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Article

Research on optimization strategies of future technology-driven intelligent collaboration systems for remote employee work engagement

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ABSTRACT

The COVID-19 pandemic has revolutionized global work habits, with remote work evolving from an ad hoc measure to a significant component of company strategy. Traditional remote work support tools, over the years, have, however, shown weaknesses in increasing workers' engagement. The current research focuses on the core issues of influence mechanisms and optimization approaches for intelligent collaboration systems in remote workers' work engagement. By integrating Self-Determination Theory, Job Demands-Resources Theory, and Task-Technology Fit Theory, a comprehensive theoretical framework emerges with direct effects, mediating processes, and boundary conditions. The study shows that innovative collaboration systems (e.g., AI-based apps, virtual reality spaces, and automated business processes) influence employees' work engagement through two mediating channels: workload reduction and autonomy development, with moderation at the individual competence level by AI literacy and at the contextual setting level by organizational support. According to the theoretical model, this paper proposes a four-dimensional framework for technology integration optimization, including technology integration optimization, human-centered design, organizational support mechanisms, and phased implementation routes. The theoretical contributions of this study are in: unifying innovative collaboration systems with the model of remote work engagement study, hoping to enlarge the theoretical boundaries of human-machine collaboration; demystifying the natural correlation between technological features and psychological need fulfillment with multi-theory combination; and making operational theoretical recommendations for organizations to balance technological effectiveness with humanistic concern in the process of smart transformation through the platform of optimization strategies. This study provides decision-making grounds and practical guidance for companies to establish man-centric smart collaboration systems, for managers to develop attention-grabbing employee support programs, and for policymakers to govern smart technology use at work.

1. Introduction

The COVID-19 pandemic has completely changed the global work patterns, and remote work has evolved from a compulsory measure to a widespread trend. Large-scale telecommuting during the initial wave of the pandemic led to record organizational restructuring [1]. This shift not only changed the conventional workplace but also had complex effects on employees' levels of work engagement. Research has shown that employees' work engagement in telework environments is dual: while some report greater work enthusiasm due to increased flexibility [2], others experience reduced productivity and increased pressure [3]. Such polarized performance reflects deeper difficulties in working from a distance. As the post-pandemic era unfolded, working remotely has evolved from a temporary fix to a core component of organizational strategy [4]. However, traditional remote work support technologies have persistently fallen behind evolving work environments. The rapid evolution of intelligent collaboration technologies has created new avenues to close this disparity, as AI-driven tools, virtual reality collaboration spaces, and workflow automation are reconfiguring the boundaries of remote collaboration. Even though technological developments have created new possibilities for remote work [5], the successful integration of such smart systems to improve employees' work commitment remains a fundamental challenge for companies. Current research is primarily directed at emergency management responses throughout the pandemic [6] and employee adaptability in telework based solely on traditional factors [7], with systematic studies on the interaction between intelligent collaboration systems and work engagement in short supply. While scholarly studies on remote work engagement have made some progress, the current literature has three major shortcomings. First, the great majority of studies address the macro level of work design [8], with sparse in-depth investigation of the mechanisms by which technological system properties match workers' psychological needs. Second, empirical examinations of factors affecting remote work participation mostly focus on common variables such as organizational support and leadership behavior [9], while ignoring the unique status of smart technology as a new work resource. Third, studies of remote work during pandemics primarily use cross-sectional designs [10], which are not grounded in theoretical notions for conceiving optimal long-term intelligent collaboration systems. The rapid development of new technologies, such as generative artificial intelligence, and their application in organizational practice [11] heightens the need to ground a systemic theoretical conception.

Building on the above background, the present study centers on the primary issue of the mechanism by which intelligent collaboration systems influence remote workers' work engagement. In particular, the present paper seeks to investigate how employee work engagement is impacted by the multidimensionality of intelligent collaboration technology, via mediating factors such as decreased workload and increased autonomy, and to examine the moderating roles of AI literacy and organizational support in this process. By cross-seeding Self-Determination Theory, Job Demands-Resources Theory, and Task-Technology Fit Theory, this research constructs an integrated theoretical framework with direct effects, mediating processes, and boundary conditions, and advances phased system-optimization strategies grounded in the above foundation. The theoretical contribution of this research is in three aspects. Firstly, integrating intelligent collaborative systems into remote work participation pushes the theoretical frontiers of human-machine collaboration. Second, through multi-theory integration, it captures the inherent interrelation between technological attributes and the satisfaction of psychological needs, thereby providing a rationale for resource investment in remote working environments. Third, the grounded four-dimensional optimization strategy framework offers an operational theory underpinning for organizations to optimize technological efficiency and humanistic care in smart transformation. At the factual level, this research offers a rationale for corporate decision-makers to evolve toward people-oriented smart collaboration systems, guides managers in formulating distinctive employee support programs, and provides policymakers with a point of reference for legislating the use of smart technology.

The paper is divided into five chapters. Chapter 1 elaborates on the setting, problems, and significance of the research. Chapter 2 develops the theoretical framework and research design model by integrating three fundamental theories and by formulating a mixed-methods research approach. Chapter 3 presents an integrated theory model and eight research propositions that explain sequentially the paths and processes by which intelligent collaboration systems impact remote employee work engagement. Chapter 4 formulates optimization strategies from four perspectives—technology integration, human-centered design, organizational support, and implementation protection mechanisms—and an implementation plan phased over time. Chapter 5 synthesizes the research contribution and its implications for practice, specifies the research limitations, and discusses future study directions.

2. Theoretical foundation and research design framework

2.1 Core theoretical perspectives

Explaining the influence of intelligent collaboration systems on remote employees' work engagement requires theoretical grounding. This research combines Self-Determination Theory, Job Demands-Resources Theory, and Task-Technology Fit Theory to conceptualize a multi-level explanatory framework from motivational psychology, work context, and technology matching perspectives. Self-Determination Theory offers the baseline framework for explaining employee intrinsic motivation. This theory argues that people's psychological well-being and optimal functioning are based on the fulfillment of three innate psychological needs: autonomy, competence, and relatedness [12]. In the context of remote working conditions, smart collaboration systems support the workers' feeling of independence through flexible arrangements and personalized assistance, competence from real-time feedback and smart assistance, and relatedness through VR/AR platforms that create immersive social presence. Virtual collaboration spaces enable avatar-based interaction, spatial audio, and shared virtual environments that foster interpersonal connection among distributed team members, mitigating the social isolation inherent in remote work [13]. When all three basic needs are met, employees are most likely to be autonomously motivated, thereby showing greater work engagement.

Job Demands-Resources Theory accounts for employee work states by the two-folded nature of the work environment, dividing job characteristics into two broad categories: job demands and job resources, with the former causing stress and burnout, and the latter, motivation and engagement [14]. Smart remote work collaboration technology alleviates workload by means of automation and offers technical support as an innovative resource at the same time. The two-pathway model of the theory demonstrates the mechanism of work engagement development: the resource enrichment pathway activates motivation, and the demand reduction pathway reduces burden. Task-Technology Fit Theory focuses on the matching between technological capability and task demands, arguing that a positive effect occurs only when technological functions are highly consistent with task demands, reminding managers to heed the fit when targeting technology utilization. These three theories are integrated because they form a causal chain from technological features to psychological needs to behavioral outcomes. Task-Technology Fit Theory illustrates how technological features are translated into helpful resources; Job Demands-Resources Theory illustrates how resources affect employee states through dual processes; and Self-Determination Theory illustrates how resource investment fulfills psychological needs, leading to intrinsic motivation. As illustrated in Figure 1, all three theories concentrate on various levels of mechanisms. The integration of multiple theories provides a robust theoretical foundation for understanding the multifaceted role of intelligent collaboration systems in remote work.

