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AI-enabled whole-of-home resident profiling and connection matching in residential aged care: a conceptual framework and simulation study

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Abstract

Loneliness is common in residential aged care, and staff across a home learn different things about each resident. This knowledge is rarely pooled to help residents connect. This paper proposes a whole-of-home framework enabled by artificial intelligence (AI). Observations from every staff role, including how residents get on with each other, are pooled into a living profile, and a transparent matching method suggests introductions that staff and residents decide on. The matching step was examined in 400 synthetic homes of 80 residents, built from published Australian statistics and stated assumptions. A hidden compatibility model, specified by the authors and never shown to the matching method, decided which pairings worked. No real resident, staff or facility data were used, and no AI model was trained or run on real data. In the simulation, whole-of-home matching placed an expected 48.6% of residents in a pairing that worked under the hidden model, against 31.7% for pairing residents on the same level (difference 16.9 points, 95% simulation interval 16.4 to 17.4). Widening the profile from care-team to whole-of-home observation was associated with a 5.7-point increase. Assigning the highest-scoring pairs first left 14.8% of residents with no suggestion, and residents preferring a language other than English gained least. The advantage fell to about 4 points when staff recorded a quarter of what was assumed. These figures describe behaviour under stated assumptions. They are not estimates of real-world effect and do not show that residents would feel less lonely. A pilot is the next step.

Keywords: residential aged care; loneliness; social connection; person-centred care; artificial intelligence; simulation

1. Introduction

Loneliness is common in residential aged care. A meta-analysis of 13 studies covering 5,115 care home residents estimated a mean prevalence of 61% for moderate loneliness and 35% for severe loneliness (Gardiner et al., 2020). A systematic review of 31 studies in nursing homes and assisted living found loneliness associated with depression, suicidal ideation and frailty (Lapane, Lim, et al., 2022). In the wider population, loneliness and social isolation are each associated with a 26% to 29% higher likelihood of death (Holt-Lunstad et al., 2015).

Loneliness in care is not simply being alone. In interviews with 11 nursing home residents, loneliness was "more than being alone among others": an unfulfilled need for meaningful relationships and the loss of self-determination were central to it (Paque et al., 2018). Residents of 182 care settings in Oregon described what matters to them as being recognised as individuals, social inclusion, meaningful engagement and being part of a community, within decision-making that rigid institutional schedules often override (Cordero et al., 2026). Socially isolated nursing home residents interviewed in China described a withdrawal that went beyond loneliness, deepened by institutional constraints and a sense of alienation (Liu et al., 2026).

Living among other people is not, on its own, a remedy. Residents of a Sydney nursing home had clear ideas of what friendship means, yet described their own networks as small and sparse. Residents whose networks held more reciprocated ties perceived more support, and residents of the dementia unit perceived the least (Casey et al., 2016). Theurer and colleagues argue for a move towards resident engagement and peer support, which give residents the chance to be socially productive and to hold a valued social identity (Theurer et al., 2015).

Observation studies find little contact. In six Australian facilities, residents spent 47.9% of observed daytime alone and 45.2% in their own rooms, and time spent with other residents was positively associated with quality of life ($r = 0.39$; Siette et al., 2022). Among 106 people living with dementia in 12 German facilities, 71.9% of observations recorded no social interaction. When there was interaction, another resident was the partner nearly as often as a staff member (40.9% against 43.4%), and it was more common in communal areas (Gebhard et al., 2024).

The burden also falls unevenly. Among 721,074 long-stay nursing home residents with dementia in the United States, those with moderate or severe cognitive impairment had lower odds of high social connectedness than those with mild or no impairment (Lapane, Dube, et al., 2022). Across assisted living facilities in Alberta, Canada, the share of residents who were lonely differed widely from one facility to the next, with a pre-pandemic interquartile range of 8.3% to 21.1% (Hoben et al., 2025). Both where a person lives and their level of impairment are associated with how connected they are.

Australia now expects more. The Royal Commission into Aged Care Quality and Safety (2021) recommended strengthening the Quality Standards. The strengthened Standards, in force since 1 November 2025, require providers to support residents to cultivate relationships

and social connections (Action 1.1.2f), to minimise boredom and loneliness (Action 7.1.1c) and to have social and personal relationships (Action 7.1.1e; Department of Health, Disability and Ageing, 2025). The Standards describe what needs to happen, not how.

This paper starts from an observation from practice. People who work in a home often come to know different things about each resident through the work they do. A personal care worker learns someone's morning routine, a cook learns who sits with whom at meals, a cleaner learns what the photographs on the dresser mean, and a lifestyle officer learns who laughs at the same jokes. Much of this knowledge appears not to be written down, or sits only in free-text notes. Nor does it appear to be used routinely to answer a simple question: which two residents in this building would enjoy each other's company?

This paper proposes a framework, enabled by artificial intelligence (AI), that brings together what every role observes into a living profile of each resident (one shared record that every role adds to and that is updated as the resident changes), and uses that profile to suggest introductions between residents. "AI-enabled" has a narrow and specific meaning here. A language model turns staff notes into structured profile facts, and a transparent scoring and matching algorithm suggests pairings. Staff and residents make every decision. The language-model step is proposed only. It was not implemented or tested, and the simulation concerns only the scoring and matching step (section 3.5). We examined the matching step in fully synthetic homes of 80 residents, to see whether its suggestions would be more compatible, and more evenly shared (fewer residents left without a suggestion or with a poor one), than what happens by default.

Research questions. The overall question is whether, in a simulated closed residential aged care population, matching residents on attributes observed by staff across the whole home produces more compatible and more evenly shared pairings than what happens by default. Five specific questions follow from it.

1. **RQ1.** Does matching on several observed attributes add compatibility beyond pairing by proximity (living on the same level), by a single shared attribute, or at random?
2. **RQ2.** Does pooling observations from every role add to a profile built by care staff alone?
3. **RQ3.** How are the results shared across resident groups, and does the rule for assigning pairs matter?

4. **RQ4.** How robust are the results to recording error, sparse recording and different assumptions about what makes two people compatible?
5. **RQ5.** Does keeping the profile up to date matter?

Contribution. This is a framework development study with a simulation-based evaluation. It offers three things, each within the bounds of what was actually done: a conceptual framework for whole-of-home profiling and connection matching; simulated comparative results for the matching step; and open code and synthetic data, so that others can repeat or challenge the results. It offers no evidence from real residents.

Structure of the paper. Section 2 reviews what is known and sets out the gap. Section 3 describes the framework. Section 4 explains how the matching step was simulated, and section 5 reports the results in the order of the research questions. Section 6 discusses what the results may mean, their limits and what should be tested next. Section 7 concludes.

2. Background and gap

2.1 Knowing the person

Person-centred care is built around the individual and depends on knowing that individual through a relationship (Fazio et al., 2018). A meta-ethnography of 10 studies identified "knowing the whole person" and "integrating families and nurturing internal and external relationships" among the aspects of person-centred care that support quality of life after a move into residential care (Davies et al., 2023). A mixed-methods review of 30 studies found that person-centred interventions built on personalised preferences and social engagement can improve residents' quality of life, while staff shortages and weak managerial support hold them back (Udkunta et al., 2026).

Life-story work is the usual way of knowing the person. An integrative review of 13 studies found it can strengthen person-centred care in long-term care, but that it needs education, time, resources and management commitment to work (Doran et al., 2019). A life story written at one point in time also becomes outdated as the person changes.

Structured knowledge of the person has measurable effects. In Australian residential aged care, 61 staff who viewed residents' digital life stories showed a stable improvement in knowledge and understanding of those residents, and reported being better equipped to personalise care (Matas et al., 2025). A stepped-wedge cluster-randomised trial followed 240

residents with dementia in 23 Swiss facilities. Monthly nurse-led person-profile interventions involving staff and family improved quality of life by 2.6 points on QUALIDEM (95% confidence interval 1.34 to 3.86), compared with measurement alone (Spichiger et al., 2025). QUALIDEM is a quality-of-life scale for people living with dementia.

The wider evidence for person-centred care is more cautious. A systematic review of 41 studies in residential aged care found, on meta-analysis, no statistically significant improvement in agitation, quality of life or neuropsychiatric symptoms for people living with dementia, and called for longer, higher-quality studies (Berkovic et al., 2024). Taken together, these studies suggest that knowing the person is a necessary basis for good care, although it is not yet shown to be sufficient. They concern how staff come to know residents. How residents come to know one another is a separate question, taken up next.

2.2 How friendships form in care homes

Friendships in care homes grow more from opportunity than from fit. In a social network study of one assisted living community (38 residents), living on the same floor predicted both acquaintance and companionship ties. Similar age predicted companionship. Moving in around the same time, similar physical limitation and higher cognitive functioning predicted acquaintance (Mauldin et al., 2021). Across four continuing care retirement communities, living in the same wing was the only consistent predictor of close ties (Ayalon & Yahav, 2019). Proximity is therefore the baseline any matching method has to beat, rather than the ideal.

Close ties are also hard to form without help. In interviews with 15 cognitively intact residents of two nursing homes, few had close relationships with peers or staff. Physical proximity and access to peers with similar interests who could communicate clearly fostered friendly peer relationships, and staff who spent non-care time and offered "little extras" fostered friendly staff relationships (Roberts, 2018). In two further nursing homes, cognitively intact residents described peer relationships as a source of belonging, purpose and significance, and organisational factors as barriers to forming them (Kang et al., 2020).

Qualitative studies describe what helps, and it is close to what this paper proposes. Interviews with 35 residents, relatives, staff and clinicians in UK care homes identified personalising activities to residents' interests, social preferences and cognitive ability, and "finding and emphasising things in common", as central to connection (Misiak et al., 2024). A study of 67 residents, staff and family members in the UK and Canada identified routine care and

everyday interactions as opportunities for social contact, family and friend knowledge as a resource, and the fostering of relationships between residents (Chapman et al., 2024). A network study of two Dutch nursing homes mapped many direct and indirect ties among residents, staff, family and neighbours, including for residents with dementia, and described them as a resource for person-centred care (van Beek et al., 2025).

Social ties also matter for health. Among 96 residents of two New South Wales facilities, 70.8% of whom had cognitive impairment, those with larger networks of family and friends had better cognitive performance (Dodds et al., 2024).

One group is largely missing from this evidence. Several of the studies above recruited only residents who passed a cognitive screen or were cognitively intact (Kang et al., 2020; Mauldin et al., 2021; Roberts, 2018). Yet 54% of people in Australian permanent residential care live with dementia (Australian Institute of Health and Welfare [AIHW], 2026). The studies that do include them show less support, less connectedness and long periods without any interaction (Casey et al., 2016; Gebhard et al., 2024; Lapane, Dube, et al., 2022). A connection method for residential care has to work for these residents, and through staff, because many cannot describe themselves to a system.

2.3 What AI already does in aged care

Three strands of work exist, and they have developed separately.

