficiary (Vargo & Lusch, 2016). Studies on digital innovation have already highlighted how the benefits generated by a technology are greater than the technology itself and are determined by the organization's pre-existing capabilities (Teece et al., 1997). The reciprocal relationship between co-creation and co-destruction that is characteristic of value enables the same feature of AI to generate value and destroy it at the same time (Echeverri & Skålén, 2011; Plé & Cáceres, 2010). The dual nature of evidence regarding the change in productivity brought about by AI (Noy & Zhang, 2023) and the negative decision synergy determined by its use (Vaccaro et al., 2024) finally leads to a task-contingent perspective according to which generative AI is mostly useful in creation tasks, in which the human evaluator is in control.

Building on these ideas three theoretical contributions are developed. Firstly, the framework under investigation here connects the S-D Logic macro-level claims about the integration of resources with the ABC model's micro-level claims about human behavior by way of Intelligence Augmentation. Secondly, the framework specifies reliance calibration as the mechanism that converts positive responses into decision quality and thus also explains why synergy is conditional. Thirdly, within the boundary-condition set of digital maturity, AI literacy, and technostress, these are treated as a single set of propositions that can be tested at multiple levels.

Thus, for HRM, the results of the survey can be used for the core functions of HRM where AI is already being applied. First, for recruitment, it is important for the experts who are in charge of recruitment to assess the output of the AI system against their own judgment, and to be in full control of the decision made by the AI system for recruitment (Ala-Luopa et al., 2024). Second, for performance management and for workforce analytics, there is a risk of the

algorithms controlling the employees and of the algorithms being opaque, and therefore, before the functions can be considered to be legitimate, there must be transparency and possibility of recourse by the employees (Kellogg et al., 2020). Third, for the resource-constrained public institutions such as the hospitals studied by Kyambade and Namatovu (2026), the constraints on the use of the AI systems are not the algorithms but the typical organizational infrastructure, skills, and governance. Hence, it is a joint design task of redesigning work, developing necessary skills, and designing appropriate oversight. This view is consistent with that of Benabou and Touhami (2025) that AI should be used to augment, rather than replace, human capability, and with the automation–augmentation paradox identified by Raisch and Krakowski (2021). Importantly, there is more to be carefully understood regarding productivity of generative AI for writing in professional contexts. A few experimental studies have investigated the immediate impact of various generative tools on writers in different professional settings. For example, Noy & Zhang (2023) studied the impact of several generative AI tools in professional writing. Positive speed and rated quality effects were found. These effects are in line with the positive creation synergy. However, this does not mean that the same tools will also lead to improved judgment in high-stakes decision-making situations. The average decision synergy is negative (Vaccaro et al., 2024). Thus, organizations that base their design decisions on positive creation synergy effects for specific writing tasks, such as fast production of first drafts, run the risk of over-reliance (Parasuraman & Riley, 1997). Value is task-contingent and therefore a first-order design variable that should not be reduced to a footnote.

Positioning against Alternative Explanations

An alternative framework for explaining use of technology would be based on the technology acceptance tradition (e.g. Davis, 1989; Venkatesh et al., 2003). Here, use of technology is explained in terms of perceived usefulness and of ease of use as well as the influence of others. Although da Silva and Cardoso (2024) identify a sharp increase in perceived usefulness under positive conditions, however, acceptance alone does not explain how use of technology leads to positive outcomes. A meta-analytic study has even shown that even the best-accepted AI and the most-used AI fail to deliver synergy when miscalibrated reliance is in place (Vaccaro et al., 2024). Indeed, trust research is above all concerned with achieving appropriate reliance rather than maximal trust (Lee & See, 2004; Glikson & Woolley, 2020). Thus, although acceptance is certainly a prerequisite for value in the second stage of the proposed framework, it is not an end in itself. Rather, it is to be integrated into value-creating processes in a calibrated manner, something that is beyond the scope of traditional accounts of adoption. In a similar vein, task-allocation accounts (Huang & Rust, 2018; Jarrahi, 2018) that propose that people allocate tasks based on their relative capability to perform them well are static in nature whereas S-D Logic emphasizes that task-allocation and thus also the integration of activities are continually renegotiated among people and between them and institutions (Vargo & Lusch, 2016).