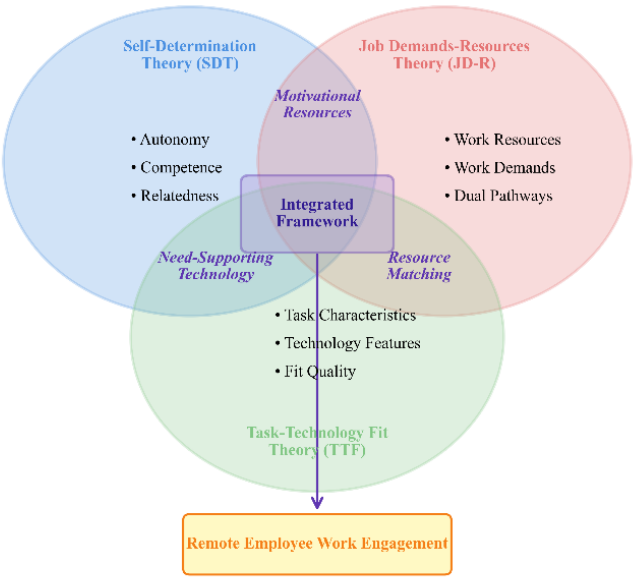

Figure 1. Integrated theoretical framework

This multi-theoretical integration has empirical precedents in technology-mediated work research. Gagné and colleagues [15] comprehensively reviewed how SDT integrates with work design theories, including JD-R, demonstrating that job resources identified in the JD-R framework can satisfy basic psychological needs, which in turn enhance autonomous motivation—particularly relevant when technology transforms remote work contexts. The incorporation of TTF with behavioral theories has been validated in pandemic-era studies, with Kamdjoug et al. [16] showing that task-technology alignment in remote work settings amplifies the positive effects of ICT resources on employee performance. Moreover, recent theoretical advances in JD-R theory have explicitly incorporated SDT constructs and proactive behaviors [14], establishing a solid foundation for multi-theory integration in understanding technology-enabled work arrangements.

2.2 Key constructs and conceptualization

The central constructs in this study need clear conceptual and operational definitions to assess the theoretical model's strength and testability through empirical studies. Intelligent collaboration systems, as the independent variable, are conceptualized as a formative construct integrating three distinct technology components that collectively form the overall system capability. AI-powered tools (intelligent task allocation algorithms, natural language processing assistants, predictive analytics systems) provide cognitive augmentation through data-driven decision support. Virtual and augmented reality platforms create immersive collaboration spaces that enhance social presence for distributed members. Automation systems enable intelligent process execution through predefined rules and machine learning, releasing employees from routine tasks. These three dimensions are treated as formative rather than reflective indicators because they represent distinct, non-interchangeable technological capabilities—organizations may implement different combinations, and each component contributes unique functionality to the overall system rather than reflecting a common underlying factor. Work engagement, as the dependent variable, refers to employees' positive psychological state at work, whose three-dimensional structure contains certain measurement indices. The vigor dimension appears as a high level of energy and psychological resilience; the dedication dimension as work meaningfulness and a sense of pride; and the absorption dimension as a state of being entirely focused on work tasks. Self-Determination Theory underscores that these manifestations of engagement are the products of fulfilled basic psychological needs. If the work context facilitates autonomy and allows experiences of competence, employees tend to demonstrate high levels of vigor, dedication, and absorption [15]. The specification of mediating variables attempts to unveil the internal mechanisms whereby intelligent collaboration systems impact work engagement. Workload, operationalized using the Job Content Questionnaire's quantitative demands subscale (5-7 items) [17], refers to perceived work pace, time pressure, and volume of tasks—explicitly excluding decision-making latitude or skill discretion to avoid overlap with autonomy measures. Sample items include "How often does your job require you to work very fast?" and "How often do you have too much work to do?", focusing purely on task load rather than control dimensions. Intelligent collaboration systems reduce workload through automation and intelligent support, allowing employees to devote the cognitive resources they save to higher-value activities. Autonomy, measured using the Work Design Questionnaire [18], refers to the degree of self-determination employees exercise over work methods, scheduling, and decision-making. Smart collaboration technology enhances autonomy through flexible options and personalized settings, activating intrinsic motivation. The two mediators account for the demand reduction pathway and resource enrichment pathway in Job Demands-Resources Theory, respectively.

The specification of moderating variables takes into account boundary conditions at individual and contextual levels. AI literacy, defined as individuals' capability to understand, use, and critically evaluate artificial intelligence technologies in work contexts [19], encompasses technical understanding, operational proficiency, critical evaluation, and collaborative competence with AI systems. Sample items for the AI literacy scale include: "I can explain how AI decision processes work" (technical understanding), "I effectively use AI tools to complete my work tasks" (operational proficiency), "I can evaluate the reliability of AI-generated recommendations" (critical evaluation), and "I know when to rely on AI versus my own judgment" (collaborative competence). This four-factor structure will be validated through the two-stage process described in Section 2.3. Employees with higher AI literacy are better able to leverage system functionality and transform technological features into productive work resources. Organizational support, measured using the short form of the Survey of Perceived Organizational Support (8 items) [20], refers to employees' perception that their organization values their contributions and cares about their well-being. To ensure contextual relevance, items are adapted to the intelligent collaboration system context—for example, the original item "My organization values my contribution" is modified to "My organization values my input on AI tool usage," and "My organization cares about my well-being" becomes "My organization provides adequate support when I encounter difficulties with intelligent systems." This contextualization maintains scale validity while enhancing specificity to technology implementation scenarios. High organizational support reduces technology change anxiety through management commitment and resource provision, enhancing the positive impacts of smart collaboration systems. The two moderating variables offer theoretical justification for developing differentiated management strategies.

While AI literacy and autonomy may correlate empirically, they are conceptually distinct. Autonomy represents a work design characteristic—the degree of self-determination in work processes across all contexts. AI literacy represents a domain-specific capability—knowledge and skills for utilizing AI technologies. Critically, they serve different theoretical roles: autonomy functions as a mediating variable explaining "how" technology influences engagement through enhanced self-determination, while AI literacy serves as a moderating variable determining "when" or "for whom" technology effects are amplified. AI literacy does not directly cause autonomy but rather moderates technology's autonomy-enhancing effects. To empirically assess multicollinearity, we will: (1) examine bivariate correlations, expecting moderate levels (r = 0.30-0.50); (2) calculate Variance Inflation Factors (VIF < 3.0 as acceptable threshold); (3) conduct confirmatory factor analysis comparing two-factor versus one-factor models to demonstrate discriminant validity; and (4) verify that average variance extracted (AVE) exceeds squared correlation (AVE > r^2). If concerns arise, mean-centering will be employed before creating interaction terms.

2.3 Proposed research design

Empirical testing of the theoretical model demands a strict research design and systematic data collection processes. The current study follows a mixed-methods research approach to maximize the strengths of quantitative and qualitative research. Quantitative research ($n > 500$) tests hypothesized relationships through large-scale surveys and structural equation modeling. Qualitative interviews (n = 20-30) serve three triangulation functions: (1) Pre-survey refinement—initial interviews (n = 8-10) verify measurement items and identify contextual factors; (2) Results explanation—follow-up interviews (n = 12-15) after SEM analysis explore unexpected findings (e.g., if workload mediation is weak, interviews investigate offsetting cognitive demands); (3) Pattern corroboration—thematic coding frequencies are compared with path coefficients to verify convergence (e.g., strong autonomy effects should align with control-related narratives). This cross-method verification enhances validity through triangulation.

