Review

AI-Based Social Connection Interventions of Emerging Categories of Support for Older Adults: Scoping Review

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Abstract

Background: Social connection is a critical determinant of well-being in later life. However, older adults often experience social isolation and increased loneliness, which are associated with mental and physical health challenges. AI-based interventions have emerged as scalable approaches to support social connection. A growing body of research has examined the effects of individual AI technologies on improving social connection across diverse devices and care settings. Despite growing evidence of their effects, little attention has been paid to the common pathways through which these interventions support social connection.

Objective: This scoping review aimed to develop a typology of common categories of support across AI-based interventions and to map how these categories are configured in different intervention contexts.

Methods: Five databases (PubMed, MEDLINE, CINAHL, PsycINFO, and Web of Science) were searched for studies published from 2016 through 2025. Studies were included if they examined AI-based interventions designed to support social connection among older adults, conceptualized as a multidimensional construct encompassing loneliness reduction, social interaction, and behavioral engagement.

Results: A total of 1110 articles were retrieved, of which 47 met the inclusion criteria. Qualitative and mixed methods studies were the most prevalent (n=32, 68%), with quantitative studies accounting for the remainder (n=15, 32%). Four common support categories were identified: relational interaction (forming ties), emotional support (enhancing interaction quality), functional support (sustaining engagement), and risk detection (reducing constraints). Relational interaction and emotional support were present across all studies. Functional support and risk detection were observed in 70% (n=33) and 17% (n=8) of studies, respectively. The most prevalent configuration combined relational interaction, emotional support, and functional support, forming a companionship-plus-routine pathway that sustained engagement in everyday contexts. Functional support was associated with sustained participation in daily routines and activities, which may have contributed to opportunities for ongoing social interaction. Risk detection, while less prevalent, functioned as a constraint-reducing condition that supported continuity of engagement.

Conclusions: This review proposes a conceptual framework that shifts attention from specific technologies to the interactional configurations that enable AI to support social connection across care settings. This framework may inform the design and tailoring of AI-based interventions to address the multidimensional nature of social connection among older adults.

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Keywords: AI; social connection; social isolation; AI interventions; loneliness; older adults; scoping review

Introduction

Background

Across many regions worldwide, rapid population aging, the rise of single-person older adult households, and the gradual erosion of traditional family–based support systems have intensified relational deficits among older adults [1]. These structural changes reduce opportunities for meaningful emotional exchanges and social interactions, thereby constraining older adults' access to consistent emotional support or social companionship [2,3].

Social connection is conceptualized as a multidimensional construct encompassing subjective emotional experiences (eg, loneliness and belonging), objective relational patterns (eg, frequency and regularity of social interactions), and related social and emotional outcomes, such as engagement and companionship [3,4]. While multifaceted, social connection is fundamentally shaped through social interaction. In later life, however, opportunities for such interactions often decline due to structural and life-course changes. As these opportunities diminish, the interactional processes through which meaning and connection are constructed may be constrained, potentially contributing to relational deficits and weakened social connectedness among older adults.

Reduced social connection, in turn, increases vulnerability to adverse mental and physical health outcomes, including depression and anxiety [5], as well as dementia, cardiovascular disease, stroke, functional decline, and all-cause mortality [6,7]. These findings highlight the role of reduced social connection as a central determinant of well-being in later life and point to the need for effective strategies to address reduced opportunities for social interaction in aging populations.

Recent years have witnessed a rapid expansion of AI technologies in care for older adults, promoted as innovative strategies to respond to growing care demands and constraints on public and human resources [8-10]. AI refers to computational systems capable of performing tasks that traditionally require human intelligence, such as reasoning, perception, learning, and decision-making. AI encompasses a broad range of approaches, including rule-based symbolic AI, machine learning, neural networks, pattern recognition, and natural language processing, enabling systems to interpret information, learn from data, and generate predictions, recommendations, or decisions toward human-defined goals [11-14]. This conceptualization is broadly consistent with the European Union AI Act, which defines AI as a machine-based system capable of generating predictions, recommendations, or decisions with varying levels of autonomy [15].

AI has been widely applied in health-related contexts, including disease detection, diagnosis, health monitoring, predictive analytics, and patient management [11,13]. In addition, technologies such as social robots, conversational agents, and voice assistants have expanded into psychosocial domains, increasingly being used to support emotional well-being, social connection, and the reduction of loneliness among older adults [14,16,17], while also serving complementary functions in health monitoring and daily living support [18,19]. As traditional forms of human delivery are increasingly constrained by scalability and accessibility limitations [20], AI-based technologies have been introduced to complement existing care services and expand opportunities for social interactions.

Accordingly, a growing body of research, using diverse methods and AI systems across countries, has examined how AI can address psychological challenges faced by older adults. AI-based interventions for social connection can be conceptualized as intervention approaches that incorporate AI-based technologies to deliver, support, or evaluate activities intended to promote social connection [14,21,22]. These interventions encompass a wide range of technologies and service models designed to reduce loneliness and isolation and foster related emotional support. Emerging evidence includes socially assistive robots, conversational agents, personal voice assistants, digital companions, and other assistive technologies. For example, socially assistive robots such as Pepper (SoftBank Robotics), ElliQ (Intuition Robotics), and Hyodol (Hyodol Inc) have been designed to engage older adults through conversation, emotional interaction, reminders, games, and companionship, with evidence suggesting benefits for emotional well-being and psychological health [17]. Similarly, AI-powered personal voice assistants (eg, Amazon Alexa) have been associated with significant reductions in loneliness and increases in perceived social support among older adults, with greater social support linked to lower loneliness [23].