- **Reading care notes.** Australian studies have applied language models to free-text nursing notes from residential aged care to identify malnutrition (Alkhalaf et al., 2025) and hospitalisation (Suddle et al., 2025). The focus is clinical risk. Language models can also read social signals: in England, a transformer model (a type of language model) identified loneliness or social isolation in sentences from 1.1 million case notes about 3,046 older long-term care users, with an F1 score of 0.92 (Rickman et al., 2025). The F1 score is a measure of accuracy from 0 to 1 that balances missed and false detections.
- **Building profiles for staff.** CareInsights, developed with seven long-term care facilities, captures caregiver and resident interactions and returns narrative feedback to caregivers (Moore, Tao, Moore, et al., 2025). A related system, Family In The Loop, turns video, notes and records into summaries for staff and updates for families, and improved staff access to resident information without increasing caregiver burden

(Moore, Tao, Ricci-De Lucca, et al., 2025). Neither abstract describes matching residents with one another.

- **Matching older adults.** ELDER-MATCH inferred personality from conversations with social robots and recommended pairings on personality, interests and location among 83 community-dwelling older adults; 76% of accepted recommendations were ongoing relationships at three months (Tseng et al., 2026). Participants lived in the community and could hold a conversation with a robot.

The evidence on AI in long-term care is mixed, and reviewers urge caution. A scoping review of responsible AI found the literature dominated by care robots and monitoring technology, with little evidence from real contexts of use (Lukkien et al., 2023). A second review catalogued the barriers that care providers perceive to adopting AI-enabled robots (Wong et al., 2024). A systematic review of 31 studies of AI for older people receiving long-term care found the interventions somewhat acceptable, the evidence of effectiveness mixed, and the risk of bias high (Loveys et al., 2022). An expert review of AI in the healthcare of older people warns of bias, lack of validation in older populations, infringements on privacy and autonomy, and insufficient transparency, and calls for a person-centred approach with clear governance (Shiwani et al., 2023). In interviews, 24 Dutch long-term care professionals described AI decision support as a balancing act between opportunities and drawbacks, and named human-centric learning loops and measures against bias among the prerequisites for responsible use (Lukkien et al., 2024).

Overall, these strands show that knowledge about residents can be captured and that older adults can be matched, while reviewers consistently call for human oversight and stronger evidence. The next subsection examines the evidence for each step the framework would need.

2.4 Evidence for each step of the framework

Beyond the three strands above, published studies show that each step the framework relies on is feasible on its own.

- **Capturing what staff notice.** Everyday staff messages already hold person-centred content. Natural language processing extracted "what matters", mobility, mentation and medication content from 30,066 text messages sent by workers in 16 nursing homes (Powell et al., 2025). A fine-tuned language model classified the same kinds of

content in 21,357 messages from 12 homes, with agreement of $\kappa = 0.73$ against clinical experts. It surfaced care preferences, cognitive changes and mobility issues (Farmer et al., 2025). Kappa measures agreement beyond chance, where 1 is perfect agreement.

- **Turning notes into facts.** In Australian residential aged care, natural language processing of free-text progress notes identified 82% of malnourished residents, against 48% from structured data alone (Alkhalaf et al., 2023). Outside aged care, open-source large language models extracted social history from clinical notes more accurately than pattern matching (Gu et al., 2025).
- **Recording preferences.** Natural language processing sorted older adults' documented care preferences into 11 categories with an average F-score of 0.88; the most common were music, photographs, entertainment and religion (Min et al., 2024). From 255 nursing home residents' responses, a machine learning recommender predicted which further preferences were likely to matter to a resident, with recall of 80.2% (the share of important preferences it found) and precision of 79.2% (the share of its predictions that were correct) (Gannod et al., 2019).
- **Presenting the profile.** EE-Profile uses a large language model to turn life narratives into short facet summaries and event timelines. In studies with 8 older adults and 31 care-team participants it improved information retrieval, reduced perceived workload and increased readiness to start personalised conversations (Li et al., 2026).
- **Tracking change against a person's own baseline.** In-home sensors and machine learning learned the daily patterns of people living with dementia and detected changes in routine, with accuracy of up to 80% (Enshaeifar et al., 2018). Personalised models using wristband sensors detected behavioural symptoms in 17 residents of a care unit, with a median AUC of 0.87. The most predictive features differed from person to person (Iaboni et al., 2022). AUC is the area under the curve, where 0.5 is chance and 1 is perfect.
- **Food.** Automated food imaging designed for long-term care classified foods with 88.9% top-1 accuracy (its first choice of food item was correct 88.9% of the time) and agreed closely with weighed estimates of nutrient intake (Pfisterer et al., 2022). An AI food scanner guided tailored nutrition for 108 residents of five long-term care facilities, with most benefit in the worst-nourished group (Seo et al., 2026).

- **Fitting the workflow.** A co-designed health information system in a 169-bed Australian home cut nurses' documentation time from 20.4% to 6.4% and raised documentation of resident-focused goals from 56% to 88% (Bail, Merrick, et al., 2022). Residents and staff found it acceptable because it saved time and improved care (Bail, Gibson, et al., 2022).

Four cautions qualify this evidence.

- **Language models are not yet robust.** An evaluation of 17 large language models on Australian residential aged care nursing notes found the best reached an F1 score of 87% for extracting entities and 83% for summarising, but robustness scores of about 4% (Vithanage et al., 2025).
- **AI-written notes must still be checked.** In an Australian outpatient trial, 58% of ambient-scribe outputs (notes drafted by an AI tool that listens to the consultation) were accepted without modification, and there was some evidence of hallucination (plausible but false content) or incorrect output (Memon et al., 2026). In a blinded comparison in primary care, human-written notes scored higher than AI-generated notes on documentation quality (Reddy et al., 2026).
- **Evidence that technology reduces loneliness is limited.** An umbrella review of technology interventions for isolation and loneliness in older adults found limited evidence with low certainty, most favourable for videoconferencing (Balki et al., 2022).
- **Adoption is constrained.** A rapid review of 28 studies of AI in nursing homes found promise across clinical, operational and social domains, held back by infrastructure cost, privacy regulation, algorithmic bias, staff resistance and limited generalisability (Mileski et al., 2026).

Taken together, these studies suggest that each step is feasible, with clear limits. None of them combines the steps to connect residents with one another, which is the gap set out next.

2.5 The gap

Each component of the framework has some evidence behind it. The combination does not. Table 1 summarises what the literature reviewed above does and does not establish.

Table 1. What existing evidence establishes, and what is missing.

Claim	What supports it	What is missing
Loneliness and thin resident networks are major problems in care homes	A meta-analysis, a systematic review, large datasets and network studies (Casey et al., 2016; Gardiner et al., 2020; Lapane, Dube, et al., 2022; Lapane, Lim, et al., 2022)	Nothing essential: the problem is well established
Staff can be given useful, structured knowledge of each resident, including with AI	Profile systems, language models reading notes, and a cluster-randomised trial (sections 2.1, 2.3 and 2.4; for example, Matas et al., 2025; Rickman et al., 2025; Spichiger et al., 2025)	Use of that knowledge to connect residents with each other
Matching on several attributes can lead to lasting relationships	One study in the community (Tseng et al., 2026); qualitative care home studies on common ground (Chapman et al., 2024; Misiak et al., 2024)	Any test inside a care home
Whole-of-home matching does better than proximity	No direct evidence	A direct test. This paper offers a simulated one
Matching can share social opportunity more evenly	Exclusion and variation between facilities are documented (Hoben et al., 2025; Lapane, Dube, et al., 2022)	Any test of whether an algorithm corrects or worsens them

The literature reviewed for this study did not identify a published test of resident-to-resident matching inside a residential care home that uses what staff observe in the course of their work. That setting differs from the community in ways that matter:

- the pool is small and closed;
- over half of residents live with dementia (AIHW, 2026), and many cannot describe themselves to a system;
- some of the people who know residents well may never write in the clinical record;
- staff, not residents, act on a suggestion;
- staff also see how residents actually get on with each other, which is direct evidence that neither matching nor profiling study above describes using.

This paper therefore offers a synthesis of evidence-supported components and an initial, simulated test of the question the literature leaves open. The gap statement rests on targeted

searching and not on a systematic review, so relevant work may have been missed. Sources were identified through question-based searches in an AI-assisted academic search engine (Consensus) and by following related records. Each cited source was then checked against its own bibliographic record and abstract. Search strings were not recorded. The framework is described next.

3. The framework

The framework has four parts: whole-of-home observation, a living profile, connection matching, and a staff feedback loop. Fig. 1 shows how they fit together.

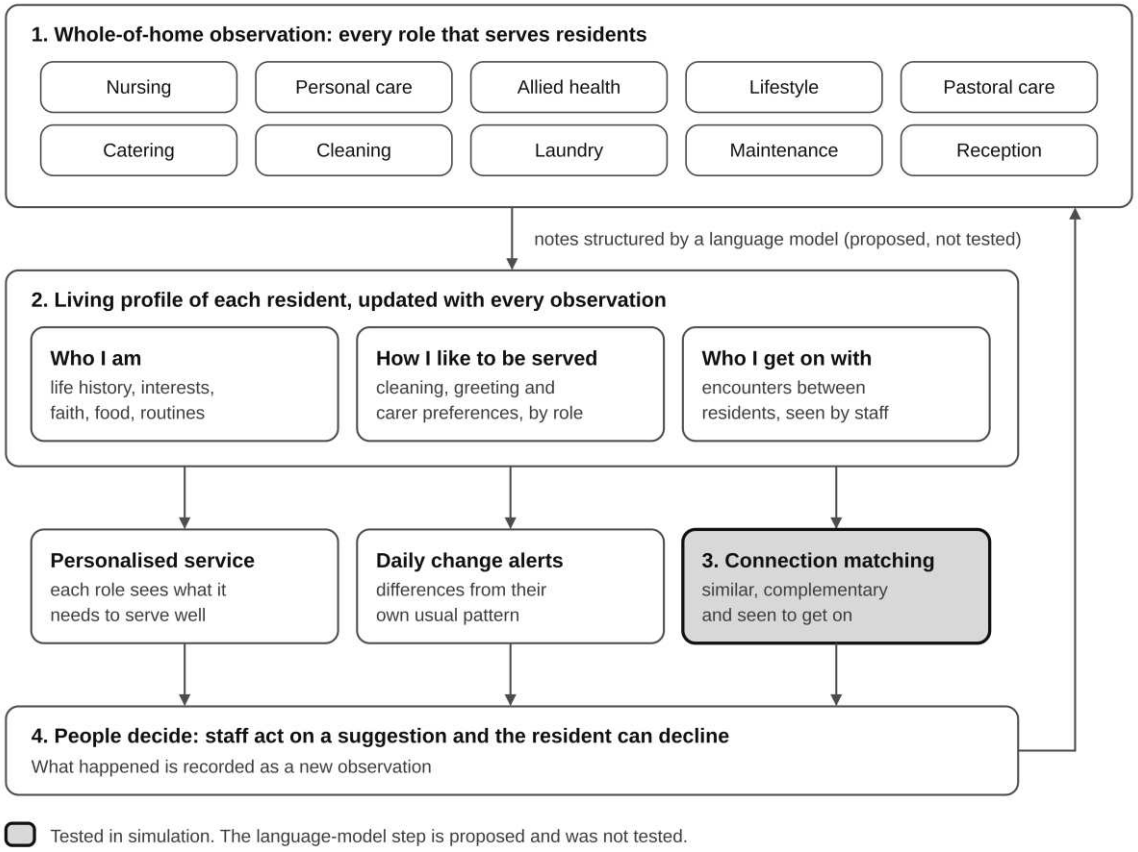


Fig. 1 Observations from every role are pooled into one living profile. The profile serves three uses, people make every decision, and each outcome returns as a new observation. The shaded step, connection matching, was tested in simulation; the language-model step is proposed and was not tested

3.1 Whole-of-home observation

"Staff" here means the whole residential aged care workforce: every person, in every section of the home, who interacts with residents to deliver a personalised service. Each role sees a different side of the same person. Table 2 lists the roles and what each is placed to notice.