Sample selection is guided by the principles of representativeness and targeting. The target sample consists of employees who have consistently followed remote collaboration practices and have at least 6 months of experience working with intelligent collaboration systems. Industry coverage includes knowledge-intensive sectors such as information technology, financial services, professional consulting, and creative industries. Specifically, targeted sectors include IT consulting (e.g., software development firms using AI-powered project management), fintech (e.g., remote financial analysts leveraging predictive analytics), and professional services (e.g., distributed consulting teams utilizing VR meeting platforms). Manufacturing industries are excluded because remote work in these contexts primarily involves operational monitoring rather than collaborative knowledge work, resulting in fundamentally different task-technology fit dynamics. Quota sampling will ensure balanced representation: 30-35% IT/software, 25-30% financial services, 20-25% consulting, 15-20% creative industries, maintaining diversity while focusing on remote-collaborative knowledge work contexts where intelligent collaboration systems are core productivity tools. The sample must include multiple levels of position, with geographical coverage spanning several countries or regions to control for cultural differences. The sample size for quantitative research must be at least 500 participants to meet the requirements of structural equation modeling, whereas qualitative research uses in-depth interviews with 20-30 employees until data saturation. This sample size is justified by anticipated effect sizes from prior literature. Meta-analyses of technology-job resources relationships report medium main effects (β = 0.25-0.40), with job resources → engagement (β = 0.30-0.45) and autonomy → engagement (β = 0.35-0.50). Moderation effects from digital literacy and organizational support studies typically show small-to-medium interactions (β = 0.10-0.20, ΔR^2 = 0.02-0.05). Power analysis indicates n = 500 provides >0.80 power to detect medium main effects ($\beta \geq 0.25$) and small-to-medium moderations ($\beta \geq 0.12$) at α = 0.05. With 25-30% attrition across three waves (final n = 350-375), power remains >0.75 for theoretically meaningful effects. Recruitment will utilize: (1) HR platform partnerships (LinkedIn, professional associations); (2) 8-10 organizational collaborations with employee access; (3) snowball referrals. An expected 35-40% response rate requires distributing ~1,500 surveys across 4-5 countries. Interviews are recruited from survey volunteers (15% rate) and organizational partners. Research budget ($12,000), institutional partnerships (2 platforms, 5 companies), and a 3-person team secured for a 9-month timeline.

Questionnaire design is made on the basis of mature measurement tools and contextualized by the situation. Measurement of intelligent collaboration systems employs 6-7 items per dimension (rather than 4-5) because formative constructs require comprehensive content coverage—each indicator contributes unique information about distinct technological facets. AI tools include task allocation, natural language processing, and predictive analytics; VR/AR platforms include spatial presence and 3D visualization; automation covers workflow routing and system integration. Item development follows: expert consultation, content validity assessment (CVR > 0.62), cognitive pretesting (n=20-25), and pilot testing (n=100-150) with VIF < 3.3. Formative constructs are evaluated through indicator weights and VIF rather than Cronbach's alpha. Pilot data (n=100-150) will report inter-dimension correlations (expected r=0.30-0.50), verify items do not conflate dimensions (e.g., excluding "AI-enhanced VR" hybrid items), and confirm formative construct validity through VIF<3.3. Work engagement uses the short form of the Utrecht Work Engagement Scale, and it measures using a total of 9 items with three subscales, i.e., vigor, dedication, and absorption. Workload is quantified with the Job Content Questionnaire and autonomy with the Job Characteristics Model. Studies on Self-Determination Theory implementation in remote working environments explore an operationalization reference framework for these variables [13]. AI literacy entails creating a new scale encompassing technical capability, algorithmic thinking, and human-machine collaboration cognition.

AI Literacy Scale Validation: A two-stage validation process will be implemented. Stage 1: Exploratory Factor Analysis (EFA) with Sample 1 (n = 200) using principal axis factoring and promax rotation. Item retention criteria: factor loadings ≥ 0.50, cross-loadings < 0.30, communalities > 0.40.

Items violating multiple criteria will be eliminated, reducing the scale to 12-15 items. Stage 2: Confirmatory Factor Analysis (CFA) with Sample 2 (n = 300) to validate factor structure. Model fit criteria: $\chi^2/df < 3.0$, CFI/TLI > 0.90, RMSEA < 0.08, SRMR < 0.08. Item deletion based on: standardized loadings < 0.60 or problematic modification indices. Validity assessment: convergent validity (AVE > 0.50, CR > 0.70) and discriminant validity (AVE > squared correlations). This rigorous validation ensures the AI literacy scale captures distinct yet related competencies (technical, operational, evaluative, collaborative) without redundancy, establishing factorial validity before testing its moderating role in the structural model. The split-sample design (total n = 500) follows scale development recommendations with a 10:1 subject-to-item ratio for EFA and 200+ for CFA power. Organizational support takes the Perceived Organizational Support Scale, where all the items are on a seven-point Likert scale. For multi-regional data collection, standard back-translation procedures will ensure cross-cultural equivalence. Two independent bilingual translators will translate English items into target languages, followed by back-translation to English. Inter-translator agreement will be assessed using Cohen's Kappa (target: $\kappa > 0.80$), with discrepancies resolved through expert panel discussion. Additionally, pilot cognitive interviews (n=10 per region) will verify item comprehension and cultural appropriateness—participants will be asked to paraphrase items and explain their interpretation, identifying potential semantic misunderstandings before full deployment. This process ensures measurement invariance across geographical contexts. Reflective scales will be assessed for reliability and validity. For reliability assessment, multiple indicators will be used depending on scale length: (1) Cronbach's alpha ($\alpha > 0.70$) for scales with 5+ items; (2) Composite reliability (CR > 0.70) for all constructs, as it accounts for different indicator loadings and is more appropriate for SEM; and (3) Omega coefficient ($\omega > 0.70$) for constructs with few items (3-4 items), as omega is less biased than alpha for short scales.

Given that some subscales have only 3 items (e.g., vigor, dedication, absorption in work engagement; work autonomy dimensions), CR and omega will serve as primary reliability indicators for these constructs, while alpha will be reported for comparison. Validity assessment includes convergent validity (AVE > 0.50) and discriminant validity (Fornell-Larcker criterion). Variable operationalization definitions ensure accurate correspondence between theoretical constructs and empirical measurements. Intelligent collaboration systems are measured through employees' perceived ratings of system functionality completeness, interface friendliness, and task fit. Work engagement is operationalized as the degree of vigor, dedication, and absorption experienced by employees. Workload is defined as perceived time pressure, task complexity, and cognitive consumption. Autonomy is operationalized as the degree of control over task execution methods, work pace, and decision-making content. As shown in Figure 2, the research design is divided into four consecutive phases: the assessment and preparation phase, which involves conducting a literature review and theoretical framework construction; the questionnaire design phase completes measurement instrument development and pretesting; the data collection phase distributes questionnaires through online platforms and employs a three-wave longitudinal design to establish temporal precedence and control for common method bias. At Time 1, participants complete measures of intelligent collaboration systems, moderators (AI literacy, organizational support), and controls (50 items, 12 minutes). At Time 2 (2 weeks later), mediators—workload and autonomy—are measured (14 items, 6 minutes), allowing technology effects on work conditions to manifest. At Time 3 (4 weeks after T2), work engagement and performance are assessed (14 items, 6 minutes), providing time for need satisfaction to translate into engagement per self-determination theory.