Research Gaps

The 38 reviewed studies proposed a total of 78 hypotheses on human–AI collaboration and value co-creation within digital ecosystems. Several interrelated limitations of the existing research were found. Firstly, even though previous research analyzed various aspects of trust, technology use and collaboration at employee level as well as organizational and platform capabilities and outcomes, the relation between employees' interactions and the

organization's financial performance is not yet sufficient established (Simón et al., 2024). Secondly, whereas intelligence augmentation has recently received increased attention at a theoretical level, the empirical analysis of the cognitive processes by which human–AI collaboration increases performance above and beyond supporting employees at tasks is still underdeveloped (Barile et al., 2024). Thirdly, the already identified different collaboration outcomes across various task types (e.g. negative synergy in decision-making tasks and positive synergy in creative tasks) as well as their relation to employees' reliance on AI for their tasks have not yet been sufficiently analyzed (Vaccaro et al., 2024; Noy & Zhang, 2023). Methodologically, the majority of the studies were based on cross-sectional designs or scenario studies and thus did not allow for sufficient causal analysis. In addition, there is a strong imbalance in the analyzed empirical cases (Blaurock et al., 2025; Sapkota et al., 2025; Dietvorst et al., 2015), mainly from the fields of finance, information technology and manufacturing, whereas only very few studies analyzed cases from the fields of health, public administration and from developing economies (Kyambade & Namatovu, 2026) such as the Gulf countries and other emerging markets. Importantly, an even larger imbalanced has been identified with respect to the integration of the issues of cybersecurity, data sovereignty, algorithm transparency and accountability into value co-creation frameworks, whereas these issues might significantly affect the aforementioned variables (Pittri et al., 2026; European Union, 2024; Floridi et al., 2018; Jobin et al., 2019). Finally, several inconsistencies were found with respect to the measurement of employees' reliance on AI as well as of several recently emerging AI-related experiences (Sapkota et al., 2025; Schoeffer et al., 2025), which prevent the results from being compared and cumulatively added to the existing body of knowledge.

Table 8
Research gaps, proposed designs and affected hypotheses

Gap	Proposed research design	Hypotheses	Level
1. Cross-level chain	Multilevel field studies linking employee reliance to unit and firm KPIs; multi-source data	**H_3, H_6**	Employee → firm
2. IA mechanisms	Pre/post problem-framing experiments on ill-structured tasks with and without AI	**H_2, H_3**	Employee
3. Task heterogeneity	Factorial experiments crossing task type (decision vs. creation) with design features	**H_1, H_4**	Task
4. Causal and longitudinal designs	Longitudinal field experiments and diary studies tracking novelty decay and recalibration	**H_1–H_5, H_7**	Employee, team
5. Sector and region	Replication in healthcare, public administration and Gulf/emerging economies	**All**	Sector
6. Risk governance	Models adding governance, privacy and cybersecurity maturity as moderators	**H_6**	Firm, network
7. Measurement	Scale development and validation for reliance, AI stressors, IA and AI literacy	**H_3–H_5, H_7**	Cross-level

Note. KPI = key performance indicator.

Methodological Agenda and Practical Implications

Construct Operationalization and Measurement

To test the framework for human-AI interaction consistently, measurement for the framework's constructs is recommended in Table 9, along with information on validation for each. Two key principles were used in developing these recommendations. First, the measurement for the human's reliance behavior must be distinct from the measurement for the accuracy of the human's outcome, since only by being better than the AI is the human's adherence to the conditions of human-AI interaction beneficial (Schoeffer et al., 2025). Second, when assessing synergy, it is necessary to compare it to the best single party and to report the results with the use of standardized effect sizes (Vaccaro et al., 2024), so as to avoid confounding synergy with augmentation.