Table 2. Proposed whole-of-home observation sources and what each may contribute (not measured).

Role	**What the role is placed to notice**
Nursing	Health, cognition, pain, hearing, medicines, habits with a health bearing
Personal care	Daily routine, mood, best time of day, conversation, what calms or unsettles
Allied health	Mobility, physical goals, exercise and gym participation
Lifestyle and leisure	Interests across games, arts, social events and entertainment; who joins in with whom
Pastoral care	Faith tradition, denomination, prayer and worship practice, life history
Catering and dining	Food choices, appetite, mealtime company, a social drink
Cleaning	Room preferences, belongings that tell a life story, visitors, mood
Laundry	Clothing preferences and pride in appearance
Maintenance and gardening	Practical interests, former trades, time spent outdoors
Reception and administration	Visitors, family contact, outings

Some of these roles already document what they see. Others hold knowledge that has nowhere to go. The framework therefore needs a capture step that takes seconds, such as a short voice note or a tap on a phone, and an AI language model that turns those notes into structured facts.

Staff record two kinds of observation: what they learn about a resident, and how residents get on *with each other*. The second kind covers who sits together, who seeks whom out, and which encounters went badly.

People outside these staff roles also know residents well. Families, volunteers, social workers (including Accredited Mental Health Social Workers) and psychology staff often hold insight into a resident's life story, preferences and social needs. They were not modelled in this study, which simulates the ten staff roles in Table 2, but a real implementation could invite their contributions with the resident's consent.

3.2 The living profile

Observations from all roles are pooled into one profile per resident, with three parts. Table 3 sets them out.

Table 3. The three parts of the living profile.

Part of the profile	Examples	Used for
Who I am	Language, life history, former work, interests, faith and practice, food, conversational style, best time of day, habits such as smoking or a social drink, hearing, mobility, cognition	Matching residents, and personalised service
How I like each role to serve me	Cleaning style (dry, wet or mixed), timing, what not to touch, chat or quiet; how I like to be greeted; gender or language of carer	Personalised service by each role
How I get on with others	Residents I enjoy, residents I avoid, observed encounters	Matching residents

The profile is "living" because each new observation updates it. A resident who stops attending a favourite activity, eats less, or becomes restless at a new time of day differs from their own baseline, and that difference is flagged to the registered nurse. This wider change-detection use is proposed and was not evaluated in this study. The same update keeps the matching current.

3.3 Connection matching

For each pair of residents, i and j, the method computes a score S from three sources. The score was developed for this study. It has no unit, and a higher value marks a pairing the method considers more likely to work. The score is lowered when cognitive ability differs widely or when both residents have hearing loss. The weights were fixed in advance and are listed in Online Resource 1.

$$S_{ij} = \mathrm{Sim}_{ij} + \mathrm{Comp}_{ij} + \mathrm{Obs}_{ij} \quad \text{for pairs that pass the filters}$$

- **Similarity (Sim):** shared interests, faith practice, rural or urban background, food culture, similar age, the same best time of day, living on the same level, and a shared smoking or social-drink routine.
- **Complementarity (Comp):** a storyteller with a listener; a resident who likes to help with a newcomer.

- **Observed interaction (Obs):** staff notes of encounters between the two that went well or badly.
- **Filters:** no suggestion is made for a resident who prefers their own company, for two people with no shared language, for two people who both have severe cognitive impairment, for a pair seen to clash more than once, or between someone quitting smoking and an active smoker.

These filters are design assumptions for the simulation and have not been validated as exclusion criteria. In practice, two residents without a shared language, or two residents with severe cognitive impairment, may still enjoy contact when it is supported, and people living with dementia can form meaningful connections without relying on shared verbal communication. In a real home, most of these filters would be better framed as flags for the support a pairing needs, such as a staff member present or an activity that does not depend on conversation, rather than as reasons to exclude a resident. The smoking filter is one example of respecting a resident's own goal, here an attempt to quit. In any real home, residents, families and staff would need to agree such rules together.

The result is a suggestion to staff with its reason, for example "both grew up on farms and enjoy cards; seat together at Thursday lunch".

3.4 Staff feedback loop

A staff member chooses whether to act on a suggestion, and the resident can always decline. What happened is recorded as another observation, so the method learns from outcomes and not only from attributes.

3.5 Where AI sits in the framework

The framework uses AI in a narrow, supporting role. Table 4 sets out each step, the kind of technique involved, and whether this study tested it.

Table 4. Where AI sits in the framework, and what this study tested.

Step	Technique	Status in this study
Capturing observations	Speech-to-text and a language model that turns short notes into structured profile facts	Proposed. Represented in the simulation by assumed coverage and error rates
Tracking change	Comparison of each resident with their own recent baseline	Proposed. Represented only by profile change over 90 days

Step	Technique	Status in this study
Scoring pairs	A transparent weighted score with fixed weights, listed in Online Resource 1	Implemented and tested in simulation
Assigning pairs	Maximum-weight matching, a standard optimisation algorithm	Implemented and tested in simulation
Explaining a suggestion	A language model drafting the reason and a conversation starter	Proposed. Not tested
Learning from outcomes	Adjusting weights from recorded outcomes	Proposed. Not tested

None of the steps makes a decision about a resident. The scoring and assignment steps are rule-based and can be checked line by line. This was a deliberate choice, because in a care setting staff must be able to see why a suggestion was made.

Each proposed step has a published precedent (section 2.4). Each also needs human checking, because current language models and AI-written notes still make errors (Memon et al., 2026; Reddy et al., 2026; Vithanage et al., 2025). For this reason, the simulation tests what happens when recording is wrong or missing.

3.6 Safeguards built into the design

- **Consent.** The Standards require informed consent to collect, use and store a resident's information (Action 2.7.2c) and support for residents who need help with decisions (Action 1.3.3; Department of Health, Disability and Ageing, 2025). Where a resident cannot give consent, their substitute decision-maker would be involved, and the resident's own wishes would still be sought as far as possible.
- **Sensitive information.** Health information and religious beliefs are sensitive information under the Privacy Act 1988 (Cth). Faith and habits are recorded only as the resident states or shows them, never inferred from background.
- **Information about other people.** Residents often share things informally, and every observed encounter involves two people. A note in one resident's profile should not disclose personal details about another resident, and information shared in confidence should be used only in ways the resident would reasonably expect.
- **Approved systems only.** The Office of the Australian Information Commissioner recommends that organisations do not enter personal information, particularly sensitive information, into publicly available generative AI tools, and that they

conduct a privacy impact assessment (Office of the Australian Information Commissioner [OAIC], 2024).

- **Role-based views.** A cleaner sees cleaning preferences and conversation starters, not clinical notes.
- **Preferences, not ratings.** The profile records how a resident likes to be served. It does not score individual staff.
- **People decide.** The method suggests; staff and residents choose.
- **Incidents between residents.** A harmful or distressing incident between residents is handled through the home's existing incident-reporting processes, not through the profile. That pair would receive no further suggestions until staff had reviewed it.

The framework described in this section is a design, not a tested system. The next section explains how one part of it, connection matching, was examined.

4. Simulation methods

This section explains how the matching step of the framework was tested. It covers the design and the reasons for it, the synthetic home, the hidden compatibility model, what staff were assumed to observe, the methods compared, the outcomes and the analysis.

4.1 Design and rationale

This was a simulation study using entirely synthetic data. No resident, staff member, care record or facility was involved, and no profile was modelled on a real person. Because the study involved no human participants and no personal data, ethics approval was not sought.

Simulation was chosen over a pilot in a real home for three reasons. First, a pilot would involve residents, many of whom live with cognitive impairment. It would need ethics approval and supported decision-making, which were outside the scope of this initial study. Second, a pilot needs a trustworthy outcome measure, and the measurement of social connection in long-term care is itself unsettled (section 6.5). Third, a simulation can change one assumption at a time and repeat the test in hundreds of homes, which a single site cannot do. The same reasoning is used in research on recommender systems for online communities, where simulators are built because real-world social experiments carry high costs and ethical risks (Zhang et al., 2025).

The study is therefore a screening step. It asks whether the idea is worth the cost of a pilot, and which parts of it appear to matter most. Simulated compatibility is not observed compatibility, and every result below should be read with that limit in view.

4.2 The synthetic home

Each simulated home had 80 residents on four residential levels, 20 per level, above a ground floor of offices. This layout was chosen as a plausible illustration. It is not meant to represent Australian homes in general. Residents were generated at random from the parameters in Table 5. A published Australian figure was used where one was available. The remaining values are stated assumptions.

Table 5. Parameters used to generate synthetic residents.

Attribute	Value used	Basis
Women	65%	About 2 in 3 people using aged care (AIHW, 2025)
Aged 85 and over	64% of women, 49% of men	Permanent residential care, 30 June 2025 (AIHW, 2025)
Living with dementia	54%	Permanent residential care, 2021–22 (AIHW, 2026)
Cognitive impairment, with dementia	10% none or mild, 43% moderate, 47% severe	AIHW (2026)
Cognitive impairment, without dementia	54% none or mild, 37% moderate, 9% severe	AIHW (2026)
Preferred language other than English	10%	Author assumption, informed by the 11% reported for respite residential care (AIHW, 2025); not an estimate for permanent care
Prefers own company	10%	Author assumption
Hearing impairment	45%	Author assumption
Smoking; social alcohol use	6%; 30%	Author assumption

Each resident also had 14 possible interests (including exercise and gym, games, arts, music and entertainment), a faith tradition and whether they practised it, a former occupation, a rural or urban upbringing, a food culture, a conversational style from listener to storyteller, a liking for helping others, time in the home, a best time of day, a level of mobility, and service preferences such as cleaning style. These further attributes, and the rows marked "Author assumption" in Table 5, are illustrative. They are not estimates for any real home.

4.3 The hidden compatibility model

A separate model, in effect a synthetic compatibility generator, decided whether an introduction between two residents would "work". A working pairing is an abstract outcome in this study. The model gave every possible pair a probability, between 0 and 1, that an introduction would lead to a companionable tie. It was not calibrated against any real measure of friendship or loneliness, and it was never shown to the matching method.

The probability rose with shared interests, shared faith practice, shared background, similar age, shared food culture, the same best time of day, a shared smoking or social-drink routine, complementary conversational styles, a helper paired with a newcomer, and living on the same level. It fell when cognitive ability differed widely, when both residents had severe cognitive impairment, when both had hearing loss, and sharply when there was no shared language. The choice of factors was informed by the studies in section 2.2 (Mauldin et al., 2021; Misiak et al., 2024; Roberts, 2018). The size of each factor is an assumption, because those studies do not provide one. The hidden model is therefore not intended as a validated model of friendship formation.