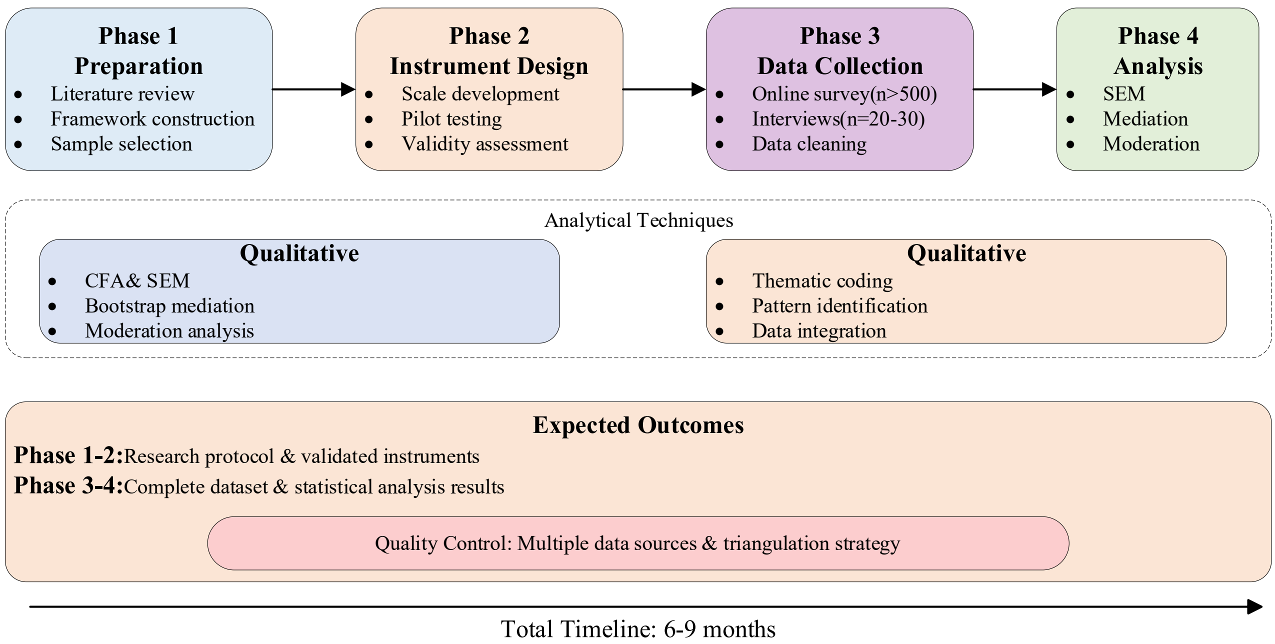

Figure 2. Proposed research design and data collection procedure

Unique identifiers enable response matching, with tiered incentives ($5/wave + $10 bonus) supporting expected 70-75% retention (350-375 complete cases). A subsample (n = 100-150) provides supervisor-rated performance at T3; and the analysis and technology phase employs structural equation modeling to test the theoretical model and conducts thematic coding analysis of qualitative data.

2.4 Proposed analytical approach

Systematic and stringent analytical methods are necessary to ensure that research results are scientifically valid. The building block of data analysis is reliability and validity testing. Reliability testing involves internal consistency reliability and composite reliability, with Cronbach's alpha used to assess scale item consistency (expected coefficients> 0.70) and composite reliability derived from confirmatory factor analysis outputs. Three types of validity testing are conducted: content validity, construct validity, and discriminant validity. Content validity addresses whether items truly represent theoretical constructs based on expert judgment; construct validity investigates measurement model fit using confirmatory factor analysis; and discriminant validity tests construct independence by comparing correlation coefficients between constructs with average variance extracted values.

Structural equation modeling, the main statistical method for testing the theoretical model, follows a stepwise, progressive approach from simple to complex. The analysis first builds a measurement model to ensure indicator variables for theoretical concepts are accurately measured, and goodness-of-fit is tested using confirmatory factor analysis. Model fit statistics should be at the following levels: chi-square to degrees of freedom ratio less than 3, comparative fit index and Tucker-Lewis index higher than 0.90, root mean square error of approximation lower than 0.08, and standardized root mean square residual lower than 0.08. Once the measurement model has been validated, a structural model is built to test cause-and-effect relationships. This two-stage approach is employed to separate measurement error and structural relationships, thereby achieving improved path coefficient estimates. Maximum likelihood estimation is employed when the sample size is sufficiently large; robust maximum likelihood estimation or Bayesian estimation procedures are employed when there is a non-normal distribution of data.

The test of mediation effect follows the Bootstrap approach to create an empirical distribution of indirect effects by repeated sampling and building confidence intervals without assuming normality. The number of repeated samples is fixed at 5,000 to guarantee estimation stability. We will use 95% bias-corrected and accelerated (BCa) confidence intervals, which correct for both bias and skewness in the bootstrap distribution, providing more accurate Type I error rates than percentile intervals. If the BCa confidence interval excludes zero, the mediation effect is significant. In the present study, workload and autonomy as mediating variables need to be estimated separately for their respective indirect and total indirect effects. To compare the two pathways, pairwise contrast tests will estimate the difference between indirect effects (ICS→workload→engagement minus ICS→autonomy→engagement) and provide bootstrap CIs. If the difference CI excludes zero, the pathways differ significantly in strength. The proportion of the total indirect effect carried by each pathway will also be reported to clarify relative importance. Moderation effects will be tested using latent moderated structural equations (LMS) within the SEM framework, allowing simultaneous estimation while accounting for measurement error. Latent interaction terms (ICS × AI literacy, ICS × organizational support) will be created and added to the structural model. Model fit comparison ($\Delta\chi^2$, AIC, BIC) will assess significance, followed by hierarchical regression probing using the PROCESS macro and Aiken & West (1991) procedures. Simple slopes analysis will be conducted at -1SD, mean, and +1SD moderator levels, with practical significance evaluated through incremental variance explained (ΔR^2). A threshold of $\Delta R^2 > 0.02$ (2% additional variance) will indicate meaningful moderation effects beyond statistical significance, ensuring that interaction terms contribute substantively to explaining work engagement variance. For moderated mediation, conditional indirect effects will be calculated at different levels of the moderator using bootstrapping (5,000 samples). The index of moderated mediation will quantify whether moderators differentially affect the two mediation pathways (workload vs. autonomy). This clarifies whether AI literacy and organizational support primarily strengthen the resource-enrichment pathway (autonomy) or the demand-reduction pathway (workload).

Multilevel analysis is necessary because organizational data are hierarchical. Estimating the intraclass correlation coefficient before data analysis is appropriate as a measure of between-group variability. If the intraclass correlation coefficient is greater than 0.05, use multilevel linear models that incorporate both individual-level predictor variables and organizational-level context variables to obtain unbiased parameter estimates. Regarding construct-level specification for multilevel modeling: Level 1 (individual-level) constructs include AI literacy, perceived workload, perceived autonomy, work engagement, work performance, and individual perceptions of ICS features. Level 2 (organizational-level) constructs include organizational support, which reflects organizational climate characteristics. ICS is primarily measured at the individual perception level, but organizational-level ICS maturity can be computed by aggregating individual perceptions if ICC(1) > 0.05 and rwg > 0.70 indicate sufficient within-organization agreement. If ICC < 0.05 for key constructs, single-level SEM is appropriate as organizational nesting effects are negligible. Qualitative data analysis uses thematic coding, where the early ideas are determined through open coding, conceptual linking is developed through axial coding, and lastly, the key themes are established through selective coding.

Two coders work separately on coding, and inter-coder reliability is calculated to maintain objectivity. Synthesis of qualitative results and quantitative outcomes follows the principle of triangulation through systematic mapping procedures. Specifically, thematic codes from interviews will be matched to corresponding SEM paths—for example, if autonomy-related themes emerge with high frequency (e.g., "flexible scheduling," "control over work methods"), this corroborates the hypothesized autonomy mediation pathway strength. Quantitative path coefficients will be interpreted alongside qualitative narratives: a strong ICS→autonomy→ engagement path (β>0.30) should align with frequent autonomy themes in interview data. Conversely, unexpected findings (e.g., weak workload mediation) will prompt targeted follow-up interviews to explore offsetting factors or measurement issues. This cross-method verification enhances validity by confirming that statistical relationships reflect genuine employee experiences.