Table 9

Construct operationalization and measurement agenda

Construct	Recommended measurement option	Operational notes & validation status
Employee ABC outcomes	Multi-item scales for perceived service quality, outcome responsibility and threat to meaning of work (Blaurock et al., 2025)	Validated in vignette experiments; requires field replication.
Reliance & decision quality	Separate metrics for advice adherence, correct overriding and final decision accuracy (Schoeffer et al., 2025)	Must separate reliance behavior from outcome accuracy.
Human–AI synergy	Standardized effect sizes (Hedges' g) comparing hybrid performance against the best single party (Vaccaro et al., 2024)	Essential for distinguishing synergy from mere augmentation.
AI-specific stressors	Taxonomy of five AI stressors (Sapkota et al., 2025)	Urgent need for psychometric scale development and validation.
AI literacy & readiness	Performance-based AI literacy tests combined with subjective readiness items (cf. Long & Magerko, 2020)	Requires continuous competence modeling rather than binary indicators.
Network performance	On-time delivery ratios, interoperability KPIs and ecosystem trust metrics (da Silva & Cardoso, 2024)	Requires daily averaging and multi-firm transaction validation.
Intelligence augmentation	Pre- and post-test problem-framing scores on ill-structured tasks	No standardized scale exists; high priority for future research.

Recommended Research Designs

Based on the above gaps, three design principles apply to test H4. First, to distinguish the curvilinear shape from linearity, the test of H4 needs to include a continuous manipulation or measurement of adherence to use of AI at several levels of accuracy. This can be tested using quadratic terms or even spline terms and pre-registered predictions. To test H1, H2, and H5, between-subjects factorial experiments can be conducted that vary the design features across participants of different levels of AI literacy and test these in real field settings. To test H3, H6, and H7, multilevel or even longitudinal field studies are required in which the outcomes of employees, as well as the firm's infrastructure and the employees' stress, are measured at different times, by different individuals. This would also help to rule out common-method bias. Finally, if primary meta-analytic work is done, reporting Hedges' g with associated statistics for between-studies heterogeneity will help to identify the moderators that account for the extremely high amount of inconsistency found so far (Higgins & Thompson, 2002).

Managerial Implications

1. Implement interface transparency and override controls. Process and outcome controls should be built into AI systems and interaction with them by human operators enabled to review and change individual AI-driven recommendations where this is required by the EU AI Act (Benabou & Touhami, 2025; European Union, 2024). This corresponds with well-established design guidelines for human interaction with AI systems, such as supporting users in understanding what AI systems can do and how well they do it, and keeping corrections cheap (Amershi et al., 2019).

2. Calibrate reliance protocols. Organizations should resist enforcing 100% compliance with AI system recommendations and instead train users to know when to follow the AI's advice and when to overrule it (Schoeffer et al., 2025). While introducing deliberate friction into human-AI interaction to combat over-reliance (e.g. by means of cognitive forcing) may be appropriate in some instances, this must be carefully traded off against user experience (Buçinca et al., 2021).

3. Prioritize infrastructure readiness before network scaling. Only deploy collaborative IIoT platforms after corresponding companies have set up required cybersecurity and achieved sufficient digital maturity, verified by means of defined standards (da Silva & Cardoso, 2024). The same constraints to interoperability and data protection apply to digital twins as well as to blockchain-based supply chains (Abanda et al., 2025; Pittri et al., 2026).

4. Mitigate AI-specific workplace stress. Take steps to mitigate workplace stress caused by AI. Organizations should clearly define the boundaries of employees' autonomy as well as the degree to which they will be monitored by algorithms. Moreover, they must be prepared to address potential changes to employees' roles and careers caused by the use of AI (Sapkota et al., 2025). Organizational support is known to be a buffer in cases of gig and platform work (S20). Designing for eustress rather than for distress, however, is a design choice and not a given (Tarafdar et al., 2019).

5. Invest in AI literacy and role redesign. Design features that deliver benefits depend on user experience. Therefore, training needs to be targeted and role redesign needs to be designed

in a way that the human evaluative role is made explicit. For creation tasks that are positive in hybrid mode, workflows should be designed in a way that the human is finally responsible for evaluation. For decision making tasks where synergy is negative on average, workflows should clearly specify when human or AI is responsible for the final decision (Vaccaro et al., 2024).

The above five actions could be implemented in a sequence of steps. The first step is to assess the organization's readiness to integrate AI into its functions, including infrastructure, data governance and security (Aldoseri et al., 2024). Then, start implementing AI in a few transparent functions with human override in the decision-making process, measure separately human reliance on AI and the quality of decisions made with or without AI. Provide appropriate training to users based on their prior experience profile. Only after sufficient reliance has been established and measured in terms of impact on stress and well-being, move to large-scale implementation within units or partner organizations, monitoring for stress and well-being indicators of users. This phased approach is consistent with the observation that achieving alignment between humans, AI, and organizational processes occurs incrementally, not at the point of AI implementation (Zhao et al., 2026; Simón et al., 2024), thus avoiding confusion between initial excitement and eventual value creation.