Existing systematic and scoping reviews have primarily examined intervention effectiveness and psychosocial outcomes, such as loneliness, social connectedness, and psychological well-being, or have organized the literature according to specific technology categories (eg, social robots and conversational AI) or phases of care delivery [14,16,17,21]. However, little attention has been paid to identifying common categories of support across diverse AI technologies and care contexts. Technologies that differ substantially in design and technical features may provide similar forms of support, while technologies within the same category may provide different forms of support. Identifying shared support categories may therefore offer a complementary way to understand the roles that AI technologies play across diverse intervention contexts. This study identifies and synthesizes common categories of support reported across AI-based interventions for older adults.

Conceptual Foundations

This study draws on 3 theoretical perspectives—the socioemotional selectivity theory (SST), the social convoy model (SCM), and the socio-ecological model (SEM)—to contextualize and interpret the support categories identified through the review. These perspectives highlight different dimensions of social connection across individual, relational, and structural contexts. Collectively, they provide a useful framework for understanding how AI-based interventions may support social connection in later life. SST posits

that as individuals perceive their remaining time as limited, they increasingly prioritize emotionally meaningful goals and relationships [24,25]. In AI-assisted care, SST offers a useful lens for understanding how AI-based interventions may help older adults engage in emotionally meaningful interactions and relationships.

While SST highlights individual-level emotional processes, the SCM extends this understanding by situating social connection within dynamic relational networks. Within the SCM, AI-based interventions may augment existing convoys by maintaining interaction, facilitating communication, or providing companionship during life transitions such as bereavement, retirement, or declining mobility that may weaken older adults' broader networks of social ties [26]. Thus, the SCM provides a conceptual basis for understanding relational interaction as a key dimension through which AI-based interventions may support older adults' social ties.

Building on these relational dimensions, the SEM further situates social connection within broader environmental and structural contexts. The SEM suggests that social connection is shaped by environmental, community, and structural conditions that enable or constrain sustained social engagement [27,28]. In the digital era, this ecological system has expanded to include the techno-subsystem, in which technological tools act as vital mediators of everyday engagement [29]. From this perspective, AI-based interventions can be viewed as an infrastructural support system that mitigates contextual barriers—such as functional decline or caregiver strain—thereby empowering older adults to sustain their social connections and agency.

Study Objectives

The specific objectives of this scoping review are to (1) identify and describe recurring categories of support that operate across AI-based interventions for social connection, and (2) map how combinations of these categories are configured within AI-based interventions and discussed alongside social connection–related outcomes in the literature. In this review, support categories are conceptualized as recurring functional and interactional processes through which AI systems engage with older adults and are discussed in relation to social connection outcomes. By explaining these categories and their combinations, this review develops a conceptual framework that may inform the interpretation and design of AI-based social connection interventions that are not tied to specific technologies or platforms.

Methods

Study Design

We used standard procedures for conducting scoping reviews. The review followed the 5 steps outlined by Arksey and O'Malley [30], including identifying the research question; identifying relevant studies; study selection; charting the data; and collating, summarizing, and reporting the results. The reporting of this review adhered to the Preferred Reporting Items for Systematic reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines [31]. The completed PRISMA-ScR checklist is available in Checklist 1.

Search Strategy

We searched 5 major databases spanning medicine, nursing, psychology, and interdisciplinary research: PubMed, MEDLINE (via ProQuest), CINAHL (via EBSCOhost), PsycINFO (via ProQuest), and Web of Science. These databases were selected to ensure comprehensive coverage of gerontology, psychosocial research, and AI and technology-related studies.

We included empirical studies that examined AI-based interventions designed to support social connection or related psychosocial outcomes among older adults. Consistent with prior research, social connection was operationalized to include both subjective (eg, loneliness and belonging) and objective (eg, social interaction patterns) dimensions, as well as related social and emotional outcomes [3,4]. Based on this operationalization, a broad set of keywords was used to reflect the multidimensional nature of social connection. All database searches were limited to studies published in English-language journals from 2016 through December 2025. This time frame was selected to reflect the rapid development of AI technologies over the past decade, including innovations designed for older adults.

The initial search was conducted in November 2025, and the updated search was conducted in January 2026. The search strategy is provided in Multimedia Appendix 1. The search algorithm included terms related to older adults (eg, "older adults," "elderly," and "seniors"), AI (eg, "AI," "social robot," and "chatbot"), and social connection–related terms (eg, "social isolation," "loneliness," "companionship," and "social connection"). All terms were searched within titles and abstracts to capture studies with an explicit conceptual and empirical focus on AI-based social connection interventions among older adults.