3. Theoretical model and research propositions

3.1 Human-AI collaboration mechanism in remote work

A virtual office environment is a unique application situation for collaboration between humans and artificial intelligence, where physical space differentiation and dependency on virtual connections coexist. Workers and intelligent systems form a highly dependent cooperative relationship, and this cooperative working pattern exhibits interactive characteristics of mutual complementarity and dynamic adaptation among humans and artificial intelligence in task execution procedures. Smart collaboration systems serve various roles as information-processing assistants, decision-support advisors, and communication facilitators among remote teams. The development of effective human-machine collaboration mechanisms involves adhering to the augmentation ethos rather than replacement, ensuring that technology augments human ability rather than undermining human autonomy and creativity [21].

Task-technology fit is especially important in virtual man-machine cooperation. Critical fit dimensions include the congruence between task complexity and system intelligence level; routine tasks should be matched with highly mechanized processing, while creative tasks require greater freedom for human judgment. In the meantime, task collaboration intensity and system communication support capability, time sensitivity and response speed, and task cognitive load and system level of intelligent assistance directly influence collaboration effectiveness. These coordination dimensions are interrelated in everyday work life, determining collectively if intelligent collaboration systems can successfully cope with the demands of remote working tasks or not.

From the viewpoint of Job Demands-Resources Theory, intelligent collaboration systems have two-edged effects on telecommuting. On the one hand, systems grant employees access to real-time data, intelligent task allocation suggestions, and workflow automation toolkits to alleviate information asymmetry and coordination challenges, while automation features handle many repetitive tasks, reducing employees' energy consumption on meaningless work. Conversely, technology could be another cause of demand; learning and adaptation to intelligent systems add more cognitive load, technical failures and system maintenance introduce uncertainty, and over-monitoring could lead to privacy issues. Nevertheless, remote human-machine collaboration also faces a lot of challenges. Present-day artificial intelligence applications are usually explainable in decision-making, and this makes it hard for employees to realize the reasoning behind algorithmic suggestions, and a lack of transparency erodes trust [22]. Moreover, human work rhythms aren't very flexible compared to intelligent systems designed with rigid rules, which may lower collaboration efficiency. Technology-converging communication may also harm emotional relationships among members. As shown in Figure 3, telework's human-machine collaborative mechanism is a multi-level system comprising a technology layer, a task layer, an individual layer, and an organizational layer, in which bidirectional influence among the layers exists.

3.2 Impact pathways of intelligent collaboration systems

The influence of smart collaboration systems on remote workers' work engagement acts through different mechanisms. The Job Demands-Resources Theory accounts for how the workplace environment shapes employee work states through two mechanisms: pressure relief and resource supplementation. Intelligent collaboration technology plays a twofold role in virtual working environments, both reducing work pressure and enhancing available resources. The resource development channel contributes to remote workers' resources through three facets: expanding autonomy, building social support, and enhancing performance feedback. Expanding autonomy is reflected in technology, which offers workers greater work flexibility and decision latitude. Intelligent scheduling software helps workers plan work according to their own rhythms, and flexible workflow software lets them choose practices that are most appropriate to them. This sort of development of autonomy directly affects the innate psychological needs in Self-Determination Theory. Social support is regained through the utilization of virtual conference rooms, chat rooms, and smart collaboration platforms' real-time co-editing features, and AI-powered communication technology also supports the success of cross-cultural collaboration. Feedback mechanisms on performance are made timely and accurate with the help of intelligent systems. Artificially intelligent software that analyzes data tracks work output in real time and displays visualized data, enabling employees to visually observe their improvement trail and thus enhance their sense of competence.

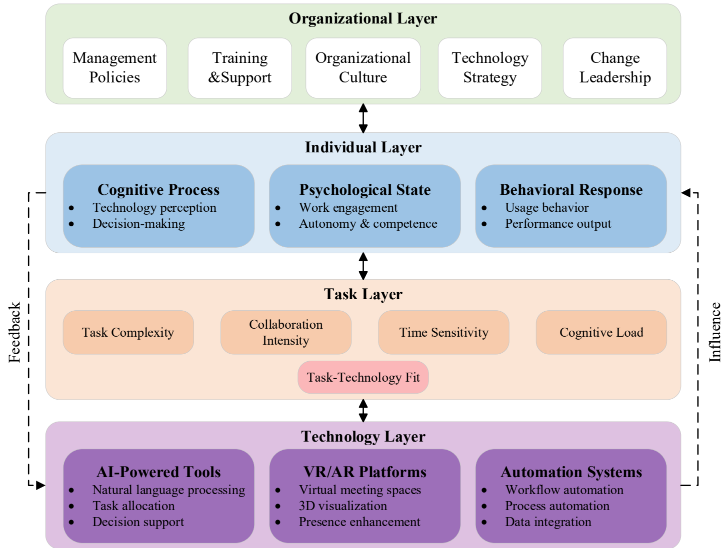

Figure 3. Human-AI collaboration mechanism in remote work

The downward demand pattern is interested in learning how intelligent collaboration platforms minimize the aggravations of remote work. Automated solutions computerize dull and energy-draining tasks such as data entry and report generation, freeing up workers' time and minds to focus on more valuable work. For instance, AI automation reduces routine task time by 20-30%, while intelligent scheduling increases perceived autonomy by 40% [14, 15]. AI-powered information filtering and prioritization capabilities help workers manage information overload, while cognitive task-assignment algorithms judiciously allocate work based on workers' competency sets and work capacity. The clarity of roles is also evident in the technical system's unambiguous definition of workflow procedures and the boundaries of responsibility. Collaborative working platforms correctly assign task owners and deadlines, reducing the role ambiguity syndrome typical of remote work. The Job Demands-Resources Theory was also used in studies on how telework interacts with family spheres [23], reminding managers to remain aware of the role that smart collaborative systems play in managing work-life boundaries.

Personal resources are the intervening variables at the center of the process by which intelligent collaboration systems influence work engagement through capability reserves such as self-efficacy, psychological resilience, and AI literacy. Employees with higher personal resources will be more likely to seek out intelligent system features independently and translate technical superiority into real improvements, whereas employees with lower personal resources will fear and resist new technology. Satisfaction of psychological needs is the strongest link from the external world to intrinsic motivation. Smart collaboration systems indirectly influence levels of satisfaction with autonomy, competence, and relatedness needs through processes of resource addition and demand reduction. It is when smarter collaboration tools get productive work done across both networks and, by making individual resources available, actually meet workers' most basic psychological needs that constant nudging of remote work activity can be achieved.

3.3 Mediating and moderating mechanisms

How intelligent collaboration systems influence remote employee work engagement is an issue of knowing mediating mechanisms and boundary conditions. The focus of this study is on two key mediating variables—autonomy and workload—and two key moderating variables—organizational support and AI literacy. Reduced workload is a key mediating pathway between intelligent collaboration systems and employee work engagement. Reduced workload for remote work encompasses task complexity, time pressure, information-processing load, and multitasking-switching costs. Smart collaboration software reduces this drudgery to a great extent through automation. Robotic process automation takes over routine work, natural language processing automates the generation of meeting minutes, and smart scheduling software optimizes the order of tasks. Where these technical capabilities function effectively, personnel experience reduced workloads, and resources that had initially been devoted to low-value issues are freed up. Reducing workload creates psychological space for employees to focus on key tasks, and recovery in concentration capacity directly benefits work involvement.