Table 10
Managerial action framework linking practices to evidence and indicators

Priority action	Supporting evidence	Link	Indicator to monitor
Embed transparency and override controls	Blaurock et al. (2025); Benabou & Touhami (2025)	**H_1, H_2**	Share of AI recommendations inspected or amended; perceived responsibility and threat scores
Calibrate reliance through training and protocols	Schoeffer et al. (2025); Vaccaro et al. (2024)	**H_4**	Adherence relative to AI accuracy; correct-override rate; final decision accuracy
Secure infrastructure and maturity before scaling	da Silva & Cardoso (2024); Pittri et al. (2026)	**H_6**	Interoperability KPIs; cybersecurity audit status; on-time delivery ratios
Govern autonomy, surveillance and career risk	Sapkota et al. (2025); Kellogg et al. (2020)	**H_7**	Stressor and well-being surveys; turnover intention; grievance and escalation rates
Build AI literacy and redesign roles	Long & Magerko (2020); Blaurock et al. (2025)	**H_5**	Performance-based literacy scores; time to proficiency; role clarity ratings

Note. Indicators are illustrative and should be adapted to the organization's context and data-protection obligations.

Policy Implications

For the regulatory and HR functions of public sectors a risk-oriented approach is recommended that combines mandatory human control with capacity building. For effective oversight, human overseers must be able to test and challenge AI outputs. This links back to AI literacy required for compliance (European Union, 2024; Long & Magerko, 2020). In addition to these measures, policymakers from low-income and developing countries should support the development of shared digital infrastructure and standards. The value of AI

collaboration in healthcare and public administration depends on the maturity and interoperability of AI systems (Kyambade & Namatovu, 2026). Finally, public entities should encourage evidence generation by supporting longitudinal evaluations of the implementation of AI in health care and public administration.

Directions for Future Research

Five avenues of future research are built upon the current research on gaps and the Measurement Agenda. Firstly, cross-level panel studies of the same organizations over time, containing information on the design of AI systems and the effects on employees, as well as their reliance on the system and the organization's performance, are needed to map out the stage-to-stage development according to the suggested framework in detail. Secondly, intervention research should test the effects of adaptive reliance support, such as explanations, displays of confidence, and cognitive forcing functions on decision making and user acceptance (Buçinca et al., 2021; Lee & See, 2004). Governance should be modeled as a boundary condition and measured by data sovereignty, cybersecurity, and governance. The usual digital maturity measures should be added as well (Pittri et al., 2026; European Union, 2024). Thirdly, more research into autonomous, generative and agentic AI systems that initiate actions are required. To date, research into such systems indicates that, in contrast to human-initiated interactions with AI systems, system-initiated interactions are of little value while the risks of co-destruction increase (Blaurock et al., 2025; Plé & Cáceres, 2010). Replication of existing studies in under-represented regions and sectors such as public administration in Europe and the Gulf economies is also required to test the boundary conditions suggested in this paper in different institutional, cultural and resource environments (Kyambade & Namatovu, 2026). Shared instruments and open reporting of effect sizes would allow for the accumulation of evidence from individual studies instead of fragmenting it.

Limitations

Several limitations qualify the conclusions. First, the review is restricted to English-language, peer-reviewed publications from January 2024 to October 2026; it therefore omits earlier foundational empirical work (which is used here only for theoretical grounding) and non-English evidence. Second, the Tier B studies were verified at abstract or bibliographic level and are used for triangulation, so the strength of evidence behind each theme varies by tier. Third, the heterogeneity of designs and outcomes precluded pooled meta-analysis, and the effect sizes reported derive from a single primary meta-analysis, which itself shows very high heterogeneity ($I^2 = 97.7\%$). Fourth, the 38-study corpus, while theoretically focused, is smaller than those of broad bibliometric reviews, and publication bias toward positive findings cannot be excluded. Finally, the framework and hypotheses are derived from the evidence rather than tested; they should be treated as propositions for empirical validation. The generalizability of the conclusions is also bounded by the sectors represented in the corpus, which, as Gap 5 notes, under-represent public administration and emerging economies, and by the pace of change in generative AI, which means that findings on specific tools may date quickly even if the underlying mechanisms of integration, reliance and strain prove durable. Future updates of this review should therefore revisit the corpus periodically and extend the search to additional languages and databases.