Eligibility Criteria

Studies were included in the review if they met all of the following criteria: (1) the intervention incorporated AI-based approaches as a core component of the intervention, with technologies considered AI-based when they used capabilities such as symbolic AI, machine learning, natural language processing, conversational agents, or adaptive decision-making functions; (2) the intervention facilitated or examined social connection, including social interaction, companionship, emotional comfort, perceived presence, loneliness, or related psychosocial experiences among older adults, regardless of whether these outcomes were the primary focus of the intervention; (3) study participants were older adults or individuals 60 years of age and older, or primarily older adults as defined by the original studies (eg, studies targeting "older adults," "elderly," "seniors," or "geriatric populations"); (4) technologies were eligible regardless of whether they were originally developed specifically for older adults or for broader populations, provided that the intervention was implemented and evaluated among older adults; (5)

original, empirical, and published in peer-reviewed journals; (6) studies published within the past 10 years (2016-2025); and (7) papers written in English.

Studies were excluded from the review if they met any of these conditions: (1) AI techniques were mentioned only tangentially or were not implemented as an intervention through which social connection or related relational or emotional experiences were examined or observed; (2) reported outcomes did not reflect social connection–relevant experiences or processes (eg, companionship, emotional or relational engagement, social interaction, and loneliness), and instead focused exclusively on physical health, cognitive training, technical performance, or usability outcomes alone; and (3) the publication was nonempirical in nature, including letters, editorials, commentaries, conference abstracts, meeting materials, study or review protocols, or literature reviews.

Study Selection

Studies were selected using a 2-stage screening process. In the first stage, titles and abstracts were screened to assess relevance to the review aims. Duplicate records were identified and removed using Rayyan (Qatar Computing Research Institute). In the second stage, full-text studies were reviewed to determine final eligibility. HK screened titles and abstracts and reviewed full-text studies using the predefined eligibility criteria.

Charting the Data

Data extraction was conducted to systematically capture relevant information from the included studies. Extracted variables included study characteristics (author, publication year, and country), intervention characteristics (AI systems, reported AI capabilities, care setting, intervention frequency, duration, and total study period), methodological features (study design and sample size), and outcome-related information (primary outcome focus and reported outcomes related to social connection). Data extraction was performed by HK and reviewed by coauthors (CR, HH, JJ, YD, and VR) to ensure accuracy and consistency. A detailed summary of extracted variables is provided in Multimedia Appendix 2.

Data Analysis

This review adopted an inductive approach to identify and organize key categories through systematic steps: (1) descriptive mapping of study characteristics, (2) analysis of AI system functions and reported outcomes, and (3) iterative cross-study comparison. All included studies were reviewed and summarized in a structured analytic matrix (Multimedia Appendix 2), providing a common framework for systematic comparison.

Data extraction and initial category development were conducted by the first author (HK). To enhance the transparency and consistency of category assignment, 2 coauthors(JJ, YD) independently reviewed the full-text studies and corresponding category assignments for all included studies. The operational criteria for assignment to the support categories are summarized in Multimedia Appendix 3. Intercoder agreement was assessed across all 4 support categories, with complete agreement for relational interaction, emotional support, and risk detection support. Functional support was the only category with coding discrepancies; Fleiss κ was 0.93. Discrepancies were resolved through discussion and consensus. Here are 2 borderline cases involving discrepancies in the functional support category [32,33]. In both cases, 2 coders initially assigned "yes," while one assigned "no," and the discrepancies were resolved through discussion and consensus. For Noguchi et al [33], the robot helped older adults communicate requests for support to family members or friends, rather than directly providing functional assistance itself. Therefore, this function was not coded as functional support. For Nagata et al [32], only functions actually provided by the intervention were coded; desired future functions were excluded.

First, a descriptive mapping of the included studies was used to characterize the overall structure of the literature. Studies were sorted according to key intervention characteristics (eg, AI systems, care settings, and intervention duration) to capture the breadth and diversity of the evidence base.

Second, a thematic analysis examined the operational features of AI-based interventions as described in the included studies. Full-text studies were analyzed to identify observable functions of AI systems and their links to reported social and emotional outcomes. To identify common categories of support across diverse AI interventions, recurrent intervention characteristics, AI system functions, and reported outcomes were compared across studies. Through iterative comparison, patterns reflecting similar forms of support were grouped into higher-order thematic categories.

Finally, through iterative cross-study comparison, recurrent patterns in AI system functions and interactional characteristics were inductively identified and grouped into higher-order categories. This bottom-up synthesis identified a set of common categories of support that characterize the ways in which AI-based interventions support social connection in later life. By grounding category identification in comparative analysis across the included studies, this approach ensured that the proposed category-based framework reflected recurring patterns observed across diverse AI technologies rather than effects attributable to any single technology. The identified categories were subsequently considered in relation to broader theoretical perspectives on social connection during the interpretation of the findings.

Ethical Considerations

This scoping review used publicly available literature and did not involve human participants or identifiable data. As a result, ethics approval was not required.

Results

Overview and Characteristics of Included Studies

Figure 1 provides a detailed outline of the search and selection process. A total of 47 studies met the inclusion criteria. Table 1 summarizes the key characteristics of the included studies. The literature spanned multiple publication years and geographic regions, indicating sustained and expanding interest in this area across national contexts. AI systems were classified according to the primary technological approach of each intervention (Table 2), which included socially assistive robots, pet-like social robots, voice-based AI assistants, telepresence robots, conversational agents, and humanoid service robots.

