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"*Will a robo-advisor help my grandpa?*": Exploring pathways to better integrate the elderly in the era of artificial intelligence

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ABSTRACT

The global aging population, particularly the increasing number of individuals over 65 in Europe, presents both significant challenges and unique opportunities. This demographic shift has sparked the rise of the Silver Economy (*i.e.*, a sector focused on the production, consumption and trade of goods and services aimed at improving the lives of the elderly), increasingly driven by technological solutions such as artificial intelligence (AI). Among these technologies, robo-advisors (RAs) hold promise in enhancing the quality of life, autonomy and social inclusion for older adults. However, while the potential of AI to integrate the elderly into society is widely acknowledged, there remain substantial gaps in understanding how best to deploy such technologies. Existing literature reveals critical limitations in methodologies and a lack of comprehensive models to guide the integration of AI into the lives of the elderly. This study addresses these gaps by adopting a constructivist approach and proposing a decision-support system to guide authorities in crafting effective policies and initiatives. The system is developed with input from field experts through participatory methods, specifically the Nominal Group Technique (NGT) and the DEcision MAking Trial and Evaluation Laboratory (DEMATEL), within a neutrosophic framework. By doing so, the study provides a more nuanced understanding of the barriers and opportunities in using RAs for the elderly, offering both theoretical advancements and practical recommendations to improve their integration into the AI-driven future of the Silver Economy.

1. Introduction

The ageing of the global population, driven by significant economic, social and clinical advancements, has led to increased life expectancy (Bresciani et al., 2022). While this demographic shift presents challenges in terms of financial sustainability and community integration, it also unlocks substantial opportunities for market development, particularly within the Silver Economy (José et al., 2024; Rogelj and Bogataj, 2019; Shie et al., 2025). The growing need to transfer intellectual processes and mechanisms to artificial systems, such as through machine learning (ML) and artificial intelligence (AI), has resulted in remarkable advances in AI theory and application (Aparicio et al., 2025; Raximov et al., 2021; Simba et al., 2025). According to Lipp and Peine (2024), information and communication technologies (ICT) have become integral to modern life, both personally and professionally. However, despite these advancements, José et al. (2024) and Weck et al. (2022a) indicate that the elderly population faces significant barriers to understanding and integrating ICT into their daily lives, resulting in social and digital exclusion.

Within this context, the intersection between ageing, digital transformation and AI raises a critical societal issue, namely the integration of

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older adults into AI-driven environments (cf. José et al., 2024; Shie et al., 2025). Current research reveals significant gaps in both conceptual and methodological approaches to the integration of the elderly into the digital age. In response, this study develops a structured multi-criteria decision-support system to inform more effective and inclusive policies for elderly inclusion in AI-driven societies.

Following this, the central research questions driving this study are:

R1. What are the key barriers and opportunities for the elderly in adopting AI-driven technologies like robo-advisors (RAs)?
R2. How can the cause-and-effect relationships between these key barriers and opportunities be identified and analyzed?
R3. How can participatory methods contribute to designing more inclusive AI solutions for the elderly?

To answer these questions, the present study adopts a constructivist approach and employs a combination of qualitative and quantitative techniques. Specifically, the study applies the Nominal Group Technique (NGT) and the DEcision MAking Trial and Evaluation Laboratory (DEMATEL) method within a neutrosophic context, ensuring a comprehensive, multi-dimensional analysis of the study topic. These methodologies have been selected for several key reasons. First, NGT has been recognized for its ability to gather and prioritize expert opinions in a structured and systematic way. It allows for a clear articulation of different viewpoints on complex issues, which is crucial when addressing the diverse challenges faced by the elderly in integrating into the AI era. Second, DEMATEL is a powerful tool for analyzing complex cause-and-effect relationships among different factors. It allows for the identification of key drivers of integration and exclusion in the AI era for the elderly, mapping out how various issues are interrelated. By applying DEMATEL, this study will provide a clearer understanding of the dynamics at play and help prioritize the most critical aspects of the problem. Third, neutrosophic logic is employed to handle the uncertainty and imprecision inherent in the decision-making process. It allows for a more flexible and nuanced approach to modeling the decision-making process, as it incorporates degrees of truth, indeterminacy and falsity. Given the complex nature of integrating elderly people into the AI world, neutrosophic logic enables the handling of incomplete or ambiguous information, providing a more robust analysis that traditional methods may fail to address.