Conclusion

This systematic review contributes to solving several unclear issues of human–AI collaboration. Value co-creation through human–AI collaboration is enabled by the integration of socio-technical resources rather than by technology. An integrated multi-level framework that connects Service-Dominant Logic (S-D Logic) and the ABC model through Intelligence Augmentation is provided. 38 peer-reviewed studies (13 Tier A studies = 13 primary full-text studies and 25 Tier B studies = 25 studies for triangulation) were synthesized. The design parameters of transparency, process control and outcome control are the most reliable ones. Calibrated reliance rather than maximum adherence is crucial for decision quality. The materialization of benefits of collaboration is dependent on AI literacy, digital maturity, interoperable infrastructures and technostress.

This paper provides seven formal hypotheses, seven research gaps, and an operational measurement agenda. To the scholar, this provides a platform for cumulative research in business, service management, HRM, and information systems. To the practitioner, human-AI collaboration should be designed, governed, and measured as an integrated system. The key issue is not if AI is deployed, but the extent to which humans and AI are integrated; the level of reliance that has been calibrated between humans and AI; and the extent to which organizations are equipped to deal with the resulting HR and service processes as AI becomes more and more autonomous. The key differentiator between those organizations that create value through human-AI collaboration and those that simply deploy technology through HRM and service processes, is their capacity to calibrate human reliance on AI; to govern and manage risk; and to ensure that the employee and service provider's well-being is sustained. This review shifts the discussion from whether human-AI collaboration creates value to the issues of how, for whom, and under what conditions human-AI collaboration can create value. By mapping design features to employees' perceptions, reliance calibration to decision-making quality, and organization readiness to network outcomes, the review presents a framework that helps guide research while providing practitioners and policymakers with a structural framework that can be used to implement human-AI collaboration in organizations.

Theoretical and Contextual Contributions of the Study

Our theoretical contributions to Service-Dominant Logic, the ABC model, Intelligence Augmentation, and the Reliance Calibration mechanism are as follows: Firstly, by integrating four different theoretical viewpoints into one holistic framework and thus adding value to the current knowledge in this field. Secondly, by clearly positioning Service-Dominant Logic as the underlying macro-logic for creating value through the integration of different resources, the ABC model as the micro-level response to any given input, Intelligence Augmentation as the mechanism to catalyze value at both the individual as well as the firm and network level, and Reliance Calibration as the underlying driver that explains how positive design features impact employee perceptions while average hybrid synergy is actually below that of the best single party ($g = -0.23$). Thirdly, by extending the logic of how value is co-destroyed by AI as an operant resource and how different employee, firm and network level boundary conditions such as AI literacy, digital maturity, interoperability and technostress impact the value created through hybrid AI systems. Finally, these theoretical contributions are translated into seven testable hypotheses, seven research gaps and a comprehensive measurement agenda.

Value because of the application of AI is created by its integration into business, by the way it is governed, and by the calibration of employees' use of AI. While deployment of AI is necessary, the main challenge for management relates to creation of value through these other dimensions. Therefore, key practical implications relate to transparency and overriding into AI systems, employees' calibration of their use of AI as opposed to strict compliance with processes, and matching of processes to tasks between creation and decision making. The implications also extend to the typical challenges of establishment of adequate infrastructure and satisfactory cybersecurity as well as to specific AI stressors. Above all, AI literacy and sufficient redesigning employees' roles to utilize AI effectively in their work are required. In terms of implementation, a phased rollout is suggested to be followed by measurement of employees' reliance on AI and decision quality.

Benefits for policy makers. The main implication of the findings for policy makers is to make meaningful human oversight possible and to understand that within the scope of the EU AI Act oversight by humans only works if they can test and challenge AI outputs. Therefore, there is a need for AI literacy, for process control and for outcome control. A risk-based approach for different tasks, the funding of shared interoperable infrastructure and standards, in particular for the public sector but also for countries in the Gulf region and other emerging economies, the protection of workers and their well-being and last but not least a longitudinal evaluation and shared measurement instruments are required.