Figure 1. Flow diagram of the study identification and selection process.

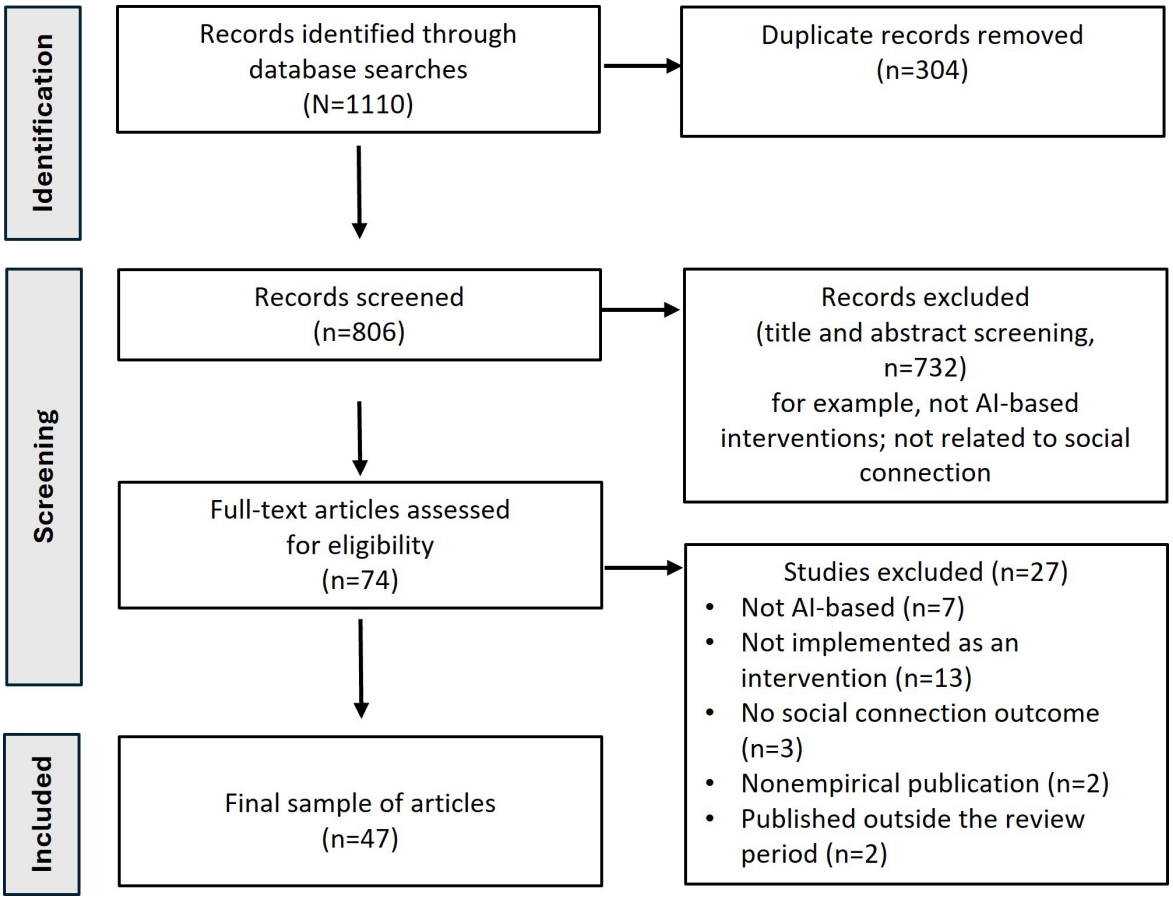


Table 1. Characteristics of the studies included in the review (N=47).

Characteristics	Count, n (%)
Publication year	
2021-2025	39 (83)
2016-2020	8 (17)
Country/region where study was conducted	
United States	16 (34)
South Korea	6 (13)
Japan	5 (11)
Taiwan	5 (11)
Canada	3 (6)
Mainland China	2 (4)
Hong Kong	2 (4)
Netherlands	2 (4)
United Kingdom	2 (4)
Other countries/regions (ie, Australia, Belgium, Ireland, and Singapore)	4 (9)

Characteristics	Count, n (%)
Study design	
Quantitative study	15 (32)
Qualitative study	16 (34)
Mixed methods study	16 (34)
Care setting	
Community-dwelling	30 (64)
Residential care facilities (eg, care homes and nursing homes)	13 (28)
Mixed/hospital	4 (9)
Intervention duration (participant exposure), (weeks)	
<4	15 (32)
4-8	18 (38)
>8	14 (30)

Table 2. Types of AI systems in the included studies (N=47)[a].