A simulation of this kind can be circular. If the same authors write the hidden model and the matching method, the method may succeed only because it mirrors the model. Three features were built in to limit this.

- **Unrecorded temperament.** Each resident had traits that no staff member observed, and each pair had its own random chemistry: a chance element of compatibility, specific to that pair, that no profile could record.
- **Uncertain weights.** The strength of every positive factor was redrawn at random for every simulated home, from wide ranges. For complementarity the range included zero.
- **Fixed method.** The matching method's weights were set once, before any results were produced, and were not tuned to the hidden model.

These features reduce the overlap between model and method. They do not remove it, because the same authors specified both. Section 4.7 therefore includes hidden models that differ from the method's assumptions.

4.4 What staff observe

Eleven sources contributed to a profile: the admission form and the ten staff roles in Table 2. Each source had a probability of learning each attribute during one observation period, nominally four weeks. Each also had a probability of recording an attribute wrongly, set between 5% and 15%. Where sources disagreed, the majority reading was used. An attribute that nobody recorded earned no credit in matching. The probabilities for each role are illustrative assumptions and are listed in Online Resource 1.

Residents on the same level met an average of four times in the period, and residents on different levels 0.25 times. Each meeting went well or badly with a probability tied to the pair's hidden compatibility. A meeting entered the profile only if a staff member noticed and recorded it, and 10% of recorded impressions were wrong.

Four data sources were compared, each adding roles to the one before.

- **Source A.** Admission form only. No encounters between residents recorded.
- **Source B.** A plus nursing, personal care and allied health. 15% of encounters recorded.
- **Source C.** B plus lifestyle and pastoral care. 30% of encounters recorded.
- **Source D, whole of home.** C plus catering, cleaning, laundry, maintenance and reception. 55% of encounters recorded.

These observation rates are assumptions. They have not been measured in any home, and section 4.7 varies them.

4.5 Methods compared

Seven ways of choosing pairs were compared. Table 6 lists them, from the simplest baselines to an upper bound that no real method could reach.

Table 6. Methods compared.

Method	**How pairs were chosen**
Random	Any two residents who passed the language and cognition filters
Same level	Random pairs within a level: the proximity baseline
Shared interests only	Best overlap of recorded interests
Similarity	All similarity attributes in the profile

Method	How pairs were chosen
Similarity and complementarity	Adds storyteller–listener and helper–newcomer pairing
Full framework	Adds observed encounters between residents
Simulation upper bound	Pairs chosen with full knowledge of the hidden model

The baselines follow the literature. Proximity predicted ties in two studies of congregate living (Ayalon & Yahav, 2019; Mauldin et al., 2021), so same-level pairing stands for what happens by default. A single-attribute baseline was included because friendship research finds ties more likely the more attributes two people share, with diminishing returns for each additional one (Block & Grund, 2014). The upper bound exists only within the simulation. It shows how much compatibility could be found if everything about every pair were known.

The same rules applied to every method. Residents who preferred their own company received no suggestion. No method paired two residents without a shared language, or two residents who both had severe cognitive impairment, because such introductions would need support that the simulation does not model. The profile-based methods applied these filters, and the others in section 3.3, using what staff had recorded. The two random baselines were given the true language and cognition information, which favours them.

Each method gave every remaining resident at most one partner. Pairs were assigned by maximum-weight matching. In plain terms, this procedure pairs as many residents as possible and, among the ways of doing so, chooses the set of pairs with the highest total score. It was run with the NetworkX library. A simpler "best pairs first" rule was run for comparison: it takes the highest-scoring pair, sets those two residents aside and repeats. One partner per resident is a simplification, since a resident may welcome several introductions.

4.6 Outcomes

Four outcomes were calculated for every method in every home. "Residents wanting company" means every resident except those who prefer their own company.

- **Residents in a working pairing (main outcome).** The expected share of residents wanting company who end up in a pairing that works. It is the average, across those residents, of the hidden probability for their suggested pair. Residents with no suggestion count as zero. In the Results, "working pairing" always means this simulated outcome. It is not an observed relationship.

- **Pair success.** The average hidden probability across suggested pairs only.
- **Coverage.** The share of residents wanting company who received any suggestion.
- **Distribution across groups.** The same outcomes for residents with cognitive impairment, a preferred language other than English, hearing loss, or wheelchair or bed-based mobility, and for the worst-served quarter of residents (the quarter of residents wanting company with the lowest values under each method).

The share of suggested pairs that crossed levels was also recorded. All of these outcomes were written into the code before any results were produced. The decision to lead with "residents in a working pairing" was made when writing up, because it reflects both the quality of suggestions and who is left without one. The other outcomes are reported in full so that readers can check whether the conclusions depend on that choice.

4.7 Sensitivity and follow-up analyses

Five sets of sensitivity analyses were built into the simulation before the full runs.

- Recording errors removed, doubled and quadrupled.
- Observation cut to 75%, 50% and 25% of the assumed amount.
- Four alternative hidden models: proximity dominant (living on the same level counts 2.5 times as much, and every other factor half as much); no complementarity (storyteller–listener and helper–newcomer effects set to zero); mostly unrecorded chemistry (recorded factors count half as much, and unrecorded temperament and pair chemistry twice as much); and a misspecified model in which only half the interests matter and residents with similar conversational styles get on better, the opposite of the method's assumption.
- A home in which the most cognitively impaired residents live together on Level 1, as in a memory-support (secure dementia) unit.
- A living-profile test: after 90 simulated days of change, matching from the day-0 profile was compared with matching from an updated profile.

The living-profile test worked as follows. Each home was first simulated as in the main analysis. Ninety days of change were then applied in one step. Each resident had an 8% chance of being replaced by a new resident on the same level, drawn from the same

population parameters. Among residents who stayed, 12% moved one step down in cognition, each interest had a 6% chance of being gained or lost, and 10% changed their best time of day. In addition, 5% developed hearing loss, 8% moved one step down in mobility, and 5% changed whether they wanted company. These rates are author assumptions.

The weights of the hidden model were unchanged. Pairs of staying residents kept their pair chemistry, and new residents drew fresh chemistry. The stale profile kept the day-0 records for staying residents and held only admission-form information for new residents. The updated profile was rebuilt from whole-of-home observation of the changed home. A suggestion that involved a resident who no longer wanted company was counted as declined.

One follow-up analysis was added after the main results had been seen, and it should be read as exploratory. It varied the language mix: twelve community languages instead of six (adding Croatian, Polish, German, Macedonian, Maltese and Spanish), and 20% instead of 10% of residents preferring a language other than English. It was added to check whether the finding for these residents depended on the illustrative choice of languages.

4.8 Analysis and reproducibility

The main analysis used 400 simulated homes, and each sensitivity or follow-up analysis used 200. Results are means across homes. Differences between methods were calculated within each home and then averaged. The 95% simulation intervals are the mean plus or minus 1.96 standard errors. They reflect variation between simulated homes only, not uncertainty about whether the assumptions are right. No hypothesis tests were carried out. With 400 homes, the 95% simulation interval for the main comparison was about one point wide.

The simulation was written in Python 3.13 with NumPy 2.5, pandas 3.0 and NetworkX 3.6. Every home was generated from a numbered random seed (0 to 399 for the main analysis), so each result can be reproduced exactly. The code was first checked on six homes. One coding error was found at that stage, in the living-profile test, and was corrected before the full runs. No parameter of the hidden model or the matching method was changed after results were seen. The code, the parameter file, an example synthetic home and all result files are provided as Online Resource 1.

Claude (Anthropic) assisted with developing and refining the simulation code under the authors' direction. The authors independently developed the research design, methodology, assumptions, analysis, interpretation and conclusions. Relevant literature was identified

through targeted searches of scholarly publications and by following related papers and references. The literature included peer-reviewed research in aged care, gerontology, nursing, health informatics and artificial intelligence, including articles published in *BMC Geriatrics*, *The Gerontologist* and the *Journal of the American Medical Directors Association*. Each cited source was checked against its bibliographic record and available abstract or full text. Claude, ChatGPT (OpenAI) and QuillBot were also used to assist with grammar, clarity, readability and language refinement. The authors retain full responsibility for the accuracy, integrity, interpretation and final content of the manuscript.

Section 5 reports the results in the order of the research questions.

5. Results

This section reports the simulation results in the order of the research questions: the comparison of methods (RQ1), the comparison of data sources (RQ2), resident groups and the pairing rule (RQ3), the sensitivity analyses (RQ4) and the living-profile test (RQ5). Unless stated otherwise, figures are percentages of residents wanting company, averaged across simulated homes. Because the same authors specified both the hidden compatibility model and the matching method, the figures describe behaviour under stated assumptions. They are not estimates of a real-world effect.

5.1 Does matching add compatibility beyond proximity? (RQ1)

In the simulation, the full framework placed 48.6% of residents in a working pairing, against 31.7% for same-level pairing. That is a difference of 16.9 percentage points (95% simulation interval 16.4 to 17.4), and the framework did better in all 400 simulated homes. Fig. 2 shows the main outcome for all seven methods.

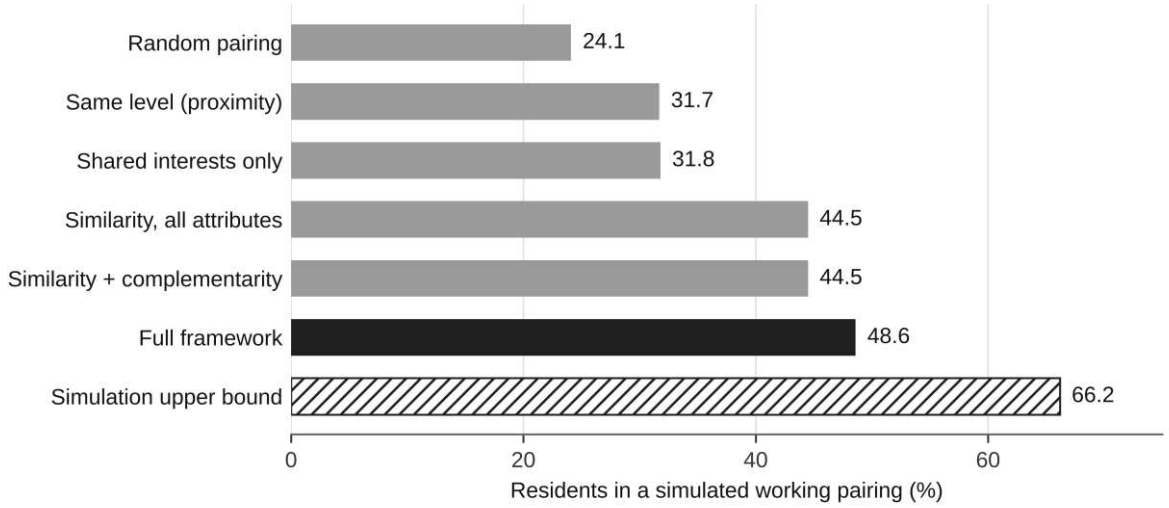


Fig. 2 Simulated share of residents in a working pairing, by matching method (mean of 400 synthetic homes)

Four points follow from Fig. 2.