This study is novel in applying multiple criteria decision analysis (MCDA) within a neutrosophic framework to this context, aiming to overcome the methodological limitations identified in prior research. By integrating expert perspectives through participatory methods, this study provides both theoretical and practical contributions.

Importantly, the study is grounded in a socio-technical systems perspective, which conceptualizes AI-enabled advisory systems such as RAs not merely as technological artefacts, but as embedded components of complex systems shaped by institutional arrangements, user capabilities and contextual conditions. Building on this perspective, the study draws on technology adoption theories in elderly populations and gerontechnology literature to reinterpret key constructs such as trust, usability, autonomy and comprehension as relational and context-dependent rather than purely individual or technical attributes.

From a theoretical standpoint, the study extends existing innovation and technology adoption frameworks by demonstrating how socio-technical complexity can be operationalized through a structured decision-modeling approach. In particular, the integration of NGT, DEMATEL and neutrosophic logic enables the transformation of abstract adoption constructs into explicit causal structures, thereby advancing socio-technical systems thinking and decision-support theory in the context of ageing societies.

This integrated approach not only enhances theoretical understanding of elderly inclusion in AI-enabled environments, but also provides actionable insights for policymakers and technology developers seeking to design more inclusive and context-aware solutions in the age of AI.

This paper is structured as follows. The next section presents a comprehensive literature review, discussing key concepts such as the Silver Economy, AI, RA and the paradigms of technological evolution, as well as examining contributions and limitations from previous studies. Section 3 details the methodologies employed in the study, while Section 4 presents the empirical application of the techniques and discusses the results. The final section concludes with key findings, limitations and suggestions for future research.

2. Literature review and research gaps

The concept of Silver Economy, as discussed by José et al. (2024), Sawinska (2018) and Weck et al. (2022b), builds upon the understanding that the aging population poses both a challenge and an opportunity for socio-economic systems. The aging of the population is a global phenomenon, with implications for healthcare, housing, social services and the workforce (Connell et al., 2024; Mois and Beer, 2020; Shie et al., 2025; Szewczyk, 2018). For example, Lipp and Peine (2024) report that, globally, the number of people aged 65 and over is growing at a faster pace than any other age group, a trend expected to continue for the foreseeable future. This demographic shift is accompanied by an increase in life expectancy, owing to advancements in healthcare, which, while contributing positively to quality of life, also increases the demand for long-term care and specialized services.

From a socio-technical systems perspective, these developments cannot be interpreted solely as demographic or economic trends but rather as the result of dynamic interactions between technological infrastructures, institutional arrangements, social practices and human capabilities. In this sense, the Silver Economy emerges as a complex socio-technical system in which technological innovation, policy design and user adoption are deeply interdependent rather than independent processes (José et al., 2024).

Rogelj and Bogataj (2019) and Weck et al. (2022c) argue that the Silver Economy is not just about addressing the care needs of the elderly but involves the creation of new economic opportunities through the design of products and services tailored to this demographic. This includes healthcare technologies, wellness products and assistive devices, which are essential for maintaining the independence and well-being of older individuals.

Bran et al. (2016) and Butt and Draheim (2021) further extend the Silver Economy's scope, proposing that it encompasses industries that enhance not only physical well-being but also social inclusion through innovations aimed at reducing isolation and facilitating communication. However, when viewed through a socio-technical lens, these contributions reveal an implicit assumption that technological availability naturally translates into social benefit. In practice, the effectiveness of such innovations depends on how technologies are embedded within everyday routines, supported by institutions and perceived by elderly users themselves. While much of the literature focuses on the demand-side aspects of the Silver Economy, such as the creation of services and products for elderly consumers, fewer studies have explored the supply-side challenges, such as the integration of these innovations into existing market structures and policies. Iwański (2024) highlights this gap, noting that despite the proliferation of Silver Economy-oriented innovations, many elderly individuals still face barriers to access, affordability and familiarity with these technologies.

The role of AI in addressing the needs of the elderly population has attracted significant attention in recent years. Jung et al. (2018), Raximov et al. (2021) and Vrontis et al. (2021) emphasize AI's potential to revolutionize healthcare, education and social engagement for the elderly. For example, Anghel et al. (2020) and Shie et al. (2025) underscore how AI technologies, ML and natural language processing (NLP) can be used to predict health outcomes, monitor vital signs and recommend lifestyle changes based on individual needs, contributing to personalized health management. Within this ecosystem, AI-based

advisory systems have emerged as a particularly relevant class of technologies. Notably, they should not be interpreted narrowly as specific-sector tools but rather as a broader category of algorithmic decision-support systems capable of generating personalized recommendations in multiple domains relevant to ageing populations (Bardaro et al., 2022).

