Understanding Elder Care AI Adoption Through Self-Determination Theory

Naomi Unkelos-Shpigel[1,*], Leon Feldman[1], Mor Hodaya Maman[1] and Ulrich Gartzke[2]

[1]Braude College of Engineering, Karmiel, Israel
[1]Braude College of Engineering, Karmiel, Israel
[1]Braude College of Engineering, Karmiel, Israel
[2]Technische Hochschule Würzburg-Schweinfurt (THWS)

Abstract

Despite promising advances in AI-assisted elder care technology, adoption remains limited. We present CareBells, a multimodal AI platform designed for elderly meal service recipients, and analyze its acceptance through Self-Determination Theory (SDT). Our exploratory pilot study ($n = 6$) examines how satisfying three fundamental psychological needs – autonomy, competence, and relatedness – influences technology adoption. Results reveal high usability scores (SUS: 78–92%) and strong acceptance, with feature engagement patterns directly corresponding to SDT need satisfaction. Medication management satisfied competence needs through simple task completion, while AI conversations supported all three needs through personalized, user-controlled interaction. Critical barriers emerged where needs were threatened: speech recognition errors undermined competence, privacy concerns threatened autonomy, and superficial conversations limited relatedness. We contribute SDT-based design principles for accessible elder care technology and demonstrate how psychological need satisfaction predicts both adoption and sustained engagement patterns.

Keywords

Elder care, Self-Determination Theory, Digital accessibility, Social isolation, Conversational agents, Inclusive interfaces

1. Introduction

The global aging population faces interconnected challenges: social isolation affecting 43% of older adults [1], medication non-adherence rates of 50–60%, and a persistent digital divide limiting access to technology-enabled healthcare [2]. While AI-driven elder care solutions show promise, 74% of elderly users abandon digital health tools within three months. Traditional explanations focus on usability barriers or generational attitudes yet fail to explain how some elderly users enthusiastically adopt technology while others reject identical systems [3].

We argue that intrinsic motivation, not merely usability, determines sustained adoption. Self-Determination Theory (SDT) [4, 5] provides a framework through three fundamental psychological needs: autonomy (experiencing control), competence (feeling effective), and relatedness (experiencing connection). When technology satisfies these needs, users engage intrinsically; when threatened, users disengage regardless of objective utility [5].

Research Questions: (1) How do SDT's three psychological needs manifest in elderly users' interactions with AI assistants? (2) Do feature engagement patterns correspond to need satisfaction levels? (3) Where do critical adoption barriers emerge in terms of SDT needs?

We present CareBells, an AI-powered platform integrating medication management, social connectivity, and conversational assistance. Through mixed-methods analysis of a testing pilot ($n = 6$), we examine how design decisions support or threaten each SDT need, revealing patterns linking need satisfaction to engagement and adoption.

Joint Proceedings of the ACM Intelligent User Interfaces (IUI) Workshops 2026, March 23–26, 2026, Paphos, Cyprus
*Corresponding author.
naomius@braude.ac.il (N. Unkelos-Shpigel); Leo.Feldman@e.braude.ac.il (L. Feldman); mor.hodaya.maman@e.braude.ac.il (M. H. Maman); Ulrich.Gartzke@thws.de (U. Gartzke)
0009-0004-6634-5236 (N. Unkelos-Shpigel)

Contribution: We provide the first SDT-grounded analysis of AI elder care adoption, demonstrating that psychological need satisfaction, not technical features alone, drives sustained engagement.

2. Related Work

2.1. Self-Determination Theory

Self-Determination Theory distinguishes intrinsic motivation (engaging for inherent satisfaction) from extrinsic motivation (engaging for external rewards) [4]. Sustained technology use requires intrinsic motivation, emerging when three basic needs are satisfied [6]:

Autonomy: Experiencing volition in one's actions. Users must feel they control technology, not vice versa. Threatened by forced features, opaque decisions, irreversible actions, or paternalistic design [4, 7, 8].

Competence: Feeling effective in producing desired outcomes. Users need successful goal accomplishment and clear feedback. Threatened by confusing interfaces, unpredictable behavior, error-prone interactions, or tasks exceeding cognitive capacity [4, 8].

Relatedness: Experiencing meaningful connection. Users need to feel understood, valued, and connected. Threatened by impersonal interactions or isolating technology [7, 8].