References

Abanda, F. H., Jian, N., Adukpo, S., Tuhaise, V. V., & Manjia, M. B. (2025). Digital twin for product versus project lifecycles' development in manufacturing and construction industries. Journal of Intelligent Manufacturing, 36(3), 801–831. https://doi.org/10.1007/s10845-023-02301-2

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30.

Ala-Luopa, S., Koivunen, S., Olsson, T., & Väänänen, K. (2024). Considerations on human–AI collaboration in knowledge work – Recruitment experts' needs and expectations. In Proceedings of the 57th Hawaii International Conference on System Sciences (pp. 2415–2424). IEEE.

Aldoseri, A., Al-Khalifa, K. N., & Hamouda, A. M. (2024). AI-powered innovation in digital transformation: Key pillars and industry impact. Sustainability, 16(5), Article 1790. https://doi.org/10.3390/su16051790

Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., … Horvitz, E. (2019). Guidelines for human-AI interaction. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (Paper 3). ACM.

Bakker, A. B., & Demerouti, E. (2007). The job demands-resources model: State of the art. Journal of Managerial Psychology, 22(3), 309–328.

Barile, S., Bassano, C., Piciocchi, P., Saviano, M., & Spohrer, J. C. (2024). Empowering value co-creation in the digital age. Journal of Business & Industrial Marketing, 39(6), 1130–1145. https://doi.org/10.1108/JBIM-12-2019-0553

Benabou, A., & Touhami, F. (2025). Artificial intelligence in human resource management: A PRISMA-based systematic review. Acta Informatica Pragensia, 14(3), 489–505. https://doi.org/10.18267/j.aip.264

Blaurock, M., Büttgen, M., & Schepers, J. (2025). Designing collaborative intelligence systems for employee-AI service co-production. Journal of Service Research, 28(4), 544–562. https://doi.org/10.1177/10946705241238751

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101.

Breidbach, C. F., & Maglio, P. P. (2016). Technology-enabled value co-creation: An empirical analysis of actors, resources, and practices. Industrial Marketing Management, 56, 73–85.

Buçinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To trust or to think: Cognitive forcing functions can reduce overreliance on AI in AI-assisted decision-making. Proceedings of the ACM on Human-Computer Interaction, 5(CSCW1), Article 188.

Bui, H. T., Filimonau, V., & Sezerel, H. (2025). Exploring value co-creation and co-destruction between consumers and generative artificial intelligence (GAI) in travel. Tourism Management Perspectives, 58, Article 101392.

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

da Silva, A., & Cardoso, A. J. M. (2024). Coopetition with the industrial IoT: A service-dominant logic approach. Applied System Innovation, 7(3), Article 47. https://doi.org/10.3390/asi7030047

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. Harvard Business Review, 96(1), 108–116.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 114–126.

Echeverri, P., & Skålén, P. (2011). Co-creation and co-destruction: A practice-theory based study of interactive value formation. Marketing Theory, 11(3), 351–373.

European Union. (2024). Regulation (EU) 2024/1689 of the European Parliament and of the Council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union, L series.

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. Minds and Machines, 28(4), 689–707.

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

Gupta, P., Lakhera, G., & Sharma, M. (2024). Examining the impact of artificial intelligence on employee performance in the digital era: An analysis and future research direction. Journal of High Technology Management Research, 35(2), Article 100520.

Hasan, S. K. K., & Crawford, C. W. (2025). A new era for digital twins: Progress and industry adoption. Digital Twin, 2(4), Article 2555877.

Hedges, L. V. (1981). Distribution theory for Glass's estimator of effect size and related estimators. Journal of Educational Statistics, 6(2), 107–128.

Heimburg, V., Schreieck, M., & Wiesche, M. (2025). Complementor value co-creation in generative AI platform ecosystems. Journal of Management Information Systems, 42(2), 491–528.

Higgins, J. P. T., & Thompson, S. G. (2002). Quantifying heterogeneity in a meta-analysis. Statistics in Medicine, 21(11), 1539–1558.

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155–172.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons, 61(4), 577–586.

Jia, Y., Zhu, W., & Cai, Y. (2026). Value co-creation between nurses and generative artificial intelligence: A grounded theory study. Journal of Nursing Management, Article 8980490.

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389–399.

Kellogg, K. C., Valentine, M. A., & Christin, A. (2020). Algorithms at work: The new contested terrain of control. Academy of Management Annals, 14(1), 366–410.