AI system	Description	Count, n (%)
Socially assistive (companion) robots	Autonomous or semiautonomous robots that engage users through language-based interaction and provide social and emotional support, with varying levels of assistance for daily activities (eg, Hyodol, ElliQ, MARIO, PIO, and Maatje-pop)	23 (49)
Pet-like (therapeutic) social robots	Physically embodied, tactile robots that engage users mainly through nonverbal sensory interaction (eg, touch and movement) and are designed primarily to offer emotional comfort, reassurance, and companionship (eg, PARO, robotic pets, and LOVOT)	11 (23)
Voice-based AI assistants (smart speakers)	Voice-based AI systems without physical embodiment (eg, Alexa and Google Assistant)	7 (15)
Conversational agents (chatbots)	Text-, screen-, or voice-based conversational AI systems accessed via messaging platforms, web interfaces, or mobile apps, including both nonembodied systems and digitally embodied agents with visual or animated representations (eg, ChatGPT and PACO)	5 (11)
Humanoid service robots (nonsocially assistive robots)	Humanoid robots designed for general social interaction or service provision but not primarily framed as socially assistive or companion robots (eg, Pepper)	1 (2)

[a]AI systems were classified descriptively based on the terminology and descriptions reported in the included studies. AI systems were treated as mutually exclusive, with each study was assigned to the single category that best reflected the primary form of the AI intervention.

Among the 47 studies, 20 (43%) referenced the COVID-19 pandemic in relation to the intervention context, implementation, or interpretation of findings. Within this subset, 3 studies were explicitly framed as pandemic-responsive interventions to address heightened isolation under social distancing or visitation restrictions [18,34,35]. The remaining 17 studies referenced COVID-19 primarily as a contextual condition shaping implementation and interpretation (eg, recruitment constraints, modified data collection, or restricted social activity), while still demonstrating the continued use and contextual adaptability of AI technologies [23,36,37].

Regarding research methodology, qualitative (n=16) and mixed methods studies (n=16) were the most prevalent (n=32, 68%), while quantitative studies accounted for 32% (n=15) in the included studies. This distribution is consistent with an emphasis on capturing in-depth user experiences and contextual insights, while also incorporating quantitative evidence. Study designs also included longitudinal designs (n=2) and multigroup comparative designs (n=10). The sample sizes across the included studies varied substantially, ranging from small-scale studies (n=4) to large-scale surveys (n=589), with 5 studies involving over 100 participants. Participants included older adults, family caregivers, and care professionals.

Most interventions were implemented in real-world care settings, emphasizing routine care practices rather than experimental control, and were delivered to community-dwelling older adults, care home residents, and older adults in mixed-care or hospital settings. The duration of interventions varied widely, ranging from a single session to 45 months. Intervention duration was defined as the length of time participants were directly exposed to the intervention, rather than the total program duration. The majority of studies focused on midrange durations: 38% (n=18) described interventions lasting 4 to 8 weeks, 32% (n=15) described short-term interventions (<4 weeks), and the final 30% (n=14) examined longer-term effects lasting more than 8 weeks.

Social Connection–Related Outcomes

Across the 47 articles, outcomes related to social connection were grouped into four domains: (1) subjective social connection outcomes (subjective experiences), (2) interaction and engagement outcomes (observable behaviors), (3) emotional and quality-of-life outcomes (psychological consequences), and (4) broader relational outcomes (relational and contextual effects). These domains capture and summarize outcome measures reported in the included studies.

Subjective Social Connection Outcomes

The most frequently reported outcomes were measures reflecting social connection, including loneliness, perceived isolation, perceived connectedness, companionship, sense of presence, and friendship. Loneliness was the most commonly assessed outcome across studies, typically measured using validated scales such as the UCLA Loneliness Scale. Twelve studies reported reductions in loneliness and perceived isolation, whereas 8 studies reported nonsignificant or mixed findings [32,38,39]. Moreover, relational aspects of connection, including companionship, perceived presence, and feelings of being socially connected, were reported in many studies, particularly in those using socially assistive robots, pet-like social robots, and conversational agents [40-42]. In addition, several studies reported related relational resources, such as perceived social support and stimulation of social networks [23,33], indicating that both subjective experiences of connection and broader relational perceptions were reported across studies.

Interaction and Engagement Outcomes

A second domain captured observable behavioral indicators of social connection, including interaction frequency, communication patterns, conversational exchanges, and participation in social or recreational activities. These outcomes involved both direct human-AI interaction and communication with family members, caregivers, or peers [43-45]. Several studies reported increases in interaction time, number of exchanges, and opportunities for conversation, as well as improvements in overall social engagement [44-46]. In some cases, AI-mediated interaction was also reported to stimulate human-human interaction, indicating that engagement outcomes extended beyond the immediate interaction with the technology.

Emotional and Quality-of-Life Outcomes

Emotional and quality-of-life outcomes included measures of emotional comfort, mood, depression, anxiety, and overall quality of life. These outcomes were reported alongside social connection outcomes in several studies. Many studies reported improvements in mood, reductions in depressive symptoms, and increased emotional comfort associated with AI-based interactions; however, findings varied across studies. While some studies showed statistically significant improvements in depression and quality of life [20,47], others reported limited or inconsistent effects across study settings and intervention types.

Broader Relational and Contextual Outcomes

Broader relational outcomes were reported in a small subset of studies. These included reductions in caregiver burden and increased reassurance among family members [48,49], as well as enhanced perceptions of safety and reduced vulnerability among older adults. In several studies, safety-related functions—such as monitoring, anomaly detection, and emergency alert systems—were described as contributing to a greater sense of security and reduced uncertainty in daily life [19,50]. In addition, some studies examined changes in digital self-efficacy, autonomy, and technology-mediated relational capacity [37,49]. These outcomes were reported at relational levels beyond the individual.