2.2. SDT in Elder Care Technology

Prior research demonstrates SDT's relevance to elderly technology adoption. Chen and Chan [3] found autonomy support predicted continued health monitoring use, while competence satisfaction mediated perceived ease of use and adoption intention. Peters et al. [5] showed that video calling systems satisfying relatedness needs demonstrated 3x higher sustained use than usability-optimized systems. However, most elder care AI research evaluates usability (System Usability Scale [9]) or acceptance (Technology Acceptance Model [10]) without examining fundamental psychological need satisfaction [11], limiting understanding of why technically excellent systems fail in practice.

2.3. Design for Elderly Users

Accessible interface design requires minimum 22px fonts, 4.5:1 contrast ratios, large touch targets (≥60px), simplified navigation (≤6 primary actions), reduced working memory demands, consistent patterns, and multimodal support [12, 13, 14]. Hehn et al. [15] note accessibility features often remain afterthoughts rather than foundational design principles. Research specifically emphasizes the need for context-aware, actionable explanations that align with caregivers' workflows in nursing contexts [16], with particular attention to speech interface quality for elderly users who may have hearing impairments or non-standard speech patterns [17, 14].

3. Method

3.1. System Design and Architecture

Following SDT design principles [4, 5, 7], CareBells integrates seven modules through a tablet interface and voice interaction (see Figure 1).

Bella AI Assistant: GPT-3.5 conversational agent with multi-language support. Provides information retrieval, medication reminders, weather updates, and social conversation. Designed to support all three SDT needs through user-controlled activation (autonomy), successful information retrieval (competence), and conversational memory (relatedness).

Medication Management: Visual cards showing dosage, frequency, and schedule. One-tap "Mark as Taken" button logs doses, preventing double-dosing. Designed to maximize competence through clear feedback and simple task completion.

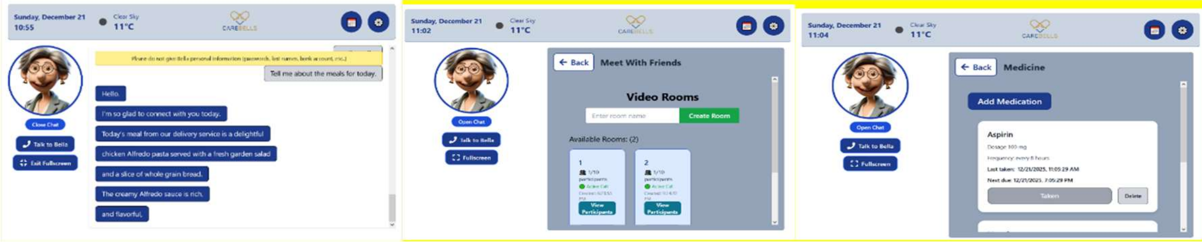

Figure 1: Bella main screens: conversational chat with Bella (left), video calling rooms under "Meet With Friends" (center), and the medication management module (right).

Social Connectivity: Contact list with large photos enabling one-button audio calls. Video rooms supporting up to 6 participants. Designed to support relatedness by facilitating human connections.

Additional Features: QR meal scanning (nutritional data, allergen warnings), region-filtered news, and an exercise library with categorized routines.

Technical Implementation: React-based interface (60px touch targets, 22px fonts, 4.5:1 contrast) following accessibility guidelines. Voice processing via OpenAI Whisper and Google Speech-to-Text. MongoDB Atlas stores user profiles and interaction logs with end-to-end encryption (TLS 1.3, AES-256).

We designed Bella with the following SDT-informed design rationale:

- **Autonomy:** User-controlled activation, dismissible reminders, customizable settings (text size, theme, language, speech rate), multiple interaction pathways.
- **Competence:** Simplified navigation ($\leq$6 primary actions), consistent patterns, immediate feedback, error prevention.
- **Relatedness:** Conversation context maintenance across sessions, personalized responses based on user history, facilitation of family/friend connections.

3.2. Participants and Procedure

Six elderly adults (Country A: $n = 4$, age 68–82, mean=74.5; Country B: $n = 2$, age 71–79, mean=75) were recruited through meal delivery programs. All lived independently with no severe cognitive impairments. Inclusion criteria: currently receiving regular meal deliveries ($\geq$3 times/week), able to provide informed consent.

Procedure: Pilot testing followed participatory design principles [18, 19]. Researcher-provided pre-configured tablets were used. Initial 45-minute onboarding covered functionality; participants then used systems independently with remote technical support available. Brief check-ins at days 4 and 10 addressed technical issues without guiding usage patterns, consistent with ecological validity requirements [3].