- **A single attribute was not enough.** Matching on shared interests alone (31.8%) did no better than pairing people on the same level (31.7%).
- **Complementarity added no measurable benefit.** Adding storyteller–listener and helper–newcomer pairing changed the result by 0.1 points (−0.2 to 0.4).
- **Observed encounters helped.** Adding staff observations of how residents got on with each other added 4.1 points (3.7 to 4.4).
- **A gap to the upper bound remained.** The framework sat 17.5 points below the upper bound. In the simulation, part of what decides compatibility is recorded in no profile, so no profile-based method can close this gap fully.

Table 7 gives the other outcomes for each method.

Table 7. Other outcomes by method (%).

Method	Receive a suggestion	Pair success	Pairs across levels	Worst-served quarter
Random pairing	95.5	25.2	75.9	4.5
Same level (proximity)	90.9	34.9	0.0	5.6
Shared interests only	97.6	32.5	76.3	7.6
Similarity, all attributes	97.6	45.5	31.7	14.8

Method	Receive a suggestion	Pair success	Pairs across levels	Worst-served quarter
Similarity + complementarity	97.6	45.6	33.9	14.8
Full framework	97.5	49.9	31.5	17.1
Simulation upper bound	97.6	67.8	41.6	39.2

Note. Worst-served quarter is the mean result for the quarter of residents wanting company with the lowest values under each method.

Three things stand out in Table 7. The profile-based methods gave a suggestion to between 97.5% and 97.6% of residents wanting company, against 90.9% for same-level pairing. The worst-served quarter of residents fared better under the full framework (17.1%) than under same-level pairing (5.6%), although it stayed far below the upper bound (39.2%). About a third of the framework's suggestions (31.5%) crossed levels. Same-level pairing cannot produce these introductions.

5.2 Does whole-of-home observation add to a care-team profile? (RQ2)

Table 8 shows the main outcome for the full framework as more roles contribute to the profile.

Table 8. Simulated share of residents in a working pairing under the full framework, by who contributes observations.

Source of the profile	Residents in a working pairing (%)
A. Admission form only	36.4
B. Plus nursing, personal care and allied health	42.9
C. Plus lifestyle and pastoral care	46.3
D. Whole of home, every role	48.6

Adding catering, cleaning, laundry, maintenance and reception to the care and lifestyle teams added 2.3 points (1.9 to 2.7). Against a profile built by nursing, personal care and allied health alone, the whole-of-home profile added 5.7 points (5.3 to 6.1). Each added group of roles raised the result, by a smaller amount each time. Two things change together from source A to source D: more attributes are known, and more encounters are recorded. The comparison does not separate them.

5.3 How are results shared across residents, and does the pairing rule matter? (RQ3)

Table 9 breaks the main outcome down by resident group.

Table 9. Simulated share of residents in a working pairing (%), by group.

Group	Same level	Full framework	Simulation upper bound
All residents wanting company	31.7	48.6	66.2
Moderate or severe cognitive impairment	32.0	47.9	65.7
Severe cognitive impairment	25.6	44.0	61.6
Preferred language other than English	18.9	30.5	39.8
Hearing loss	29.4	46.7	64.1
Wheelchair or bed-based mobility	31.1	48.2	65.7

Every group in Table 9 had a higher share under the framework than under same-level pairing. The gain for residents with moderate or severe cognitive impairment (15.9 points) was close to the gain for all residents (16.9 points). Two findings qualify this.

Language. Residents who preferred a language other than English gained 11.7 points, which was less than English-preferring residents gained. The gap between the two groups widened from about 14 points under same-level pairing to about 20 under the framework. Under the framework 24% of them still received no suggestion, against 44% under same-level pairing. In 16% of cases nobody else in the home shared a language with them, so even the upper bound reached only 39.8%.

The pairing rule. How pairs were assigned affected who was left out. A "best pairs first" rule, with the same scores, left 14.8% of residents with no suggestion, against 2.5% under maximum-weight matching. Only 57.5% of residents with severe cognitive impairment received a suggestion under best-pairs-first, against 96.1%. The result for the worst-served quarter fell from 17.1% to 5.7%, and the overall share in a working pairing fell from 48.6% to 44.3%.

5.4 How robust are the results? (RQ4)

Table 10 repeats the comparison between the full framework and same-level pairing under each altered condition.

Table 10. Simulated share of residents in a working pairing (%) under altered conditions, 200 homes each.

Condition	Same level	Full framework	Difference (95% simulation interval)	Homes where framework did better
Recording as assumed	32.2	48.9	16.6 (16.0 to 17.3)	100%
No recording errors	32.2	51.2	19.0 (18.3 to 19.6)	100%
Recording errors doubled	32.2	46.3	14.1 (13.5 to 14.7)	100%
Recording errors quadrupled	32.2	42.4	10.2 (9.6 to 10.8)	99%
Three-quarters as much observed	31.4	45.6	14.2 (13.5 to 14.9)	100%
Half as much observed	31.4	41.9	10.6 (9.9 to 11.2)	98%
A quarter as much observed	31.4	35.5	4.1 (3.5 to 4.8)	83%
Hidden model: proximity dominant	44.0	48.0	4.0 (3.1 to 5.0)	77%
Hidden model: no complementarity	30.0	45.7	15.7 (15.1 to 16.3)	100%
Hidden model: mostly unrecorded chemistry	29.2	46.4	17.2 (16.3 to 18.0)	100%
Hidden model: misspecified	29.5	45.3	15.8 (15.0 to 16.5)	100%
Memory-support unit on Level 1	29.2	45.2	16.0 (15.3 to 16.6)	100%

The average advantage remained positive in every condition, but it shrank sharply in two: when staff recorded only a quarter of what was assumed, and when living on the same level was the dominant driver of compatibility. In those two conditions the framework did better in 83% and 77% of homes. In roughly one home in five, therefore, it did no better than same-level pairing. Section 6.2 returns to the first of these conditions.

When the method's complementarity assumption was wrong, the complementarity term made results slightly worse, by 1.0 point (0.6 to 1.4). When compatibility was mostly unrecorded chemistry, observed encounters carried the method, adding 11.1 points (10.4 to 11.8).

In the memory-support variation, same-level pairing reached only 14.5% of residents with severe cognitive impairment, because the simulation does not pair two severely impaired residents without support. The framework reached 95.9% by pairing across levels. In a secure unit such introductions would need staff support, so this result should be read with caution.

Language mix (follow-up analysis). The main analysis spread the 10% of residents who preferred another language across six community languages (Italian, Greek, Cantonese, Mandarin, Vietnamese and Arabic), an illustrative choice. Spreading them across twelve languages left the overall advantage at 16.5 points (15.9 to 17.2), but cut the share of these residents who received a suggestion from 76% to 68%. Doubling their share of the home to 20% left the advantage at 16.6 points (15.9 to 17.2) and raised the share receiving a suggestion to 89%. In the simulation, the number of residents who shared a language set the ceiling for this group, whatever the method.

5.5 Does keeping the profile current matter? (RQ5)

After 90 simulated days, an average of 6.5 of the 80 residents were new and others had changed. Matching from an updated profile placed 45.0% of residents in a working pairing, against 39.2% from the day-0 profile, a difference of 5.8 points (5.2 to 6.4). For new residents the difference was 13.8 points (11.9 to 15.8). The stale profile also produced about three suggestions per home for residents who had since come to prefer their own company.

In summary, the full framework had a higher main outcome than same-level pairing in the main analysis and, on average, in every sensitivity condition. The size of the advantage depended on how much staff recorded and on how strongly proximity drove compatibility. Section 6 considers what these results may and may not mean.

6. Discussion

6.1 Interpretation of the findings

In synthetic homes, suggestions drawn from a whole-of-home profile were more often compatible than pairing residents who live on the same level. The average advantage persisted under noisy recording, sparse recording and several different assumptions about what makes people get on, although it became small in two conditions. The paragraphs below place these results against the literature and then comment on five of them.

These results should be read against what was already known (Table 1). The literature reviewed supports the need, supports resident profiling, and supports the importance of personal fit in social connection. It did not yield a test of whole-of-home matching against proximity inside a care home. The nearest decision-support work found matches older adults to services, not to one another. One system combined machine learning with a knowledge

base to help professionals choose monitoring devices and services, such as walking groups and recreational programs, and was validated on 121 users (Caragiuli et al., 2026). The simulation provides an initial computational test of that kind, under stated assumptions. It is a reason to consider a pilot, not a substitute for one.

Two results fit what observational research would predict. Proximity was a strong baseline, as studies of resident networks suggest (Ayalon & Yahav, 2019; Mauldin et al., 2021). Matching on one shared attribute did no better than proximity, in line with evidence that friendship depends on several shared attributes at once (Block & Grund, 2014); that evidence comes from adolescent networks, so the parallel is suggestive only.

Complementarity showed no benefit. Pairing a storyteller with a listener is intuitive. In the simulation it added 0.1 points on average, and it lowered the result by 1.0 point when the assumption behind it was wrong. This reflects the hidden model, in which the strength of complementarity was allowed to be zero. It is not evidence about real residents. Published work leaves the question open. ELDER-MATCH reported lasting relationships among community-dwelling older adults when personality was part of the matching (Tseng et al., 2026). Among 24,726 adults in English neighbourhoods, similarity within social networks was associated with wellbeing only up to a point, and the authors concluded that diverse networks bring benefits that homogeneous ones cannot (Ramos et al., 2024). Neither study tested pairings inside a care home. Until real data are available, complementarity is best treated as optional rather than assumed.

Observed encounters between residents added value beyond recorded attributes in the simulation. Observed encounters added most when compatibility was hardest to predict from attributes: 11.1 points when it was mostly unrecorded chemistry. The abstracts of the two closest published systems do not describe using this kind of information (Moore, Tao, Moore, et al., 2025; Tseng et al., 2026). It also needs no assumption about why two people get on.

The pairing rule shaped who was left out. A best-pairs-first rule, which takes the highest-scoring pairs first, left out the residents who were hardest to match, in this simulation mainly those with severe cognitive impairment. Requiring the method to find a partner for as many residents as possible removed most of that effect and also raised the average. A related risk has been reported outside aged care. In a field experiment on a digital social platform, similarity-based matching increased engagement but further marginalised less engaged users

(López Vargas et al., 2022). More even distribution was a question we asked in this study, not something we expected, and it appeared only under a pairing rule designed for it.

Residents who preferred a language other than English gained least. Their share in a working pairing rose under the framework, but the gap between them and English-preferring residents widened. In the simulation this followed from numbers: where nobody else in the home shared a resident's language, no pairing method could help. A matching tool could therefore widen an existing gap unless other measures accompany it. Unequal participation is already described in long-term care. An ethnographic study in Switzerland, reported as a conference abstract, found systematic inequalities in participation between social groups, shaped by cognitive or physical impairment, gender and migration background (Staudacher et al., 2025).

The advantage persisted under imperfect recording, within limits. Published evaluations report that language models extracting facts from aged care notes are accurate on average but not robust (Vithanage et al., 2025). In the simulation the advantage over same-level pairing shrank as recording errors rose, but it was still 10.2 points when errors were four times the assumed rate. The amount recorded mattered more than its accuracy: with a quarter of the assumed observations the advantage fell to 4.1 points.