Autonomy enhancement is the dynamics of the journey of resource enhancement. Innovative collaboration systems heighten the autonomy barriers; parameterizable collaboration platforms enable individual adjustment, and intelligent recommendation systems offer alternatives for task performance. If artificial intelligence generates data-driven recommendations rather than obligatory commands, workers have the ultimate decision-making power and experience control over labor processes. Self-Determination Theory specifies autonomy as a fundamental need for intrinsic motivation. When workers enjoy the autonomy of independent decision-making, work is not a constraint imposed by external factors but a channel of self-expression, and the ensuing autonomous motivation is translated into high work engagement.

AI literacy as a person difference variable moderates the degree to which intelligent collaboration system impacts are achieved. People with greater literacy more profoundly comprehend the mechanics of artificial intelligence, can correctly gauge the trustworthiness and relevant boundaries of algorithmic output, and optimize technological gains. In contrast, people with low literacy might exhibit cognitive biases against technology, or even experience technology anxiety and resistance. That there are moderating effects implies that the same technological investment yields differentiated returns across employee groups with varying literacy levels, suggesting that AI literacy training is a complementary policy to technology adoption for organizations. The moderating influence of organizational support indicates that contextual factors shape technological impacts. Organizational support of the firm facilitates a positive climate for technology adoption. Employees take technological change seriously when management makes a clear priority through smart collaboration systems. Proper training facilities reduce technical barriers, ongoing technical support services facilitate timely help, and a safe psychological environment motivates workers to experiment and comment. These four mechanism variables collectively depict how intelligent collaboration systems affect remote employee work engagement. These two mediating variables encapsulate the internal process of technological action, and these two moderating variables mark the boundary conditions of technological effects, collectively determining whether and how technological resources can be successfully converted into realized benefits.

3.4 Research propositions

This research presents eight propositions based on the theoretical model outlined above, a comprehensive theoretical framework that incorporates direct effects, mediating processes, moderating factors, and downstream effects. Task-Technology Fit Theory suggests that when technological capabilities are highly compatible with task requirements, technology use is apt to enhance individual work conditions directly. Smart collaboration systems combine AI tools, virtual reality platforms, and automated processes. From the Job Demands-Resources Theory perspective, the system functions as both a resource and a demand, and the two pathways complement each other to produce positive outcomes. Self-Determination Theory shows that promoting employee autonomy and competence through technology satisfies basic psychological needs, thereby creating intrinsic motivation. Hence, Proposition 1 predicts that intelligent collaboration systems exert a highly positive, direct influence on the work engagement of remote workers.

Workload is a critical mediating variable, consistent with the demand reduction pathway. Intelligent collaboration systems reduce workers' workload substantially by automating much of the work. The Job Demands-Resources Theory posits that reduced work demands can free up resources for more useful work content. Proposition 2 posits that intelligent collaboration systems indirectly enable work engagement through workload reduction , with studies showing 20-30% workload reduction [14]. Proposition 3 also elaborates that workload exercises a partial mediating role between intelligent collaboration systems and work engagement. The mediating process of the resource-strengthening path is autonomy strengthening. Intelligent collaboration systems grant employees more work flexibility and decision autonomy. Self-Determination Theory regards autonomy as a fundamental construct of intrinsic motivation. Proposition 4 posits that intelligent collaboration systems indirectly induce work engagement by enhancing autonomy, increasing perceived autonomy by approximately 40% [15]. Proposition 5 posits that autonomy partially mediates between intelligent collaboration systems and work engagement.

AI literacy, being a different variable, moderates the effects of technology. Literacy level reflects workers' overall capacity to comprehend, exploit, and modify intelligent technology. The Conservation of Resources Theory supposes that individual resources moderate workers' capability to utilize the utilitarian benefits of intelligent systems adequately. Subsequently, Proposition 6 assumes that AI literacy positively moderates the effect of intelligent collaboration systems on work engagement, such that the positive relationship is stronger at higher levels of AI literacy. Employees with greater AI literacy can more effectively leverage system functionalities, translating technological features into realized benefits [23]. If preliminary analyses suggest that the two mediation pathways (workload reduction and autonomy enhancement) are differentially influenced by AI literacy levels, three-way interactions (ICS × AI literacy × workload; ICS × AI literacy × autonomy) will be tested to clarify whether high-literacy employees benefit more from demand reduction or resource enrichment mechanisms.

Organizational support, as a situational element, delineates the environmental limits of technological impacts. Perceived Organizational Support Theory posits that employees' perceptions of organizational appreciation and concern influence attitudes and behaviors. Social Exchange Theory posits that employees respond with favorable attitudes when they observe organizational investment. Proposition 7 supposes that organizational support positively moderates the effect of intelligent collaboration systems on work engagement. Work engagement also affects motivation and work performance. The three aspects of work engagement are vigor, dedication, and absorption, and all these have positive correlations with excellent quality work performance. There is extensive empirical evidence supporting the positive correlation between the two. Proposition 8 assumes that remote workers' work engagement strongly influences their work performance.

These eight research hypotheses collectively form a theoretical model, as shown in Figure 4. Intelligent collaboration systems influence work engagement through two mediating channels: decreased workload and enhanced autonomy. AI literacy and organizational support moderate effect intensity at the individual and context levels, respectively. Work engagement influences work performance, and a causal chain forms.

4. Optimization strategies and implementation framework

4.1 Technology integration optimization

Optimizing technology integration is the foundation for improving the productivity of smart collaboration systems, and its essence lies in aligning technological capabilities with the demands of remote work tasks. Empirical evidence from the Task-Technology Fit Theory for remote work during the pandemic confirms that the level of fit between technological capabilities and task attributes directly affects the effectiveness of system use and worker acceptance [16]. Thus, technology integration will have to begin from the organization's internal work environment rather than absolutely aiming at technological advancement.

The choice and configuration of AI collaboration tools must align with the principles of progressive deployment and differentiated customization. To start, in the first stage, the strategy should be to use mature tools such as smart meeting assistants that automatically generate meeting minutes and natural language processing tools that aid document writing. As employees become more skilled, step-by-step predictive analytics software, smart recommendation systems, and machine-learning-based optimization algorithms for task assignment can be introduced. At the configuration level, the individual needs of different jobs need to be taken into account: offering tools that stimulate creativity to support creative work, facilitating analytical work with data-digging capabilities, and implementing intelligent scheduling systems to support coordination work. Product interoperability is crucial; product standards and open interfaces need to be selected to enable smooth data sharing and achieve synergistic outcomes. Virtual and augmented reality technologies must strike a balance between immersion and usability. Immersive spatial design is primarily aimed at restoring lost spatial presence in telework. Virtual meeting rooms must replicate real offices but also be as easy and intuitive as possible to minimize cognitive load. Functionally, virtual environments need access to complete digital advantage, for example, three-dimensional data visualization and virtual whiteboards with multi-user collaboration. Since hardware demands and technical constraints can become adoption barriers, a hybrid strategy can be adopted initially: provisioning core teams with high-end equipment and offering lighter versions to reduce entry barriers. The design of smart integrated platforms defines the maintainability and scalability of the overall technology ecosystem.