Ethics: Approved by institutional review boards at both institutions. Informed consent was obtained from participants and family members where appropriate. All data was encrypted; participants could request data deletion at any time.

3.3. Measures

Quantitative Measures:

- System Usability Scale (SUS) [9]: 10-item post-study questionnaire, a validated measure of perceived usability.
- Feature engagement tracking: interaction frequency, duration, and temporal patterns logged automatically.
- Task completion rates: success rates for medication marking and appointment creation.

Qualitative Measures:

Table 1
Evaluating CareBells features based on [7]

Feature	Autonomy	Competence	Relatedness	Pred. Engag.
Bella AI	High	Medium	Medium	High
Medication	Medium	High	Low	Medium
Call Contacts	High	High	High	High
Exercise	Medium	Low	Low	Low
Meal Scanning	Low	Low	Medium	Low

- Semi-structured interviews: 30–45 minutes exploring experiences, perceived value, and concerns [20].
- Open-ended survey questions about autonomy, competence, and relatedness perceptions.
- Observational notes during onboarding and check-ins.

Analysis Approach: Convergent mixed-methods examined quantitative engagement patterns alongside qualitative need-satisfaction accounts. Interview transcripts were coded for SDT themes using deductive coding with inductive sub-codes [18, 19]. Triangulation of quantitative patterns (e.g., low exercise engagement) with qualitative explanations (e.g., competence threats from complex instructions) helped surface SDT mechanisms [3].

4. Results

4.1. Overall Acceptance and Need Satisfaction

Country A participants achieved SUS 78% (3.9/5.0, "good"); Country B 92% (4.6/5.0, "excellent"), consistent with previous findings that appropriately designed interfaces can achieve high acceptance among elderly users [3, 11]. Critically, 100% expressed willingness to continue using CareBells, with 5 participants stating "yes, gladly", indicating strong intrinsic motivation [4].

Lower relatedness scores suggest this need was least satisfied, consistent with research showing relational agents face challenges in creating genuine connection [21].

4.2. Feature Engagement and SDT Predictions

Table 1 analyzes CareBells features following the evaluation framework of [7].

Features satisfying multiple SDT needs received the highest engagement, supporting SDT predictions [4, 5]. The Call Contacts discrepancy (predicted high, actual medium) suggests users maintained external calling habits, consistent with prior findings about technology integration into existing practices [22]. These findings illustrate the gap between stated preferences in surveys versus actual behavior – a well-documented phenomenon in HCI [23] – and underscore the necessity of real-world deployment testing beyond controlled evaluations.

4.3. Autonomy: Control and Agency

Support Evidence: 73% of calls were made via voice command (vs. 27% button), demonstrating user choice of preferred interaction method. Mean 5.2 customization actions per user. Zero "forced" reports. Users dismissed medication reminders most of the time, exercising autonomy [4].

Threats: Privacy concerns (50% overall, 100% Country B), consistent with growing awareness of data sensitivity issues [24]: "Who can see my medication list?", "I don't understand where my conversations go." Opaque AI decisions [25, 24, 23]: "How does it know this is right for me?" Irreversible actions: participants could not undo mistaken medication marking, violating autonomy support principles [4].

Key Insight: "I like that I can ignore Bella when I want, but I wish I understood better what it's doing with my information." This captures the tension between autonomy through control (dismissible interactions) and autonomy through understanding (transparent data practices), consistent with explainable AI research [25, 24, 26, 23].

4.4. Competence: Effectiveness and Mastery

Support Evidence: 100% task completion for medication marking, demonstrating successful competence support [3]. Low technical support need (M=1.2/5.0). 100% used the phrase "easy to understand," consistent with perceived ease of use being critical for elderly users [3, 11].

Threats: Speech recognition errors (100% mentioned), consistent with prior research showing speech interfaces disproportionately affect elderly users [14]: "Interruptions with humming," "Sometimes Bella misunderstands me and I feel stupid." This quote illustrates how errors threatened competence perceptions, not merely usability. Exercise complexity: 4% engagement despite 67% interest; GIF demonstrations overwhelmed users, exceeding cognitive capacity thresholds [12]. Response delays (50% mentioned) created uncertainty about whether the system processed input, undermining competence feedback [4].

Critical Finding: Speech errors disproportionately threatened competence compared to button errors. Unlike button failures, speech failures made users question communication ability: "When my daughter doesn't understand me, I can explain differently. When Bella doesn't understand, I feel like I'm doing something wrong." This reveals modality-specific vulnerability in competence satisfaction [14].