6.2 Implications for practice, to be tested

A simulation cannot tell a provider what to do. It can suggest what a pilot should look for. Each point below gives the finding, what it may imply and where the implication stops.

- **Existing records may be a workable starting point.** In the simulation, a profile built from the admission form alone gave 36.4%, against 31.7% for same-level pairing. A home may not need every role involved before a trial begins. Whether real admission forms hold enough usable detail is untested.
- **Wider observation may add value.** Each added group of roles raised the result. Catering, cleaning, laundry, maintenance and reception staff added less than the care and lifestyle teams, but still added 2.3 points. These amounts depend on assumed observation rates that have not been measured.
- **Recording effort appears to be the weak point.** The advantage fell from 16.6 to 4.1 points when staff recorded a quarter of what was assumed (Table 10). This suggests that design effort belongs in making capture quick. A review of AI-enabled robots in

long-term care found that care providers may decline to use a technology for their own reasons, and that their voices need to be included (Wong et al., 2024). Co-design may help: a system designed with staff and residents in an Australian home reduced documentation time and was accepted by both (Bail, Gibson, et al., 2022; Bail, Merrick, et al., 2022).

- **Language needs its own plan.** Matching could not connect a simulated resident with nobody who shared their language. Volunteers, community visitors, bilingual staff and links with other homes are possible responses, and a profile could at least identify who needs them. None of these was tested here.
- **A profile would need to stay current.** A profile left unchanged for 90 simulated days gave a result 5.8 points lower, and the difference was largest for new residents (13.8 points). New residents are plausibly among those most in need of an introduction. A similar idea is being developed for dementia activity programming: a conference abstract describes a platform that compares each person's engagement with their own evolving baseline to adjust later activity suggestions, with resident outcomes still to be reported (Skrajner et al., 2025).
- **Recording has to work for every kind of staff.** Contracted, agency and casual staff may have limited access to systems, little time for training and less continuity with residents. Unless the capture step suits them, what they notice will be lost.
- **Preferred solitude is not the same as withdrawal.** A resident's established preference for their own company should be respected. A new or growing withdrawal is different: it may signal low mood, grief, pain or illness, and should prompt clinical or psychosocial review rather than a social suggestion.
- **Connections can end.** When a resident someone has come to know dies, moves or becomes unwell, the loss can be keenly felt. Introductions would need to sit alongside appropriate bereavement and emotional support.

Four cautions from the wider literature apply. First, the evidence for AI in long-term care is mixed and at high risk of bias (Loveys et al., 2022), and expert reviewers warn of bias, weak validation in older populations and threats to privacy and autonomy (Shiwani et al., 2023). Keeping staff and residents as the decision-makers, with outcomes fed back, matches the human-centric learning loops that long-term care professionals name as a prerequisite for

responsible use (Lukkien et al., 2024). In the simulation the feedback loop was more than a safeguard: observed outcomes added most where recorded attributes predicted least. Adoption is a further hurdle. Interviews with 24 stakeholders of an AI-assisted decision-support tool in a hospital record system described barriers and facilitators that included awareness, accuracy and trust, accessibility and transparency. The authors recommended engaging stakeholders from the start (Finkelstein et al., 2024).

Second, a matching method has to outperform the structural forces that already shape who meets whom, such as routines, communal space and staffing (Gebhard et al., 2024; Hoben et al., 2025); it cannot assume them away. Case studies of long-term care homes in Canada, Norway and Germany likewise found that location, building layout, staffing levels, work organisation and regulation influence whether and how residents take part in social life (Lowndes et al., 2021).

Third, lifestyle programs are thinly resourced. In a survey answered by 153 Victorian residential aged care facilities, 8% had a full-time coordinator for their social program and 57% offered a social program at weekends (Clune et al., 2023). The framework is meant to direct scarce lifestyle time to the introductions most likely to work, not to replace the people who make them.

Fourth, person-centred approaches themselves rest on uncertain evidence. The meta-analysis cited in section 2.1 found no statistically significant improvement in three outcomes (Berkovic et al., 2024). An earlier systematic review of seven studies in aged care facilities reported some benefits for residents and staff, an increased risk of falls in two studies, and study designs too weak for firm conclusions (Brownie & Nancarrow, 2013). A profile that helps staff know residents should not be assumed to improve outcomes until that is measured.

The framework is designed to support obligations providers already have under the strengthened Quality Standards: to understand each person (Outcome 1.1), to record and respond to changes in quality of life (Action 1.3.6), and to minimise loneliness and support relationships (Action 7.1.1; Department of Health, Disability and Ageing, 2025).

6.3 Limitations

We have grouped the limitations by the kind of conclusion each one restricts.

Internal validity: does the comparison show what it appears to show?

- **The authors specified both the hidden model and the matching method.** Unrecorded temperament, random weights and a misspecified scenario reduce the overlap but do not remove it. The size of the advantage is therefore a property of the simulation, not an estimate of a real-world effect.
- **Observer parameters are assumptions.** What each role notices, and how often they would record it, has not been measured. The practice observation that non-care staff hold unrecorded knowledge needs empirical confirmation. The answer to RQ2 depends directly on these values.
- **No language-model step was tested.** The simulation assumed that notes are converted to structured facts with stated error rates. Published evaluations suggest that step is feasible but not yet robust (Vithanage et al., 2025). No conclusion about the AI components themselves can be drawn. The study therefore evaluates an AI-enabled framework concept, not the performance of an AI model.
- **The pairing filters were set by the authors.** They were not derived from resident preferences or from validated safeguarding criteria. They may affect coverage and the results for some groups, and they would need co-design and testing before any use.

Construct validity: does the outcome stand for social connection?

- **A "working pairing" is uncalibrated.** It measures compatibility under the hidden model. It does not measure interaction, engagement, support, loneliness or quality of life, which are distinct aspects of social connection (Liougas et al., 2024). The study therefore shows nothing about loneliness.
- **Compatibility was treated as mutual.** A pairing worked for both residents or for neither. Real ties are often one-sided, and reciprocity, which is associated with perceived support (Casey et al., 2016), was not modelled.
- **Pairs only.** Connection may also happen in small groups, and a resident may welcome several introductions. Results may differ for group matching.

External validity: where might the results apply?

- **One home design.** Results are for 80 residents on four levels. They may differ in smaller, larger or differently arranged homes.

- **The home was reduced to its levels.** Routines, communal spaces, staffing and time of day shape whether residents meet at all (Gebhard et al., 2024), and loneliness varies between facilities with their organisational context (Hoben et al., 2025). The simulation represented these only through how often residents on the same and different levels met.
- **The source evidence under-represents cognitive impairment.** The studies that informed the hidden model mostly recruited residents without significant cognitive impairment (Kang et al., 2020; Mauldin et al., 2021; Roberts, 2018). The assumptions are least certain for the residents who most need connection, and results for those groups should be read with particular caution.
- **Real staffing and practice may differ from the assumptions.** Actual staffing arrangements, including contracted and casual staff, the time it takes to record observations, and existing lifestyle-planning practices such as seating plans and activity groups were not modelled. Each may change how much staff can record and how much a matching method adds to what a home already does.

Conclusion validity: how firm are the numbers and the gap statement?

- **The intervals are narrow by construction.** They reflect variation between simulated homes, and adding homes would narrow them further. They say nothing about whether the assumptions hold.
- **No systematic review was done.** The gap statement rests on targeted searching, so relevant studies may have been missed.

6.4 Contribution

This study makes three bounded contributions. Conceptually, it sets out a framework in which every role in a home contributes to one living profile, including what staff see happen between residents, and in which suggestions remain decisions for staff and residents. Empirically, it reports simulated comparisons suggesting that, under stated assumptions, such a profile could yield more compatible and more widely shared suggestions than proximity. It also identifies the conditions under which that advantage becomes small. Practically, it provides open code and synthetic data that others can rerun with different assumptions. It does not contribute evidence about real residents, real staff recording or any AI model.

6.5 Future research

The limitations above point to the following studies.

1. A systematic or scoping review of AI-supported social connection in residential care.
2. A staff survey, with ethics approval, of what each role knows about residents and what they would be willing to record.
3. A co-design study with residents, families and staff on consent, wording of suggestions and the right to decline.
4. A pilot in one home, with ethics approval, measuring loneliness and social contact before and after. Outcome measures need care. A systematic review of 38 measures found none with satisfactory measurement properties for social connection among long-term care residents (Dewan et al., 2024). Existing measures cover seven different aspects, from networks and interaction to loneliness (Liougas et al., 2024). The pilot should include residents with cognitive impairment, with supported decision-making. The studies reviewed show them to be less connected (Casey et al., 2016; Lapane, Dube, et al., 2022) and under-represented in friendship research (Kang et al., 2020; Mauldin et al., 2021; Roberts, 2018).
5. Whether staff-mediated matching increases reciprocated ties more than proximity or ad hoc matching. Reciprocated ties are the ones associated with perceived support (Casey et al., 2016).
6. Which resident features produce the safest and most effective matches for people living with dementia.
7. Whether whole-of-home matching can improve the distribution of social opportunity without excluding residents who are already less connected.
8. Matching residents with staff. The Standards already ask providers to involve residents in selecting their workers and to maximise continuity (Action 3.2.8; Department of Health, Disability and Ageing, 2025), and the same profile could support it.

7. Conclusion

Loneliness is common in residential aged care, and the knowledge that could help residents find one another is spread across every role in a home. This paper proposed pooling that knowledge into a living profile and using it to suggest introductions that staff and residents decide on. It then examined the matching step in synthetic homes.

The research questions can be answered within the limits of that simulation.

- **RQ1.** In the simulation, matching on several observed attributes placed more residents in a simulated working pairing than same-level pairing (48.6% against 31.7%), random pairing or matching on shared interests alone.
- **RQ2.** Widening the profile from nursing, personal care and allied health observation to whole-of-home observation was associated with a 5.7-point increase, with a smaller gain from each added group of roles. The comparison does not separate more roles from more recorded encounters.
- **RQ3.** Every resident group examined had a higher share under the framework. Residents who preferred a language other than English gained least, and a "best pairs first" rule left 14.8% of residents with no suggestion.
- **RQ4.** The average advantage remained positive under every condition tested. It fell to about 4 points when staff recorded a quarter of what was assumed, or when proximity dominated compatibility.
- **RQ5.** Matching from an updated profile gave a result 5.8 points higher than matching from a profile left unchanged for 90 simulated days.

These answers describe how a method behaves under stated assumptions. They are not estimates of real-world effect, and they do not show that any resident would feel less lonely. Showing that would need a pilot in a real home, with ethics approval, consent and an outcome measure that residents and staff trust.

The practice observation behind this paper is a modest one. The people who clean a room, serve a meal or answer the front desk may each know something that could help two residents meet. The simulation suggests that this knowledge is worth testing as a resource, alongside the judgement of staff and the choices of residents.