Together, these 4 domains illustrate the multidimensional nature of social connection, encompassing subjective, behavioral, psychological, and relational levels across AI-based interventions.

Support Categories for AI-Based Social Connection Interventions

Overview of Support Categories

This section delineates the common categories through which AI-based social connection interventions were implemented and evaluated. Inductive analysis identified 4 categories of support underlying AI-based interventions for social connection among older adults: relational interaction, emotional support, functional support, and risk detection. Each category reflects a distinct pathway through which AI technologies support social connection in later life.

Relational interaction and emotional support were present across all 47 included studies. These categories frequently co-occurred with functional components and, in some cases, risk-related components (Tables 3 and 4).

Table 3. Support categories in AI-based social connection interventions (N=47).

Support category	Operational examples	Count, n (%)
Relational interaction	Conversational exchange, reciprocal dialogue, companionship, and perceived social presence	47 (100)
Emotional support	Emotional comfort, reassurance, affective responsiveness, and mood stabilization	47 (100)
Functional support	Reminders, routine structuring, medication adherence, information access assistance, and structured activity–based programs (eg, cognitive, physical, or recreational activities)	33 (70)
Risk detection	Safety monitoring, emergency detection, fall, or health-risk alerts	8 (17)

Table 4. Category combinations and corresponding studies (N=47).

Category combination	Studies	Count, n (%)
Relational support, emotional support, and functional support	[18,23,35-39,45,49,51-66]	25 (53)
Relational support and emotional support	[32-34,40,42,46,47,67-73]	14 (30)
Relational support, emotional support, functional support, and risk detection	[19,20,41,50,74-77]	8 (17)

Identified Support Categories

The support categories were derived through an iterative analysis of observable operational behaviors of AI technologies and their reported links to social and emotional outcomes across the 47 studies. These categories represent distinct patterns through which AI-based interventions were operationalized and described. The 3 theoretical perspectives introduced in the conceptual foundations (SST, SCM, and SEM) were applied as interpretive lenses to contextualize these categories within broader understandings of social connection. The first category, relational interaction, emerged across AI-based systems that engaged in and facilitated ongoing social interactions. These systems fostered a sense of interpersonal presence and closeness by providing human-like social interactions—such as conversation and companionship—or by enabling communication between older adults and others (eg, family members). Relational interaction was consistently observed across studies, regardless of the type of AI technology. It was associated with multiple social connection outcomes. For example, more frequent relational interactions with AI—such as greetings or initiating conversation—were associated with greater reductions in loneliness [63]. Similarly, AI-based communication features were linked to reduced self-disclosure anxiety and reengagement with family and friends [33].

Second, the emotional support category encompassed AI functions that responded to users' internal emotional states, including mood-aware dialogue, humor, reassurance, and other emotionally responsive interactions across the reviewed studies. The emotional support category was reflected in patterns such as emotional comfort, reduced loneliness and anxiety, improved mood, and enhanced psychological well-being [46,60,76]. These functions were described as alleviating negative emotional states, including loneliness, anxiety, and depression. For example, one participant described how the companion robot said "I love you" and "You are my best friend" during moments of distress, thereby contributing to reduced loneliness and emotional relief [41]. Emotional support was consistently observed across studies, regardless of the type of AI technology.

Third, the functional support category involved AI-enabled assistance with everyday activities that reduced practical barriers to social participation by supporting the planning, continuity, or execution of daily tasks. Within the reviewed studies, these functions included features such as medication or appointment reminders, prompts for daily routines, assistance with communication or information access, and structured activity-based programs (eg, cognitive, physical, or recreational programs) that supported daily functioning [35,37,52,62]. Functional support was coded based on implemented intervention functions rather than psychosocial outcomes alone. Therefore, companionship, meaningful engagement, reminiscence, memory recall, or social interaction that emerged through conversational exchange alone was not coded as functional support unless they were linked to a specific AI-delivered support function. Reported outcomes associated with functional support included improved daily routines, enhanced engagement in activities, increased autonomy, and sustained participation in everyday life.

Finally, risk detection and safety monitoring were reflected in AI-enabled monitoring and safety-related functions designed to identify potential health or environmental risks, such as falls, emergencies, or abnormal patterns in daily activity or conversation. Reported functions included monitoring systems integrated with socially assistive robots and nurse call systems. For example, Obayashi et al [76] showed that integrating socially assistive robots with bedside monitoring and nurse call systems enhanced older adults' sense of reassurance and continuity of care, particularly at night. Together, these 4 categories provided a structured way of organizing the diverse functions of AI-based interventions identified across the included studies. The following analysis examines how these categories co-occurred across studies and were configured in relation to social connection outcomes.

Configurations of Support Categories

We mapped how the categories were configured across the 47 articles. Across studies, AI-based interventions did not rely on a single category in isolation but instead reflected combinations of multiple categories. Accordingly, these combinations constituted the primary unit of analysis for understanding how AI-based interventions supported social connection. Three recurring configurations were identified.