Medication management success correlated with clear feedback (visual confirmation, timestamp) and simple tasks (single button press), suggesting elderly users value task simplicity over feature richness when competence is at stake [3, 12].

4.5. Relatedness: Connection and Understanding

Four participants noted "Bella remembers our conversations," demonstrating personalization supporting relatedness [21].

Conversational affect: Almost all participants indicated "It's nice to have someone to talk to when I'm alone," illustrating the relatedness function [27, 7].

Threats: Conversational depth: "Less stereotypical responses," "More nuanced conversation," consistent with limitations of current conversational agents [21]. No human replacement: 100% stated Bella could not replace human contact, establishing clear boundaries. Quotes: "Personal communication cannot be replaced," "Bella is helpful for information, but I still want to talk to my children." Video calling underuse was due to technical barriers preventing the competence satisfaction required for relatedness [22].

Instrumental vs. Direct Relatedness: CareBells supported relatedness through (1) a direct relationship with Bella and (2) instrumental facilitation of human connections [21]. Bella served primarily an instrumental purpose (companionship during gaps) rather than as a genuine relational partner, consistent with findings that elderly users maintain boundaries with AI [21].

News Pattern: Universal interest (100%), yet only a few used the News Module directly. Users preferred conversational information retrieval (asking Bella) over efficient but impersonal article browsing, revealing how relatedness needs shape information-seeking behavior [20]. This pattern demonstrates users prioritizing social interaction over task efficiency when both needs compete [5].

4.6. Critical Barriers Through the SDT Lens

Following the SDT framework [4, 7], we identified three critical barriers where need threats undermined adoption:

1. Competence Threat – Speech quality: 100% mentioned issues, directly undermining effective communication [14]. This created anxiety about future interactions, consistent with technology anxiety effects on elderly adoption [3]. Users began avoiding voice features despite initial enthusiasm, demonstrating how competence threats reduce engagement [4].

2. Autonomy Threat – Privacy opacity: Lack of transparent data practices reduced perceived control [25, 24, 28]. Users could not articulate what data was collected or how it was used, violating autonomy through understanding. The threat persisted despite strong encryption (TLS 1.3, AES-256), demonstrating that perception matters more than objective reality for autonomy satisfaction [4].

3. Relatedness Threat – Conversational superficiality: Participants requested "more nuanced conversation." Generic responses failed to convey understanding of individual circumstances [21]. Users distinguished "information" (satisfied) from "connection" (unsatisfied), preventing intrinsic motivation for social interaction [7]. Limited depth prevented full relatedness satisfaction despite high engagement [5].

4.7. Predicting Engagement from Need Satisfaction

Engagement patterns aligned with SDT predictions [4, 5]: Bella AI satisfied all three needs through user-initiated interaction (autonomy), successful information retrieval despite speech errors (competence), and conversational memory (relatedness). Medium-engagement features satisfied fewer needs – medication provided competence through clear task completion but lacked relatedness [3], while calling satisfied all needs yet competed with external habits [22]. Low engagement features threatened competence through complexity [12] or technical barriers without offsetting relatedness benefits [22]. While $n = 6$ precludes statistical testing, the consistent gradient (multi-need satisfaction predicts higher engagement) warrants validation in larger samples [3, 5].

5. Discussion

5.1. Theoretical Contributions

SDT as a Predictive Framework: Features satisfying multiple psychological needs attracted higher engagement, while single-need features saw minimal use. This pattern supports SDT's utility for understanding elder care technology adoption [4, 5], extending beyond traditional usability or acceptance models [9, 10]. Need satisfaction, not utility of a single feature alone, drives sustained interaction [7].

Autonomy Primacy: Privacy concerns (50% overall, 100% Country B) despite strong security demonstrated that perceived autonomy, not actual capabilities, determines trust [25, 24]. This aligns with SDT's emphasis on subjective psychological experience over objective conditions [4]. The finding extends explainable AI research [16] by showing elderly users require transparency for autonomy satisfaction even when systems objectively protect privacy.

Competence Fragility: Speech recognition errors disproportionately threatened competence compared to other interface errors [14], suggesting modality-specific vulnerability. Elderly users may attribute speech failures to personal inadequacy rather than system limitations, consistent with technology self-efficacy research [3]. This finding has implications for voice-first interface design for aging populations [14].