Despite this potential, technology acceptance among elderly populations remains uneven, suggesting that adoption cannot be explained by functional performance alone. Existing studies implicitly point to acceptance-related dimensions such as perceived usefulness, ease of understanding, trust and perceived loss of control, which are particularly salient for older users (José et al., 2024). These dimensions reinforce the view that AI adoption among the elderly is a relational and contextual process rather than a purely individual or technical decision.

Jiang et al. (2022) and Ma (2023) argue that while AI-based applications in healthcare have shown promising results, they are often limited by issues such as data privacy, algorithmic transparency and usability concerns, particularly for older users who may not be familiar with technology. From a gerontechnology perspective, these limitations highlight a persistent mismatch between technological design assumptions and the cognitive, sensory and emotional realities of aging. This reinforces calls for human-centered and participatory approaches that actively incorporate elderly users' values and capabilities into system design.

Moreover, Cruces et al. (2024), Koh et al. (2021) and Lipp and Peine (2024) point out the specific value AI brings to sectors like healthcare, where it can not only assist in routine tasks (*e.g.*, medication reminders and appointment scheduling) but also enable emotional support through virtual assistants or RAs. These technologies, designed to assist the elderly, aim to improve their autonomy and social engagement, reducing the risk of isolation and promoting a more active lifestyle. However, Zhao and Li (2024) caution that while AI may enhance physical well-being, it could also inadvertently increase dependence on technology, leading to a decline in social skills and face-to-face interactions. This tension illustrates a core socio-technical dilemma: AI systems may simultaneously empower and constrain elderly users, depending on how responsibilities, decision rights and agency are distributed between humans and machines. Achieving balance between assistance and autonomy is therefore central to sustainable adoption.

The concept of the RA, as discussed by Agnew and Mitchell (2019), Anshari et al. (2022) and Arenas-Parra et al. (2024), is particularly relevant in the context of the elderly. Originally emerging from financial advisory contexts, RAs have progressively expanded toward broader AI-enabled applications, including health and lifestyle support for elderly users, where they support functions such as chronic disease management, medication adherence and personalized recommendations related to health, diet, exercise and social engagement (Bardaro et al., 2022). As such, RAs have been conceptualized in the literature as a unified class of AI-enabled decision-support systems that generate personalized recommendations across multiple domains, including financial planning, healthcare support and daily life management (cf. Bardaro et al., 2022; Oehler et al., 2022; Zhang et al., 2021). Across these domains, RAs rely on data-driven personalization, continuous user interaction and context-sensitive recommendations to support individual decision-making.

By treating RAs as a representative case of AI-based advisory technologies, the present study examines key barriers and opportunities common to these applications, including trust, comprehension, user engagement and ethical considerations. This unified perspective enables a more comprehensive understanding of RA adoption among elderly users, ensuring relevance across both financial and health/social care contexts and supporting their positioning as a coherent class of AI technologies for elderly inclusion in digital society.

Zhang et al. (2021) argue that RAs provide not only practical assistance but also emotional support, as they are available around the clock, allowing the elderly to access guidance whenever needed. However, the integration of RAs into elderly care also raises important ethical concerns. As highlighted by Qian et al. (2021), the use of AI in personal care settings may lead to data privacy risks and the potential for bias in AI algorithms. Zhao et al. (2023) further stress the importance of developing robust ethical frameworks that safeguard users while ensuring the benefits of technology. Additionally, older adults' digital literacy and informed consent should be carefully considered to ensure they understand how their data is collected, used and shared. These concerns align directly with Responsible AI (RAI) principles, which emphasize transparency, accountability and user protection in AI-driven systems.

Beyond these concerns, ethical reflection should also consider the autonomy of older adults. While RAs can provide guidance and support, they should not replace the individual's ability to make informed decisions about their own care. Preserving autonomy ensures that technology serves as an enabler rather than a constraint, reinforcing dignity and respect in elderly care. In this sense, autonomy becomes a core design principle of human-centered and RAI systems rather than a secondary ethical constraint.