First, the most prevalent configuration combined relational interaction, emotional support, and functional support, accounting for more than half of the 47 (n=25, 53%) studies. This configuration commonly supported social connection through a companionship-plus-routine pathway, in which conversational engagement fostered perceived companionship and emotional reassurance, while routine-oriented features—such as reminders, structured activities, and daily prompts—supported sustained engagement in everyday life [20,36]. In some studies, this pattern was further reinforced by personified or anthropomorphic interaction, through which older adults related to AI systems as social or relational partners [41,63].

Across studies, this configuration was frequently described in relation to reductions in loneliness and improvements in socioemotional well-being, particularly in contexts where relational and emotional exchanges were embedded in everyday routines [41,49,59].

Second, 14 (30%) studies focused primarily on relational and emotional categories but lacked functional support for organizing daily routines. Interventions in this group typically relied on physically embodied social robots, particularly pet-like therapeutic robots such as PARO, which provided tactile interaction, through which older adults were reported to relate to the robots as social or companion-like entities, commonly described as fostering emotional bonds and a sense of being with another presence [46,71,73]. These interventions were described as fostering a sense of presence,

providing emotional comfort, and strengthening affective bonds.

However, there was limited evidence that these emotional gains were associated with longer-term behavior changes, such as increased social participation or changes in everyday routines. This pattern was often described alongside a lack of functional features—such as reminders, scheduling, or activity coordination.

Third, a smaller subset of studies (n=8, 17%) incorporated all 4 categories, including risk detection alongside relational, emotional, and functional components. These interventions combined companionship and routine support with features such as anomaly detection and monitoring [50], emergency response and alerting [74], and caregiver-facing information sharing [75]. In this group, loneliness outcomes were reported together with a broader range of co-occurring outcomes, including emotional reassurance, support for daily living, and safety or peace of mind [50,74,76]. These studies often presented loneliness as one of multiple reported outcomes rather than as an analytically distinct end point or as a causally linked risk-detection component [19,75].

Overall, different configurations of support categories were associated with distinct patterns in reported social connection outcomes across the included studies.

Discussion

Principal Findings

This study proposes a category-based synthesis of AI-based social connection interventions, shifting attention from technology-centered classification to underlying support functions. We argue that social connection may be understood in relation to relational, emotional, functional, and risk-detection supports across different AI-based interventions. By mapping these support categories, our framework highlights how these supports work in coordination and may contribute to social connection in later life. Ultimately, this approach may inform the development of AI interventions that are responsive to the diverse social needs of older adults.

The 4 support categories identified in this review can also be interpreted through the theoretical perspectives introduced in the conceptual foundations. Relational interaction can be understood as an entry point through which older adults initiate and maintain social contact, whereas the emotional support category captures both emotion-sensitive responses and interactional features that provide emotional reassurance and comfort. Emotional support may function as a stabilizing mechanism that helps older adults manage emotional vulnerability and maintain psychological well-being. Functional support provides the practical stability necessary to sustain social participation in later life. Risk detection functions reduce uncertainty and perceived vulnerability, thereby lowering the psychological threshold for social participation.

SST helps explain why emotionally meaningful interactions and supportive relationships were consistently associated with perceived benefits, as older adults prioritize emotionally meaningful goals and relationships in later life [24,25]. The SCM situates AI-based interventions as supplementary elements within existing relational networks, supporting continuity of engagement rather than replacing human ties [26]. From a social-ecological perspective, functional support and risk detection operate as contextual enablers that reduce practical and safety-related constraints, thereby making sustained participation feasible [27,28].

The findings suggest that social connection outcomes varied with the configuration of relational, emotional, functional, and risk-detection support. Relational and emotional support categories were consistently associated with perceived companionship and affective comfort, although their presence across all included studies can be understood in relation to the review's eligibility criteria, which focused broadly on social connection, including social interaction, companionship, emotional comfort, perceived presence, loneliness, and related psychosocial experiences. Functional support was more commonly associated with sustained engagement in everyday life, whereas risk-detection support was primarily associated with a broader range of reported outcomes, including perceived safety and reassurance.

To illustrate how these common categories operate across contexts, empirical studies provide further insight. Evidence from multiple studies using the same technology underscores the value of a category-based perspective. A series of 5 studies by Lee et al [41,55-57,75] used the same companion robot, Hyodol, across different populations and implementation contexts but reported varying outcomes related to loneliness, depressive symptoms, and emotional well-being. These variations suggest that outcomes may be understood in relation to the configuration of support categories within specific contexts, as well as the technology used. Across these studies, Hyodol consistently demonstrated support in the relational, emotional, and functional categories. Complementing this pattern, Abdollahi et al [60] provided experimental evidence that outcomes can differ within the same robotic platform when specific categories are configured differently. Compared with a nonempathic condition, an empathic interaction mode elicited greater user engagement and improved mood indicators.

Beyond cross-context variation, evidence from recent studies highlights the fragility of AI-based social connection, particularly when underlying support processes fail to adapt over time. Findings from Lei et al [58] and Lee et al [75] show that when relational and emotional mechanisms are weak, misaligned, or insufficiently adaptive, interventions may fail to reduce loneliness or may even increase disengagement. In Lei et al [58], this misalignment is particularly evident when systems do not match users' communicative and cultural expectations (eg, local language recognition and culturally familiar forms of interaction). Relatedly, Lee et al [75] documented a novelty effect, in which short-term reductions in depression and improvements in health-related

quality of life were observed at 3 months. However, these benefits were not sustained at 6 months, as the underlying categories plateaued and failed to adapt to users' changing emotional needs. These findings indicate that sustained psychosocial benefits depend on adaptive, evolving motivations rather than on static intervention features.