Relatedness Complexity: The distinction between instrumental relatedness (enabling human connection) and direct relatedness (relationship with technology) requires refinement in elder care contexts [21]. Users accepted AI as a companion during isolation but maintained boundaries: it was "nice to have someone to talk to" but could not "replace personal communication." This extends relational agent research [21] by demonstrating that elderly users differentiate information needs (satisfied by AI) from connection needs (requiring humans).

5.2. Design Principles for Need-Satisfying Elder Care AI

Our findings yield several critical design principles:

1. **Autonomy Support:** Provide transparent privacy controls with plain-language explanations [25, 24], enable reversible actions, and offer multiple interaction pathways (voice, touch, text) allowing user choice [4, 14].
2. **Competence Support:** Prioritize speech recognition quality over feature quantity given elderly users' modality-specific vulnerability [14]. Provide immediate multimodal feedback and design appropriately challenging tasks [3, 12].
3. **Relatedness Support:** Maintain conversation context across sessions to create a sense of being known [21]. Balance instrumental relatedness (facilitating human connections) with direct AI interaction, and transparently acknowledge AI limitations versus human relationships [5, 7, 21].

5.3. Limitations and Future Directions

- **Sample Size:** $n = 6$ participants in a testing pilot provides exploratory insights, not generalizable conclusions [3]. Testing whether SDT predicts engagement requires validation with $n = 100+$ participants across 6+ month deployments with control groups and objective outcome measures [29].
- **Selection Bias:** Participants were relatively high-functioning elderly adults already comfortable with external assistance (meal services) [3]. Findings may not transfer to cognitively impaired [8], fully isolated, or technology-averse populations. Future research needs diverse samples including nursing home residents [29].
- **Measurement Limitations:** SDT need satisfaction was measured via self-report; future work should employ validated scales [4, 7] with multiple measurement points. Medication adherence was based on self-reported button presses, not verified pill-taking. Objective measures (pharmacy records [29], social isolation scales [1, 7]) are needed for validation.
- **Cultural Differences:** Vastly different sample sizes ($n = 4$ Country A, $n = 2$ Country B) prevent meaningful cross-cultural analysis. Observed differences in privacy concerns require validation with matched, adequately powered samples examining cultural contexts of data sensitivity [24].

Future research directions we are planning include:

- A randomized controlled trial comparing autonomy-supportive vs. controlling interfaces on sustained adoption [4].
- Longitudinal analysis of how need satisfaction changes as novelty wears off [5].
- Examination of need satisfaction profiles predicting which elderly users abandon vs. continue technology use [3].
- Investigation of whether different needs (autonomy, competence, relatedness) matter more at different adoption stages [7].
- Integration of explainable AI methods [25, 16, 26, 28] for health recommendations requiring transparency.

6. Conclusion

Self-Determination Theory reveals that psychological need satisfaction (autonomy, competence, relatedness) determines engagement patterns more reliably than technical features or usability alone [4, 5]. When AI systems respect user agency (autonomy), enable effective task completion (competence), and facilitate meaningful connection (relatedness), elderly users engage enthusiastically. Where systems threaten these needs (through opaque data practices, error-prone speech recognition, or superficial interactions), users disengage regardless of objective utility.

Technology adoption is not merely a design problem but a motivational problem [4]. Creating elder care AI that bridges rather than widens the digital divide requires designing for intrinsic motivation through fundamental psychological need satisfaction [3, 5]. As aging populations increasingly depend on technology-enabled care [23], understanding these motivational dynamics becomes essential for developing effective, sustainable solutions [20, 29].

Declaration on Generative AI

During the preparation of this work, the authors used X-GPT-4 and Claude AI in order to: Grammar and spelling check. Claude (Anthropic) assisted in manuscript structure, literature synthesis, and technical descriptions. After using these tools and services, the authors reviewed and edited the content as needed and take full responsibility for the publication's content. All research design, data collection, analysis, and interpretation remain the authors' original contributions.

References

[1] AARP Foundation, Social isolation and loneliness among older adults, https://www.aarp.org/pri/departments/research/, 2022.

[2] A. Reis, D. Paulino, H. Paredes, I. Barroso, M. J. Monteiro, V. Rodrigues, J. Barroso, Using intelligent personal assistants to assist the elderly, in: Proceedings of the 9th International Conference on Software Development and Technologies for Enhancing Accessibility, 2018, pp. 213–220.

[3] K. Chen, A. H. Chan, Predictors of gerontechnology acceptance by older Hong Kong Chinese, Technovation 34 (2014) 676–687.

[4] E. L. Deci, R. M. Ryan, The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior, Psychological Inquiry 11 (2000) 227–268.