Supplementary Information

Online Resource 1 Simulation code, parameter file, one example synthetic home and all result files for the main, sensitivity and follow-up analyses (ESM_1.zip)

References

Alkhalaf, M., Vithanage, D., Shen, J., Chang, H. C., Deng, C., & Yu, P. (2025). Fine-tuning large language models for effective nutrition support in residential aged care: A domain expertise approach. *Healthcare*, *13*(20), 2614. https://doi.org/10.3390/healthcare13202614

Alkhalaf, M., Zhang, Z., Chang, H. C., Wei, W., Yin, M., Deng, C., & Yu, P. (2023). Malnutrition and its contributing factors for older people living in residential aged care facilities: Insights from natural language processing of aged care records. *Technology and Health Care*, *31*(6), 2267–2278. https://doi.org/10.3233/THC-230229

Australian Institute of Health and Welfare. (2025). *People using aged care: Fact sheet 2025*. GEN Aged Care Data. https://www.gen-agedcaredata.gov.au

Australian Institute of Health and Welfare. (2026). *Dementia in Australia: Residential aged care*. https://www.aihw.gov.au/reports/dementia/dementia-in-aus/contents/aged-care-and-support-services-used-by-people-with-dementia/residential-aged-care

Ayalon, L., & Yahav, I. (2019). Location, location, location: Close ties among older continuing care retirement community residents. *PLOS ONE*, *14*(11), e0225554. https://doi.org/10.1371/journal.pone.0225554

Bail, K., Gibson, D., Hind, A., Strickland, K., Paterson, C., Merrick, E., Gibson, J., Kozlovskaia, M., O'Dea, A., Smith, B., & Redley, B. (2022). 'It enables the carers to see the person first': Qualitative evaluation of point-of-care digital management system in residential aged care. *Journal of Clinical Nursing*, *32*(1–2), 174–190. https://doi.org/10.1111/jocn.16285

Bail, K., Merrick, E., Gibson, D., Hind, A., Strickland, K., & Redley, B. (2022). A co-designed health information system implementation into residential aged care: A mixed-method evaluation. *Journal of Nursing Scholarship*, *55*(2), 521–535. https://doi.org/10.1111/jnu.12840

Balki, E., Hayes, N., & Holland, C. (2022). Effectiveness of technology interventions in addressing social isolation, connectedness, and loneliness in older adults: Systematic umbrella review. *JMIR Aging*, *5*(4), e40125. https://doi.org/10.2196/40125

Berkovic, D., Macrae, A., Gulline, H., Horsman, P., Soh, S. E., Skouteris, H., & Ayton, D. (2024). The delivery of person-centered care for people living with dementia in residential aged care: A systematic review and meta-analysis. *The Gerontologist*, *64*(5), gnad052. https://doi.org/10.1093/geront/gnad052

Block, P., & Grund, T. (2014). Multidimensional homophily in friendship networks. *Network Science*, *2*(2), 189–212. https://doi.org/10.1017/nws.2014.17

Brownie, S., & Nancarrow, S. (2013). Effects of person-centered care on residents and staff in aged-care facilities: A systematic review. *Clinical Interventions in Aging*, *8*, 1–10. https://doi.org/10.2147/CIA.S38589

Caragiuli, M., Germani, M., Prieto-Santamaría, L., & Rodríguez-González, A. (2026). An AI-driven multi-criteria decision-support system for elderly care personalization. *Expert Systems with Applications*, *315*, 131826. https://doi.org/10.1016/j.eswa.2026.131826

Casey, A. N., Low, L. F., Jeon, Y. H., & Brodaty, H. (2016). Residents perceptions of friendship and positive social networks within a nursing home. *The Gerontologist*, *56*(5), 855–867. https://doi.org/10.1093/geront/gnv146

Chapman, H., Bethell, J., Dewan, N., Liougas, M. P., Livingston, G., McGilton, K. S., & Sommerlad, A. (2024). Social connection in long-term care homes: A qualitative study of barriers and facilitators. *BMC Geriatrics*, *24*, 857. https://doi.org/10.1186/s12877-024-05454-8

Clune, S., Rayner, J. A., McAuliffe, L., & Fetherstonhaugh, D. (2023). A snapshot of social activities programs in residential aged care facilities in Victoria: A brief report. *Australasian Journal on Ageing*, *42*(3), 592–597. https://doi.org/10.1111/ajag.13189

Cordero, L., Dys, S., & White, D. L. (2026). What matters to residential long-term care residents: Contextualizing perceptions of person-centered care. *Journal of the American Medical Directors Association*, *27*(4), 106104. https://doi.org/10.1016/j.jamda.2025.106104

Davies, M., Zúñiga, F., Verbeek, H., Simon, M., & Staudacher, S. (2023). Exploring interrelations between person-centered care and quality of life following a transition into long-term residential care: A meta-ethnography. *The Gerontologist*, *63*(4), 660–673. https://doi.org/10.1093/geront/gnac027

Department of Health, Disability and Ageing. (2025). *Strengthened Aged Care Quality Standards*. Australian Government. https://www.health.gov.au

Dewan, N., Sommerlad, A., Chapman, H., Banerjee, S., Corazzini, K., Edvardsson, D., Liougas, M. P., Livingston, G., McGilton, K. S., O'Rourke, H. M., & Bethell, J. (2024). Assessing social connection for long-term care home residents: Systematic review using COSMIN guidelines. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*, *10*(3), e12492. https://doi.org/10.1002/trc2.12492

Dodds, L., Brayne, C., & Siette, J. (2024). Associations between social networks, cognitive function, and quality of life among older adults in long-term care. *BMC Geriatrics*, *24*, 221. https://doi.org/10.1186/s12877-024-04794-9

Doran, C., Noonan, M., & Doody, O. (2019). Life-story work in long-term care facilities for older people: An integrative review. *Journal of Clinical Nursing*, *28*(7–8), 1070–1084. https://doi.org/10.1111/jocn.14718

Enshaeifar, S., Zoha, A., Markides, A., Skillman, S., Acton, S. T., Elsaleh, T., et al. (2018). Health management and pattern analysis of daily living activities of people with dementia using in-home sensors and machine learning techniques. *PLOS ONE*, *13*(5), e0195605. https://doi.org/10.1371/journal.pone.0195605

Farmer, M. S., Popescu, M., & Powell, K. R. (2025). Development and evaluation of a 4M taxonomy from nursing home staff text messages using a fine-tuned generative language model. *Journal of the American Medical Informatics Association*, *32*(3), 535–544. https://doi.org/10.1093/jamia/ocaf006

Fazio, S., Pace, D., Flinner, J., & Kallmyer, B. (2018). The fundamentals of person-centered care for individuals with dementia. *The Gerontologist*, *58*(suppl 1), S10–S19. https://doi.org/10.1093/geront/gnx122

Finkelstein, J., Gabriel, A. S., Schmer, S., Truong, T. T., & Dunn, A. S. (2024). Identifying facilitators and barriers to implementation of AI-assisted clinical decision support in

an electronic health record system. *Journal of Medical Systems*, *48*(1), 89. https://doi.org/10.1007/s10916-024-02104-9

Gannod, G. C., Abbott, K. M., Van Haitsma, K., Martindale, N., & Heppner, A. (2019). A machine learning recommender system to tailor preference assessments to enhance person-centered care among nursing home residents. *The Gerontologist*, *59*(1), 167–176. https://doi.org/10.1093/geront/gny056

Gardiner, C., Laud, P., Heaton, T., & Gott, M. (2020). What is the prevalence of loneliness amongst older people living in residential and nursing care homes? A systematic review and meta-analysis. *Age and Ageing*, *49*(5), 748–757. https://doi.org/10.1093/ageing/afaa049

Gebhard, D., Lang, L., Maier, M., & Dichter, M. (2024). Social interaction of people living with dementia in residential long-term care: An ecological momentary assessment study. *BMC Health Services Research*, *24*, 1640. https://doi.org/10.1186/s12913-024-12056-y

Gu, B., Shao, V., Liao, Z., Carducci, V., Romero Brufau, S., Yang, J., & Desai, R. J. (2025). Scalable information extraction from free text electronic health records using large language models. *BMC Medical Research Methodology*, *25*, 23. https://doi.org/10.1186/s12874-025-02470-z

Hoben, M., Dampf, H., Devkota, R., Corbett, K., Hogan, D. B., McGrail, K. M., & Maxwell, C. J. (2025). Facility-level variation of resident loneliness in assisted living and associated organizational context factors: A repeated cross-sectional study. *International Journal of Geriatric Psychiatry*, *40*(5), e70093. https://doi.org/10.1002/gps.70093

Holt-Lunstad, J., Smith, T. B., Baker, M., Harris, T., & Stephenson, D. (2015). Loneliness and social isolation as risk factors for mortality: A meta-analytic review. *Perspectives on Psychological Science*, *10*(2), 227–237. https://doi.org/10.1177/1745691614568352

Iaboni, A., Spasojevic, S., Newman, K., Schindel Martin, L., Wang, A., Ye, B., Mihailidis, A., & Khan, S. S. (2022). Wearable multimodal sensors for the detection of behavioral and psychological symptoms of dementia using personalized machine

learning models. *Alzheimer's & Dementia: Diagnosis, Assessment & Disease Monitoring*, *14*(1), e12305. https://doi.org/10.1002/dad2.12305

Kang, B., Scales, K., McConnell, E. S., Song, Y., Lepore, M., & Corazzini, K. (2020). Nursing home residents' perspectives on their social relationships. *Journal of Clinical Nursing*, *29*(7–8), 1162–1174. https://doi.org/10.1111/jocn.15174

Lapane, K. L., Dube, C. E., Jesdale, B. M., & Bova, C. (2022). Social connectedness among long-stay nursing home residents with Alzheimer's and dementia: Exploring individual and facility-level variation. *Dementia and Geriatric Cognitive Disorders*, *51*(3), 249–261. https://doi.org/10.1159/000525343

Lapane, K. L., Lim, E., McPhillips, E., Barooah, A., Yuan, Y., & Dube, C. E. (2022). Health effects of loneliness and social isolation in older adults living in congregate long term care settings: A systematic review of quantitative and qualitative evidence. *Archives of Gerontology and Geriatrics*, *102*, 104728. https://doi.org/10.1016/j.archger.2022.104728

Li, Y., Yang, J., Zhou, J., Chen, H., & An, N. (2026). EE-Profile: Structuring life narratives into event-enhanced profile for elder care. *International Journal of Human–Computer Interaction*. Advance online publication. https://doi.org/10.1080/10447318.2026.2688929

Liougas, M. P., Sommerlad, A., O'Rourke, H. M., Chapman, H., Dewan, N., McGilton, K. S., & Bethell, J. (2024). Assessing social connection for long-term care home residents: A scoping review of measure content. *Alzheimer's & Dementia: Translational Research & Clinical Interventions*, *10*(3), e12488. https://doi.org/10.1002/trc2.12488

Liu, H., Lu, Y., Chen, H., Huang, Q., Wu, J., Ou, B., & Xiao, H. (2026). "It's not just loneliness": Cognitive-emotional-behavioral signatures of social isolation in residential aged care. *The Gerontologist*, *66*(6), gnag034. https://doi.org/10.1093/geront/gnag034

López Vargas, K., Runge, J., & Zhang, R. (2022). Algorithmic assortative matching on a digital social medium. *Information Systems Research*, *33*(4), 1138–1156. https://doi.org/10.1287/isre.2022.1135