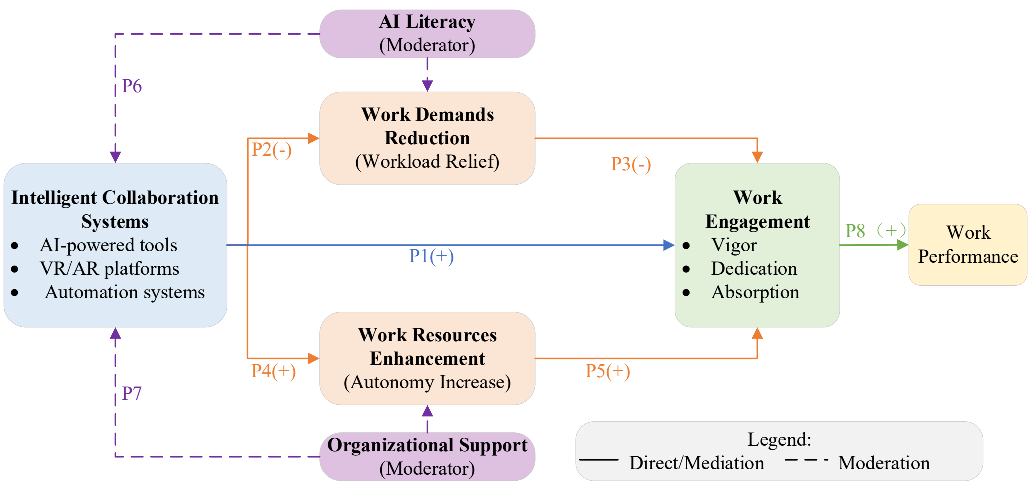

Figure 4. Integrated theoretical model with research propositions

The ideal design would adopt a modular approach, with AI tools, virtual collaboration software, and automation systems as independent modules within a highly standardized interface. The data layer must provide a shared data management platform, the user interface layer must provide a shared access portal, and the security element must be implemented across all architectural design elements. Cloud-native design enables elastic scaling, and microservice design provides increased system fault tolerance. A technology readiness evaluation provides incremental deployment through a science-driven methodology. The evaluation model employs four dimensions: functional maturity, stability, user acceptability, and ecosystem enablement. Businesses can categorize future technologies into three levels according to this model: deployment, pilot experimentation, and continuous monitoring. Top priority needs the deployment of high-maturity technology to enable the core business, experimentation with medium-maturity technology in segregated environments, monitoring low-maturity technology, and postponing overall investment at scale. A dynamic assessment process also has to exist; regular reexamination will ascertain, in a timely fashion, new opportunities offered by breakthroughs in technology and reorient deployment plans accordingly.

4.2 Human-centered design strategies

The genuine role of technology is to support, not supplant, humans, and this culture must permeate the entire process of developing intelligent collaboration systems. Human-centered design principles aim to protect and preserve fundamental human values in pursuit of technological efficacy, ensuring that workers do not lose their natural place in human-machine collaboration. It is when employees see technology as complementing rather than in conflict with them that they will fully embrace and optimize intelligent systems. The human autonomy versus automation trade-off is the most significant design trade-off. Although more automation than necessary promotes short-term efficiency, it can take away decision-making opportunities and feelings of achievement from personnel and degrade skills and the meaning of work. The optimal point of balance depends upon the nature of the task. For tasks for which there are well-defined rules, extreme automation must be employed while leaving human intervention interfaces untouched. For tasks that are complex and require creative thinking, automation must be defined as a supporting function, providing information support while leaving the final decision to human beings. Controllable automation-level design enables workers to independently choose the intervention depth based on their capacity and task conditions. Displaying decision logic helps employees clearly understand the system's working mechanism and its capability limits.

The strategy of augmentation rather than replacement aligns with the overall trajectory of technology adoption. Intelligent systems are worth the trouble since they expand the universe of what human beings can do. Technology's mission is to take on what human beings do not do well, e.g., vast information processing and pattern spotting, while leaving human beings with greater space to perform things creatively and humanely. AI tools need to be crafted as intelligent helpers, not independent decision-makers, that allow workers to access information more quickly and examine alternatives more efficiently, while always keeping humans in the loop. Virtual workplaces need to be crafted to augment, not replace, face-to-face interaction, bridging the loss of information due to physical distance through technology. User experience design directly affects real-world adoption and long-term usage of systems. Good user experience is founded on deep analysis of employees' workflows, and technology must be able to fit imperceptibly into existing work habits. Interface design needs to follow the principle of intuitiveness; frequently used functions should be self-documenting, while advanced functions should use progressive disclosure to avoid information overload. Personalization features enable the system to be configured to meet the needs and capabilities of individual users. Response time is one of the most critical experience factors in remote work environments.

Reducing automation bias is a primary process for ensuring high-quality human-machine collaboration. Automation bias describes the overreliance on automated system output and the disregard for human judgment. This can be corrected by enhancing algorithm transparency—systems should provide the reasons and the degree of confidence for their suggested solutions. When the algorithm's confidence level is low, this must be communicated with suggestions for manual verification. Including information from a single source is intended to promote cross-validation among users. Figure 5 illustrates the entire optimization strategy framework embracing four dimensions: technology integration, human-centered design, organizational support, and implementation safeguards.

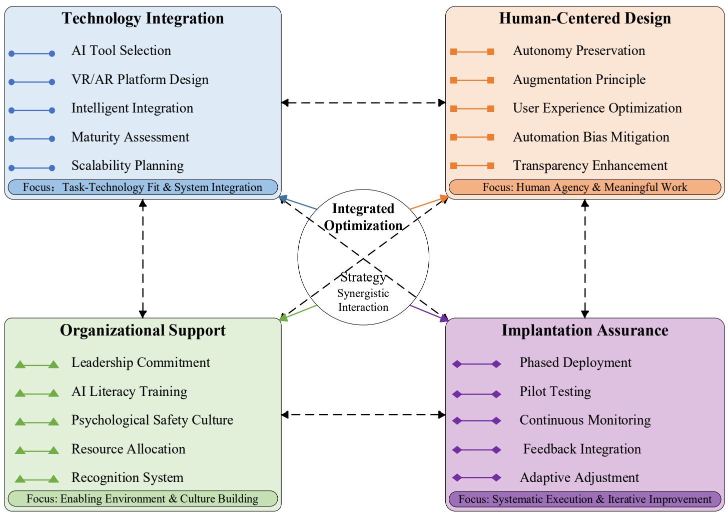

Figure 5. Four-dimensional optimization strategy framework

4.3 Organizational support mechanisms

Organizational support systems are the institutional foundation and cultural bedrock on which effective intelligent collaboration system implementation rests. No matter how sophisticated technology is, unless there is complementary support at the organizational level, it will not be able to play its rightful role and may even suffer passive resistance from employees. Adequate organizational support is not merely about the adequacy of resource investment, but about creating conditions conducive to the adoption and reuse of technology through leadership demonstration, capability building, culture building, and reward system design. Transformational leadership plays a vital role in guiding technological change and fostering organizational change toward technological innovation through intellectual stimulation, visionary motivation, and individualized consideration. Transformational leaders need to offer an unambiguous explanation of the strategic value of smart collaboration systems for future organizational development, connecting technology adoption to organizational purpose and employee development. Leadership example-setting has deep exemplary effects. When management starts learning about and adopting smart systems and their advantages in public spaces, it maximally enhances employees' acceptance and willingness to adopt them. Intellectual stimulation requires that leaders challenge employees to think critically about the application of technology, proposing change while challenging existing practices. Individualized consideration is evidenced by sympathizing with employees' challenges in adapting to technology and by providing additional assistance to those who have difficulty.

The systematic development of AI literacy training programs is the strongest driving force in establishing employees' technical ability. The training needs to apply differentiated stratification and classification strategies and provide content adapted to employees' job titles and existing skill levels. Basic-level training is for every employee and focuses on basic operations; advanced-level training is for jobs with more extensive technology application and focuses on advanced functions; expert-level training develops internal technology champions for the company. Training modes must be varied and flexible, blending e-learning, practice, and peer-to-peer learning. Contextualized instructional design integrates learning technology into real-world contexts. Establishing a culture of psychological safety creates the conditions for workers to learn new technology. Psychological safety is a team member's feeling that it is safe to take interpersonal risks within the team—they can speak up, make mistakes, and ask for help without fear of negative reaction. Psychological safety in the implementation of intelligent collaboration systems is especially crucial because technology learning necessarily entails trial and error and failure. The managers must send inclusive signals through their behavior and attitudes, viewing technical failures and use errors as opportunities to learn, not as opportunities for punishment.