These insights suggest that AI-based interventions may be particularly valuable when integrated with existing human care and social relationships rather than used in isolation. Because AI alone has limited capacity to adapt over time, its effectiveness depends on how well it supports and complements ongoing human interactions. Building on these observations, AI-based social connection interventions may benefit from tailoring the configuration of support categories to the specific needs and risk profiles of target populations. For example, interventions emphasizing relational and emotional supports may be appropriate for community-dwelling older adults with relatively low levels of social vulnerability, whereas interventions that integrate functional support and risk detection may be better suited for older adults with greater care needs or safety concerns. This category-based perspective may help guide the development of more tailored and context-sensitive AI interventions.

Future Directions

Future intervention research should focus on using longitudinal and mixed methods approaches that can capture the evolution of AI-based social connections over time. First, longitudinal observations are essential to determine whether AI-based interventions can meaningfully produce sustained improvements in multiple dimensions of social connection and function as an everyday form of relational infrastructure. While this review finds that AI interventions are associated with indicators of social connection, existing evidence also suggests a potential novelty effect, whereby perceived benefits may be confined to the initial phase of use and attenuate over time, resulting in limited sustained impact [75].

Second, mixed methods approaches are critical for examining how common support categories interact with cultural context, service systems, and individual life trajectories. Methodological approaches that hold technological artifacts constant—such as those demonstrated in the Hyodol studies—offer a particularly promising strategy for disentangling the effects of support categories from contextual influences and advancing theory-driven comparisons.

Third, in this type of review, it would be valuable to examine whether outcome patterns cluster within specific category configurations. This would help us observe the discriminative value of the proposed typology and further refine its application across different intervention contexts.

Limitations

Several limitations of this scoping review should be recognized. First, this review was limited to peer-reviewed journal articles published in English. As a result, relevant studies published in other languages, regions, or formats—including gray literature like policy reports, technical documents, and conference proceedings—may have been excluded. The broader AI research landscape, particularly studies published in computer science venues (eg, ACM Digital Library), may not have been fully captured. Moreover, given the rapid evolution of AI technologies, reliance on database searches alone may have resulted in the omission of some emerging interventions.

Second, the review is constrained by the characteristics of the existing evidence base, including the research questions, study designs, and analytic approaches used in prior studies. In addition, many included studies were short-term, individually delivered, and conducted within specific cultural or service contexts, limiting the conclusions about long-term sustainability and the broader applicability of AI-based social connection interventions.

Third, although full-text studies and category assignments were independently reviewed by coauthors, the initial stages of study selection and data extraction were conducted primarily by the first author (HK). Future reviews may benefit from implementing independent, multireviewer procedures throughout the study selection and coding process from the outset, to further enhance methodological rigor.

Conclusions

This scoping review analyzes 47 empirical studies and proposes an initial category-based conceptual framework for AI-driven social connection interventions. By identifying relational, emotional, functional, and risk-detection support categories as distinct yet interdependent pathways, this study shifts the analytical focus from technology-centered approaches to category-attentive, contextually grounded intervention design. In addition, the findings show that social connection outcomes span multiple dimensions, including subjective, behavioral, emotional, and relational domains, underscoring their multidimensional nature.

Across the reviewed studies, AI-based interventions rarely relied on a single support category in isolation; rather, they integrated multiple categories, underscoring the layered and interdependent nature of AI-based social connection. Future research may use this framework to examine how these categories evolve over time and across diverse care contexts, particularly through longitudinal and mixed methods approaches. This framework can provide a basis for designing AI interventions that are grounded in support categories, are context-sensitive, and are responsive to the social needs of older adults.

Generative AI Use

HK used ChatGPT (OpenAI) for English translation and English-language editing of text originally written by the author. All AI-assisted revisions were critically reviewed and edited by HK. All authors reviewed and approved the final manuscript.

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Data Availability

Data sharing is not applicable to this article because no datasets were generated or analyzed during this study.

Authors' Contributions

Conceptualization: HK
Data curation: HK
Formal analysis: HK (lead), CR (supporting)
Investigation: HK
Methodology: HK, CR, HH
Supervision: CR
Validation: HK, CR, JJ, YD
Writing – original draft: HK
Writing – review & editing: HK, CR, HH, JJ, YD, VR

Conflicts of Interest

None declared.

Multimedia Appendix 1

Search strategy across databases.
[DOCX File (Microsoft Word File), 18 KB-Multimedia Appendix 1]

Multimedia Appendix 2

Characteristics of AI intervention in the studies.
[XLSX File (Microsoft Excel File), 22 KB-Multimedia Appendix 2]

Multimedia Appendix 3

Operational criteria for support-category coding.
[DOCX File (Microsoft Word File), 16 KB-Multimedia Appendix 3]

Checklist 1

PRISMA-ScR checklist.
[DOCX File (Microsoft Word File), 88 KB-Checklist 1]

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Abbreviations

PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews
SCM: social convoy model
SEM: socio-ecological model
SST: socioemotional selectivity theory

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