Moreover, algorithmic bias poses risks of unequal treatment or unintended discrimination (Zhao et al., 2023). For instance, if RAs are trained on datasets that underrepresent certain subgroups of the elderly population, their recommendations may inadvertently favor some individuals over others. Addressing these biases in AI-based RAs requires continuous monitoring, transparency in decision-making processes and inclusion of diverse perspectives in the design of AI systems. Therefore, privacy, autonomy and fairness are interdependent concerns in the context of RAs for elderly users. Neglecting any of these dimensions may undermine trust and reduce adoption, even if the technology is functionally effective. Ethical considerations should be embedded from the earliest stages of RA system design, aligning the technology with societal values and the real needs of older adults. Such reflection is not only morally imperative but also strategically relevant, as ethically robust RAs are more likely to achieve sustained adoption, improve quality of life and enhance social inclusion for elderly users. Taken together, these arguments position ethical and societal considerations as foundational pillars of RAI in elderly-focused digital ecosystems.

Technological integration into the lives of the elderly has made significant strides, yet research suggests that many older individuals face barriers in utilizing digital technologies. José et al. (2024) identify these barriers as stemming from issues such as digital illiteracy, cognitive impairments and sensory limitations. Moreover, the literature often overlooks the complex relationship between older adults and technology, especially when these technologies are perceived as difficult to use or intrusive.

Notable contributions from Choi et al. (2024) and Li et al. (2024) underscore the importance of creating user-friendly interfaces and designing technologies that account for sensory limitations, such as hearing or vision impairments. Furthermore, Mhlanga (2024) and Paramasivam et al. (2024) argue that there is a need for more inclusive design principles in the development of digital platforms/devices for the elderly, emphasizing the importance of accessibility and usability. Collectively, these studies suggest that many failures in AI adoption among the elderly stem not from resistance to technology *per se*, but from misalignments between system design, user capabilities and institutional support structures. This reinforces the need to integrate ethical, usability and inclusion dimensions within a unified RAI and socio-technical design perspective.

Despite growing interest, most studies have concentrated on the healthcare sector, with limited focus on other areas like financial services, retirement planning or consumer behavior (cf. Anshari et al., 2022; Arenas-Parra et al., 2024). José et al. (2024) stress the importance of broadening the focus of research to include these areas, particularly as they relate to the elderly's financial independence and social participation. Additionally, existing research often involves controlled scenarios, which do not capture the real-world complexities of aging populations. This highlights the need for context-sensitive

models that take into account diverse living environments, socio-economic conditions and cultural differences.

Overall, the literature reveals several gaps in the integration of AI with the Silver Economy, especially in addressing the multidimensional needs of the elderly. First, there is a lack of research on the multi-sectoral impact of AI technologies beyond healthcare and how these technologies can enhance the elderly's participation in various spheres, including finance, leisure and social activities. Second, while there is substantial work on the use of AI in healthcare, there is limited research on its broader applications, such as financial services or marketing, which are crucial for the elderly's economic autonomy. Third, existing studies often suffer from geographical and sample limitations, focusing on specific regions or small sample sizes that do not adequately reflect the diversity of elderly populations globally.

Building on the clarified cross-domain conceptualization of RAs, this study addresses the identified gaps by integrating MCDA tools, namely the NGT and DEMATEL, together with neutrosophic logic, to develop a comprehensive decision-support framework. This methodological combination enables a more nuanced understanding of the key barriers and opportunities shaping elderly interaction with AI-enabled advisory systems, particularly in terms of their interdependencies and causal relationships. By doing so, the study contributes to the development of more inclusive, context-aware and user-sensitive approaches to AI adoption in ageing societies, supporting policy design aimed at enhancing autonomy, social inclusion and well-being among older adults.

3. Methodological background

The techniques selected for the present study were incorporated based on a constructivist logic that integrates both objective and subjective variables, including the uncertainties and indeterminacies involved in the decision-making process. This integration follows a sequential and complementary MCDA architecture commonly adopted in complex socio-technical problem contexts, where different methods are combined to address distinct but interrelated analytical needs (cf. Belton and Stewart, 2002). The decision support phases are structured as follows: (1) structuring; (2) evaluation; and (3) recommendations. The first phase applies the NGT, while the second phase employs neutrosophic logic and DEMATEL to facilitate the quantitative assessment of cause-and-effect relationships. The final phase enables recommendations to be formulated based on the results obtained from the previous two phases. This staged design ensures methodological coherence by aligning each technique with a specific function in the decision process, moving from knowledge elicitation to causal modeling under uncertainty.