Constant feedback and two-way communication channels provide dynamic streamlining of the technology implementation process. Regular feedback surveys on system use harvest employees' assessments of the system; focus group sessions allow in-depth discussion; technical support hotlines offer real-time resolution of everyday problems. Organizations are under an obligation to act on feedback received and to provide feedback improvement outcomes to employees. Employees appreciate the value of giving an opinion when their views are taken seriously. Reward and recognition systems motivate workers to use intelligent collaboration systems effectively by reinforcing good behavior, publicly honoring technology-use role models, instituting technology-innovation awards, and enabling peer recognition processes that allow employees to nominate and reward one another.

4.4 Phased implementation roadmap

Successful deployment of intelligent collaboration systems requires adhering to a phased roadmap, minimizing change risk by proceeding step by step, and ensuring quality at each phase. The whole implementation process is advised to be split into four phases: evaluation and preparation, pilot launch, full launch, and further development, with an overall duration of over twelve months. Preparation and evaluation are the foundation stage of the overall implementation roadmap, planned to be executed within the first three months of initiation. The key activity in this stage is to thoroughly evaluate the organization's status quo and prepare well for the upcoming implementation. Needs analysis provides detailed insight into specific work situations within job roles and departments through questionnaires, interviews, and workflow observation, and identifies pain points in remote collaboration and technology requirements. Technology research explores intelligent collaboration tools and platforms available in the market, examining their functional features, cost models, and compatibility. Infrastructure analysis assesses whether existing network, hardware, and software infrastructures can support the operation of intelligent collaboration systems and gauges an organization's readiness. From this, a complete implementation plan is developed, including objectives, actions, accountable staff, and deadlines for each phase, and a cross-functional project team is formed to coordinate implementation.

The pilot phase spans months three to six and establishes the feasibility of the technical solution by conducting small-scale tests and gaining implementation experience. Pilot department selection should be technology-forward, reflect real-world cases, and be medium-sized to facilitate management. System deployment deploys and configures selected smart collaboration tools within the pilot scope, and the system becomes stable and compatible with existing business systems. Training programs conduct intensive training for pilot department employees, combining small-group instruction with one-on-one coaching. Usage support provides round-the-clock technical support services during the pilot period, rapidly responding to and resolving problems encountered by employees. Data collection tracks pilot effectiveness through multiple channels, including system logs, usage feedback, and performance metrics. Regular pilot review meetings summarize feedback from all parties and discuss improvement plans.

Rollout on a scaled basis occurs between months six and twelve, extending solutions piloted to the entire organization. Rollout planning must be an incremental batch-by-batch process based on department readiness and business priority. System rollout is organization-wide, but must be configured to meet individual departmental needs. Training scale increases exponentially, leveraging pilot department personnel as internal trainers. Change management tasks infuse the whole rollout process. Monitoring systems constantly measure system utilization and effectiveness metrics on a department-by-department basis. Knowledge management systems are starting to be developed.

The sustainable development phase begins at month twelve and onward, with the focus on consolidating technology application and continuously building organizational competencies. System optimization refinement continuously improves technical configurations based on usage patterns and user feedback. Advanced training provides progressive courses to users already familiar with basic operations. Innovative applications encourage employees to discover new uses of the technology. Performance measurement periodically evaluates the long-term effect of intelligent collaboration systems on organizational performance. Technology evolution tracking keeps focus on new technologies. As shown in Figure 6, the phased implementation roadmap outlines the entire process from evaluation and preparation to sustainable development.

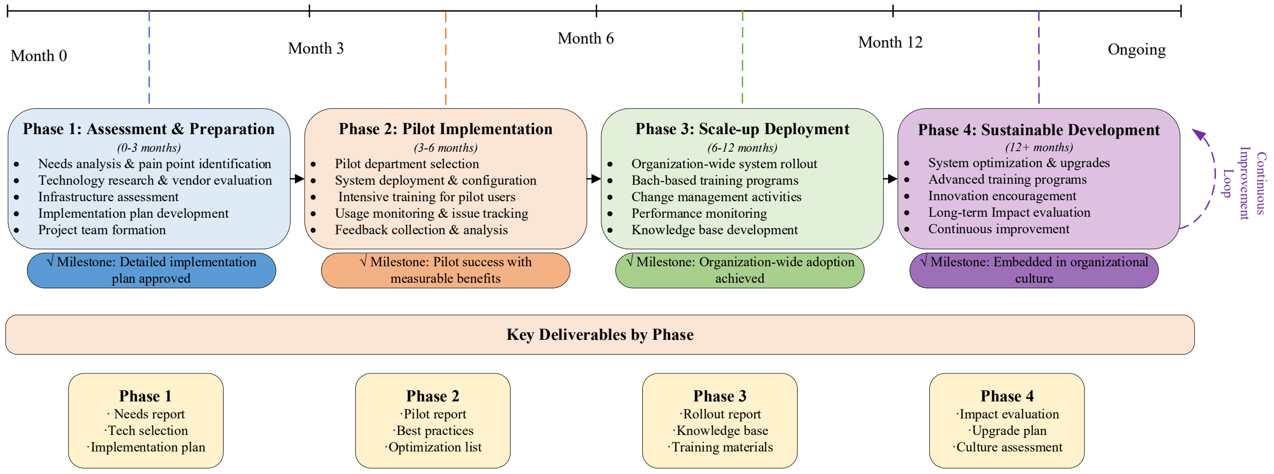

Figure 6. Four-dimensional optimization strategy framework

5. Conclusion

This research examines the mechanisms and optimization strategies by which intelligent collaboration systems influence remote workers' work engagement. The theoretical framework illustrates multi-level mechanisms: intelligent collaboration systems impact work engagement through two mediating channels—workload reduction and autonomy enhancement—moderated by AI literacy at the individual level and organizational support at the contextual level. Work engagement ultimately translates into performance output, forming a complete causal chain. Integrating Task-Technology Fit Theory, Job Demands-Resources Theory, and Self-Determination Theory, the model encompasses technological features, work environment, and psychological requirements. The optimization strategy provides guidelines across four dimensions: technology integration, human-centered design, organizational support mechanisms, and phased implementation. The theoretical contribution manifests in three aspects. First, the study incorporates intelligent collaboration technology as work resources, broadening previous research that focused solely on social factors, and reveals bidirectional mechanisms of resource augmentation and demand relief. Second, by expanding the application of Self-Determination Theory, it explains how technology interacts with intrinsic motivation through satisfying basic psychological needs, advancing human-computer collaboration research from behavioral observation to motivational foundations. Third, multi-theory integration avoids single-framework limitations, forging an unbroken explanatory link from technological characteristics to psychological needs to behavioral outcomes. Practical implications address multiple stakeholders. Successful deployment requires systematic management support and cultural nurturing beyond technological innovation—including transformational leadership, AI literacy training, psychological safety culture, and continuous feedback channels. Technology designers must adopt human-centered philosophies that emphasize augmentation over replacement. Policymakers face emerging challenges, including data privacy protection and algorithmic fairness legislation. Research limitations include a lack of large-scale empirical validation and insufficient examination of cross-level mechanisms. Future research should conduct longitudinal studies, explore the impacts of generative AI, and test the universality of a cross-cultural framework to advance understanding of intelligent collaboration systems in remote work contexts. Research limitations include a lack of large-scale empirical validation and insufficient examination of cross-level mechanisms. Future research should conduct longitudinal studies, explore the impacts of generative AI, and test the universality of a cross-cultural framework to advance understanding of intelligent collaboration systems in remote work contexts.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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