Kyambade, M., & Namatovu, A. (2026). Exploring HR professionals' experiences with generative AI in recruitment: A phenomenological study in public hospitals in Uganda. SAGE Open, 16(1).

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. Human Factors, 46(1), 50–80.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. Organizational Behavior and Human Decision Processes, 151, 90–103.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (pp. 1–16). ACM.

Lusch, R. F., & Nambisan, S. (2015). Service innovation: A service-dominant logic perspective. MIS Quarterly, 39(1), 155–176.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. Academy of Management Review, 20(3), 709–734.

Noy, S., & Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. Science, 381(6654), 187–192.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. Systematic Reviews, 10(1), Article 89.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. Human Factors, 39(2), 230–253.

Paul, J., & Criado, A. R. (2020). The art of writing literature review: What do we know and what do we need to know? International Business Review, 29(4), Article 101717.

Pinho, J. C., Fontes, A., & Santos, G. G. (2026). Balancing the double-edged sword of artificial intelligence: Job demands, resources, and work–life balance. Computers in Human Behavior Reports, 15, Article 100412.

Pittri, H., Godawatte, G. A. G. R., & Forster, A. M. (2026). Blockchain-enabled construction supply chain management: A scientometric and content analysis of applications, barriers and future prospects. Engineering, Construction and Architectural Management, 33(2), 412–435.

Plé, L., & Cáceres, R. C. (2010). Not always co-creation: Introducing interactional co-destruction of value in service-dominant logic. Journal of Services Marketing, 24(6), 430–437.

Prahalad, C. K., & Ramaswamy, V. (2004). Co-creating unique value with customers. Strategy & Leadership, 32(3), 4–9.

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. Information Systems Research, 19(4), 417–433.

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210.

Sapkota, P., Makkonen, M., Pirkkalainen, H., & Salo, M. (2025). From technostressors to AI-stressors: A systematic literature review of stressors associated with AI systems. In Proceedings of STPIS 2025 (pp. 15–28). RWTH Aachen.

Saxena, S., Amritesh, Mishra, S. C., & Mukerji, B. (2024). A multi-method bibliometric review of value co-creation research. Management Research Review, 47(2), 183–203.

Schoeffer, J., Jakubik, J., Vössing, M., Kühl, N., & Satzger, G. (2025). AI reliance and decision quality: Fundamentals, interdependence, and the effects of interventions. Journal of Artificial Intelligence Research, 82, 471–501.

Simón, C., Revilla, E., & Sáenz, J. (2024). Integrating AI in organizations for value creation through human–AI teaming: A dynamic-capabilities approach. Journal of Business Research, 182, Article 114783.

Su, H., Du, X., Chen, Y., Tian, S., Ma, Q., & Zhong, W. (2025). Value co-creation mechanism for AI-based enterprises with systems thinking: Case study of Baidu. Systems Research and Behavioral Science, 42(4), 1142–1162.

Tarafdar, M., Cooper, C. L., & Stich, J.-F. (2019). The technostress trifecta – techno eustress, techno distress and design: Theoretical directions and an agenda for research. Information Systems Journal, 29(1), 6–42.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533.

Thomas, J., & Harden, A. (2008). Methods for the thematic synthesis of qualitative research in systematic reviews. BMC Medical Research Methodology, 8, Article 45.

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. British Journal of Management, 14(3), 207–222.

Vaccaro, M., Almaatouq, A., & Malone, T. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. Nature Human Behaviour, 8(12), 2293–2303. https://doi.org/10.1038/s41562-024-02024-1

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. Journal of Marketing, 68(1), 1–17.

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: Continuing the evolution. Journal of the Academy of Marketing Science, 36(1), 1–10.

Vargo, S. L., & Lusch, R. F. (2016). Institutions and axioms: An extension and update of service-dominant logic. Journal of the Academy of Marketing Science, 44(1), 5–23.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

Wilson, H. J., & Daugherty, P. R. (2018). Collaborative intelligence: Humans and AI are joining forces. Harvard Business Review, 96(4), 114–123.

Zhao, R., Niu, L., Chen, Z., Wu, Y., & Van Looy, A. (2026). From human-centric to value co-creation: A staged model of human–AI collaboration in smart manufacturing. Journal of Manufacturing Technology Management, 37(1), 112–135.