3.1. Nominal Group Technique

The Nominal Group Technique (NGT) is widely recognized as a consensus-building method aimed at fostering general agreement or harmony regarding opinions on a specific topic. It is commonly used to generate ideas and establish priorities in complex problem-solving scenarios (DeLong et al., 2024). The application and definition of consensus in NGT vary across studies depending on the research goals and it is considered one of the most effective methods for reaching agreement on ideas or values (McMillan et al., 2014). This technique can be conducted either face-to-face or virtually and is praised for being time- and cost-efficient, as well as for its effectiveness in quickly generating results. It is valued for its transparent process and inclusive nature, ensuring that all participants are involved (Harvey et al., 2024; Vainio et al., 2024).

As described by Potter et al. (2004) and Riley-Bennett et al. (2024), an expert panel typically begins with one or two questions posed by the facilitator ahead of time. These questions should be clear, broad and objective, allowing for a wide variety of ideas to emerge. Initially, participants are given up to 20 min to silently reflect on the question and record their thoughts (*i.e.*, the silent step). Following this, the facilitator conducts a round-robin, where each participant takes turns sharing one idea at a time, without interrupting others, until no new ideas are offered. This phase continues until the group has exhausted all possible ideas, with no discussions allowed and ideas being recorded in writing (*e.g.*, on a whiteboard) (Nasir et al., 2024; Potter et al., 2004).

The next phase is the clarification or discussion of ideas, which may include grouping similar ideas together with the group's consensus. This step also allows participants to modify, remove or refine ideas, ask for clarification and explore them in more depth. This ensures that participants have a clear understanding of the ideas, which helps in making informed decisions during the subsequent voting process (McMillan et al., 2014; Potter et al., 2004). In the final phase, participants privately vote on the ideas based on criteria such as importance or feasibility, typically ranking their preferred ideas, with the highest-ranking idea receiving the most points. The facilitator then analyzes the results to determine which ideas are most favored by the group. If necessary, additional rounds of voting or discussion may take place to reach a final consensus (McMillan et al., 2014; Potter et al., 2004). NGT employs a mixed-methods approach, as its outcomes can be presented both qualitatively and quantitatively (Onu et al., 2024).

In the context of elderly-AI research, the use of NGT is particularly appropriate, as it enables the structured elicitation of diverse expert perspectives on a complex and evolving phenomenon, where empirical data may be fragmented or incomplete. By ensuring balanced participation and minimizing dominance effects, NGT enhances the reliability and transparency of the problem-structuring phase, which is critical in constructivist and participatory research designs.

3.2. Neutrosophic logic

Neutrosophy, introduced by Smarandache in 1995, is a branch of philosophy that studies the origin and scope of neutralities (cf. Abdel-Basset et al., 2019; Rivieccio, 2008; Gil et al., 2026). This approach has been applied in various fields to solve numerous problems. According to Alzadjali et al. (2020), Çipi et al. (2026) and Gil et al. (2026), neutrosophic logic is particularly useful in decision-making environments where there is indeterminacy, as it helps identify unexpected parameters hidden in certain propositions.

The crucial principle of neutrosophic logic, which is a non-normalized tripartite analysis (Kavitha et al., 2012), is that ideas not only have a degree of truth (T), but also a degree of falsity (F) and a degree of uncertainty/indeterminacy (I), all of which should be included as independent components in decision-making processes (Cevallos, 2024). This approach manages to go beyond classical binary logic or even fuzzy logic, as it can effectively identify and reduce uncertainties, where it recognizes and formalizes the notion of truth, falsity and uncertainty simultaneously (Essameldin et al., 2022; Molina-Borja et al., 2025). Neutrosophic logic is thus a multivariate logic, in which the values of the logical variable x are given as a set of three components: T, I and F. Statistically, they are subsets, but dynamically T, I and F are operators that depend on many known or unknown parameters and are presented as any standard or non-standard real subsets of $]-0, 1+[$. That is, $T =]-0, 1+[$; $I =]-0, 1+[$; and $F =]-0, 1+[$ (Lemos et al., 2022).

According to Wajid and Zafar (2021), where U is a universe of discourse and X is a set defined in U, an element $x \in U$ is noted with respect to the set X as $x(T, I, F)$. Thus, in T, I and F, beyond the interval in which they are defined, when the three components are independent, we have $0 \leq T + I + F \leq 3+$, with no additional restrictions. In practice, according to Ferreira and Meidutė-Kavaliauskienė (2025), this approach makes it possible to ask experts their opinion on a given statement and they can say, for example, that the possibility of a statement being true (T) is 0.5, that its degree of uncertainty (I) is 0.2 and that the possibility of it being false (F) is 0.6. In neutrosophic notation, this can be represented as x (0.5, 0.2, 0.6).