[5] D. Peters, R. A. Calvo, R. M. Ryan, Designing for motivation, engagement and wellbeing in digital experience, Frontiers in Psychology 9 (2018) 797.

[6] N. Unkelos-Shpigel, Go with the Flow, Get to the Point: Leveraging Motivational Theories for Designing Gamification for Collaborative Requirements Engineering, Ph.D. thesis, University of Haifa, Israel, 2023.

[7] J. Holt-Lunstad, T. B. Smith, M. Baker, T. Harris, D. Stephenson, Loneliness and social isolation as risk factors for mortality: A meta-analytic review, Perspectives on Psychological Science 10 (2015) 227–237.

[8] N. Unkelos-Shpigel, I. Hadar, Gamifying software development environments using cognitive principles, in: CAiSE Forum, 2015, pp. 9–16.

[9] J. Brooke, SUS: A "quick and dirty" usability scale, Usability Evaluation in Industry 189 (1996) 189–194.

[10] V. Venkatesh, F. D. Davis, A theoretical extension of the technology acceptance model, Management Science 46 (2000) 186–204.

[11] R. Hoque, G. Sorwar, Understanding factors influencing the adoption of mHealth by the elderly, International Journal of Medical Informatics 101 (2017) 47–56.

[12] J. Hermann, S. van Ledden, C. Meske, E. Löhrke, E. Naroska, T. Dimitrov, S. Ölcer, A. Dogangün, ExpliCareNEXT: Human-centered explainable AI solutions for nursing care, in: Proceedings of ACM IUI Workshops, 2025.

[13] Pew Research Center, Tech adoption climbs among older adults, Technology Survey, 2021.

[14] R. Vipperla, M. Wolters, K. Georgila, S. Renals, Speech input from older users in smart environments, in: Proceedings of the International Conference on Universal Access in Human-Computer Interaction, 2009, pp. 117–126.

[15] J. Hehn, D. Mendez, F. Uebernickel, W. Brenner, M. Broy, On integrating design thinking for human-centered requirements engineering, IEEE Software 37 (2020) 25–31.

[16] C. Meske, B. Abedin, M. Klier, F. Rabhi, Explainable and responsible artificial intelligence, Electronic Markets 32 (2022) 2103–2106.

[17] F. Ibarra, M. Baez, L. Cernuzzi, F. Casati, A systematic review on technology-supported interventions to improve old-age social wellbeing, Journal of Healthcare Engineering 2020 (2020) 2036842.

[18] W. Brenner, F. Uebernickel, T. Abrell, Design thinking as mindset, process, and toolbox, in: Design Thinking for Innovation, Springer, 2016, pp. 3–21.

[19] T. Brown, Design thinking, Harvard Business Review 86 (2008) 84–92.
[20] A. Lorenz, R. Oppermann, Mobile health monitoring for the elderly, in: Proceedings of Pervasive Computing, 2009, pp. 873–881.
[21] L. P. Vardoulakis, L. Ring, B. Barry, C. L. Sidner, T. Bickmore, Designing relational agents as long term social companions for older adults, in: International Conference on Intelligent Virtual Agents, Springer, 2012, pp. 289–302.
[22] M. T. Ribeiro, S. Singh, C. Guestrin, "why should I trust you?": Explaining the predictions of any classifier, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, pp. 1135–1144.
[23] World Health Organization, Ageing and health: Key facts, 2022.
[24] C. A. Mueller, G. L. Alexander, M. Ersek, B. R. Ferrell, M. J. Rantz, J. L. Travers, Calling all nurses: Now is the time to take action on improving the quality of care in nursing homes, Nursing Outlook 71 (2023) 101897.
[25] A. Adadi, M. Berrada, Peeking inside the black-box: A survey on explainable artificial intelligence (xai), IEEE Access 6 (2022) 52138–52160.
[26] M. T. Ribeiro, S. Singh, C. Guestrin, Anchors: High-precision model-agnostic explanations, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2018.
[27] M. Berg-Weger, J. E. Morley, Loneliness in old age: An unaddressed health problem, The Journal of Nutrition, Health & Aging 24 (2020) 243–245.
[28] F. Xu, H. Uszkoreit, Y. Du, W. Fan, D. Zhao, J. Zhu, Explainable AI: A brief survey on history, research areas, approaches and challenges, in: Natural Language Processing and Chinese Computing, Springer, 2019, pp. 563–574.
[29] D. A. Norman, The Design of Everyday Things: Revised and Expanded Edition, Basic Books, 2013.