Loveys, K., Prina, M., Axford, C., Ristol Domènec, Ò., Weng, W., Broadbent, E., Pujari, S., Jang, H., Han, Z. A., & Thiyagarajan, J. A. (2022). Artificial intelligence for older people receiving long-term care: A systematic review of acceptability and effectiveness studies. *The Lancet Healthy Longevity*, *3*(4), e286–e297. https://doi.org/10.1016/S2666-7568(22)00034-4

Lowndes, R., Struthers, J., & Ågotnes, G. (2021). Social participation in long-term residential care: Case studies from Canada, Norway, and Germany. *Canadian Journal on Aging*, *40*(1), 138–155. https://doi.org/10.1017/S0714980820000318

Lukkien, D. R. M., Nap, H. H., Buimer, H. P., Peine, A., Boon, W. P. C., Ket, J. C. F., Minkman, M. M. N., & Moors, E. H. M. (2023). Toward responsible artificial intelligence in long-term care: A scoping review on practical approaches. *The Gerontologist*, *63*(1), 155–168. https://doi.org/10.1093/geront/gnab180

Lukkien, D. R. M., Stolwijk, N. E., Ipakchian Askari, S., Hofstede, B. M., Nap, H. H., Boon, W. P. C., Peine, A., Moors, E. H. M., & Minkman, M. M. N. (2024). AI-assisted decision-making in long-term care: Qualitative study on prerequisites for responsible innovation. *JMIR Nursing*, *7*, e55962. https://doi.org/10.2196/55962

Matas, E., Bhar, S., Collins, R., Bhowmik, J., Anderson, K., & Blair, A. (2025). Digital life stories within residential aged care settings: Implications for staff knowledge and person-centred care practices. *Journal of Clinical Nursing*. Advance online publication. https://doi.org/10.1111/jocn.17675

Mauldin, R. L., Fujimoto, K., Wong, C., Herrera, S., & Anderson, K. A. (2021). Social networks in an assisted living community: Correlates of acquaintance and companionship ties among residents. *The Journals of Gerontology: Series B*, *76*(7), 1463–1474. https://doi.org/10.1093/geronb/gbab079

Memon, S., Brand, A., Taylor, B., Michael, A., & Smithson, R. (2026). Performance, acceptability, and impact of ambient listening scribe technology in an outpatient context: A mixed methods trial evaluation. *BMC Health Services Research*, *26*, 182. https://doi.org/10.1186/s12913-025-13954-5

Mileski, M., Mendoza Torres, A., Beauvais, B., Betancourt, J., Ramamonjiarivelo, Z., Topinka, J. B., Shanmugam, R., Shapley, R., & McClay, R. (2026). The role of

artificial intelligence in enhancing quality of care in nursing homes: A rapid review. *Healthcare*, *14*(11), 1455. https://doi.org/10.3390/healthcare14111455

Min, S. H., Woo, K., Song, J., Alexander, G. L., O'Malley, T. A., Moen, M. D., & Topaz, M. (2024). Understanding daily care experience preferences across the lifespan of older adults: Application of natural language processing. *Western Journal of Nursing Research*, *47*(2), 71–81. https://doi.org/10.1177/01939459241306946

Misiak, M. M., Bethell, J., Chapman, H., & Sommerlad, A. (2024). How can care home activities facilitate social connection in residents? A qualitative study. *Aging & Mental Health*. Advance online publication. https://doi.org/10.1080/13607863.2024.2345130

Moore, D. E., Tao, S., Moore, S. R. R., Morgan, B., Tadin, D., Tadin, C. S., & Murnane, E. L. (2025). CareInsights: AI-enabled infrastructure for person-centered dementia care in resource-constrained facilities. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *9*(4), 1–42. https://doi.org/10.1145/3770687

Moore, D. E., Tao, S., Ricci-De Lucca, E., Tadin, C. S., Tadin, D., Morgan, B., & Murnane, E. L. (2025). Family In The Loop: Enabling family involvement and person-centered dementia care at long-term care facilities with collaborative AI tools. *Proceedings of the ACM on Human-Computer Interaction*, *9*(7), 1–45. https://doi.org/10.1145/3757599

Office of the Australian Information Commissioner. (2024). *Guidance on privacy and the use of commercially available AI products*. https://www.oaic.gov.au

Paque, K., Bastiaens, H., Van Bogaert, P., & Dilles, T. (2018). Living in a nursing home: A phenomenological study exploring residents' loneliness and other feelings. *Scandinavian Journal of Caring Sciences*, *32*(4), 1477–1484. https://doi.org/10.1111/scs.12599

Pfisterer, K. J., Amelard, R., Boger, J., Keller, H., Chung, A., & Wong, A. (2022). Enhancing food intake tracking in long-term care with automated food imaging and nutrient intake tracking (AFINI-T) technology: Validation and feasibility assessment. *JMIR Aging*, *5*(4), e37590. https://doi.org/10.2196/37590

Powell, K. R., Isnainy, M., Lee, S., Farmer, M. S., Amewudah, P., Popescu, M., Woods, A., Alexander, G. L., & Mehr, D. R. (2025). Using novel natural language processing approaches to examine age-friendly communication about nursing home residents with dementia. *The Gerontologist*, *66*(3), gnaf285. https://doi.org/10.1093/geront/gnaf285

Ramos, M. R., Li, D., Bennett, M. R., Mogra, U., Massey, D. S., & Hewstone, M. (2024). Variety is the spice of life: Diverse social networks are associated with social cohesion and well-being. *Psychological Science*, *35*(6), 665–680. https://doi.org/10.1177/09567976241243370

Reddy, A., Gunnink, E. J., Wheat, C. L., Pawlikowski, S., Payne, C. M., Wiltz, S. A., et al. (2026). Rapid evaluation of artificial intelligence technology used for ambient dictation in primary care: Comparing the quality of documentation of artificial intelligence-generated and human-produced clinical notes. *Annals of Internal Medicine*, *179*(6), 765–772. https://doi.org/10.7326/ANNALS-25-02772

Rickman, S., Fernandez, J. L., & Malley, J. (2025). Understanding patterns of loneliness in older long-term care users using natural language processing with free text case notes. *PLOS ONE*, *20*(4), e0319745. https://doi.org/10.1371/journal.pone.0319745

Roberts, T. J. (2018). Nursing home resident relationship types: What supports close relationships with peers and staff? *Journal of Clinical Nursing*, *27*(23–24), 4361–4372. https://doi.org/10.1111/jocn.14554

Royal Commission into Aged Care Quality and Safety. (2021). *Final report: Care, dignity and respect*. Commonwealth of Australia. https://apo.org.au/node/311218

Seo, Y., Jung, S., Kang, H. J., Lim, H., Hong, J. Y., Paik, J. K., Shin, D., Lee, Y., Kang, S. W., & Park, Y. K. (2026). Tailored nutritional intervention based on AI-assessed dietary assessment in nutritionally compromised older adults: Impact on anthropometric, cognitive, and EEG parameters. *Nutrients*, *18*(15), 2415. https://doi.org/10.3390/nu18152415

Shiwani, T., Relton, S. D., Evans, R., Kale, A. U., Heaven, A., Clegg, A., et al. (2023). New horizons in artificial intelligence in the healthcare of older people. *Age and Ageing*, *52*(12), afad219. https://doi.org/10.1093/ageing/afad219

Siette, J., Dodds, L., Surian, D., Prgomet, M., Dunn, A., & Westbrook, J. (2022). Social interactions and quality of life of residents in aged care facilities: A multi-methods study. *PLOS ONE*, *17*(8), e0273412. https://doi.org/10.1371/journal.pone.0273412

Skrajner, M. J., Gorzelle, G., Zeisel, J., Palaniappan, S. K., & Saxena, V. (2025). CONNECT powered by BRAIN: Harnessing AI-driven behavior analysis to foster person-centered dementia programming [Conference abstract]. *Innovation in Aging*, *9*(Suppl 2), igaf122.3738. https://doi.org/10.1093/geroni/igaf122.3738

Spichiger, F., Koppitz, A. L., Riese, F., Kipfer, S., Nagl-Cupal, M., Büscher, A., Volken, T., Larkin, P., & Meichtry, A. (2025). Person Profile Dementia Intervention in long-term care: A stepped-wedge cluster-randomized trial. *Journal of the American Medical Directors Association*, *26*(1), 105351. https://doi.org/10.1016/j.jamda.2024.105351

Staudacher, S., Peduzzi, N., Soiron, S., Jungo, K., Reiffer, N., Staehli, A., Kaiser-Grolimund, A., & Zúñiga, F. (2025). Participation and equity in long-term care: Systemic and societal perspectives [Conference abstract]. *Innovation in Aging*, *9*(Suppl 2), igaf122.2693. https://doi.org/10.1093/geroni/igaf122.2693

Suddle, M. K., Yu, P., Vithanage, D., & Deng, C. (2025). Pilot application of a large language model to identify hospitalisation from unstructured electronic health records in residential aged care facilities. In *MEDINFO 2025* (Studies in Health Technology and Informatics). IOS Press. https://doi.org/10.3233/SHTI250918

Theurer, K., Mortenson, W. B., Stone, R., Suto, M., Timonen, V., & Rozanova, J. (2015). The need for a social revolution in residential care. *Journal of Aging Studies*, *35*, 201–210. https://doi.org/10.1016/j.jaging.2015.08.011

Tseng, H. T., Hsu, M. H., Tsai, C. Y., & Lo, C. L. (2026). ELDER-MATCH: A personality-aware expert system for elderly social connection through AI-powered social robots. *Expert Systems*, *43*(3), e70206. https://doi.org/10.1111/exsy.70206

Udkunta, K., Efstathiou, N., & Guo, P. (2026). Models of care and interventions to improve person-centred care for older people in long-term care facilities: A mixed methods systematic review. *Journal of Advanced Nursing*, *82*(10), 8857–8890. https://doi.org/10.1111/jan.70527

van Beek, A. P. A., Portegijs, S., Groenewegen, P., Huygens, M. W. J., & Völker, B. (2025). Social networks of neighbourhood inhabitants, residents of a care facility, and nursing staff: A case study in two long-term care facilities in the Netherlands. *BMC Geriatrics*, *25*, 316. https://doi.org/10.1186/s12877-025-05948-z

Vithanage, D., Yu, P., Xie, Q., Xu, H., Wang, L., & Deng, C. (2025). A comprehensive evaluation of large language models for information extraction from unstructured electronic health records in residential aged care. *Computers in Biology and Medicine*, *197*(Pt A), 111013. https://doi.org/10.1016/j.compbiomed.2025.111013

Wong, K. L. Y., Hung, L., Wong, J., Park, J., Alfares, H., Zhao, Y., Mousavinejad, A., Soni, A., & Zhao, H. (2024). Adoption of artificial intelligence–enabled robots in long-term care homes by health care providers: Scoping review. *JMIR Aging*, *7*, e55257. https://doi.org/10.2196/55257

Zhang, G., Li, D., Gu, H., Zhang, P., Lu, T., Shang, L., & Gu, N. (2025). RECOSIM: A universal, accurate, and scalable simulation framework for online community recommendations. *ACM Transactions on Information Systems*, *44*(1), 1–42. https://doi.org/10.1145/3768342

Supplementary Files

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- OnlineResource1.zip