This methodological approach offers greater flexibility for decision-makers, allowing them to describe the impacts not only as positive or negative but also as indeterminate (Lemos et al., 2022). In this context, the procedure is associated with a neutrosophic adjacency matrix of dimensions $n \times m$ (*i.e.*, $n = m$ represents the number of factors and/or criteria), which includes values defined by the neutrosophic evaluations of all cause-and-effect relationships between the relevant variables. The simplified neutrosophic matrix D is derived using Equation (1), in which the n decision criteria and the degree of intensity of their interrelationships are represented as follows (Lemos et al., 2022):

$$D = (\alpha_{ij})_{m^*n} = \begin{bmatrix} (t_{11}, i_{11}, f_{11}) & (t_{12}, i_{12}, f_{12}) & \cdots & (t_{1n}, i_{1n}, f_{1n}) \\ (t_{21}, i_{21}, f_{21}) & (t_{22}, i_{22}, f_{22}) & \cdots & (t_{2n}, i_{2n}, f_{2n}) \\ \vdots & \vdots & \vdots & \vdots \\ (t_{m1}, i_{m1}, f_{m1}) & (t_{m2}, i_{m2}, f_{m2}) & \cdots & (t_{mn}, i_{mn}, f_{mn}) \end{bmatrix}. \quad (1)$$

To transform the three neutrosophic components T, I and F into a single value or component (*i.e.*, crispification), it is necessary to operationalize the values. While there are several functions available for neutrosophic aggregation, one approach to crisping the neutrosophic weights is provided by Equation (2) (Çipi et al., 2026; Lemos et al., 2022):

$$w_k = \frac{1 - \sqrt{\left((1-\mathrm{T}_k)^2 + (\mathrm{I}_k)^2 + (\mathrm{F}_k)^2\right)/3}}{\sum_{k=1}^{r}\left\{1 - \sqrt{\left((1-\mathrm{T}_k)^2 + (\mathrm{I}_k)^2 + (\mathrm{F}_k)^2\right)/3}\right\}}, w_k \geq 0 \text{ and } \sum_{k=1}^{r} w_k = 1. \quad (2)$$

In short, Equation (2) allows experts to determine their own neutrosophic decision weights (*i.e.*, w_1, w_2 …, w_r), so that each $w_k = (T_k, I_k, F_k)$ is represented by a neutrosophic number. A single component value facilitates the application of neutrosophic logic to other methodologies, including the DEMATEL method (Lemos et al., 2022). Notably, the crispification procedure and the associated parameter choices presented in Equation (2) were selected based on their established use in neutrosophic-DEMATEL applications and their ability to balance the truth, indeterminacy and falsity components into a single, interpretable measure (cf. Çipi et al., 2026; Gil et al., 2026; Vaz-Patto et al., 2024). Conceptually, this formulation preserves the relative weighting of each neutrosophic component while enabling integration into the DEMATEL causal modeling process. Alternative formulations were considered during preliminary model development, but they either distorted the relative contributions of the neutrosophic components or reduced the interpretability of the resulting cause-and-effect relationships. By adopting the chosen crispification method, the model maintains both mathematical coherence and practical interpretability, aligning with the constructivist, decision-oriented nature of our approach.

The inclusion of neutrosophic logic is especially relevant in the present context, as decision-making regarding AI adoption by elderly populations involves high levels of ambiguity, incomplete knowledge and subjective judgment. By explicitly modeling indeterminacy alongside truth and falsity, this approach provides a more realistic representation of expert reasoning compared to traditional deterministic or fuzzy approaches, thereby strengthening the robustness of the subsequent causal analysis.

3.3. DEMATEL

MCDA is a crucial field in decision-making that demonstrates the influence exerted by the chosen components and their respective cause-and-effect relationships (Bali et al., 2023; Trivedi, 2018). Its focus is on developing realistic models to determine the best alternative, considering multiple criteria in the selection process. One of the fundamental techniques in this field is the DEMATEL method, developed by André Gabus and Emilio Fontela in 1972 at the Battelle Memorial Institute in Geneva (cf. Gabus and Fontela, 1972).

It is widely accepted as one of the best tools for identifying cause-and-effect relationships among evaluation criteria (Çipi et al., 2026; Sumrit and Anuntavoranich, 2013). This method helps solve complex group decision-making problems by managing the criteria that require the most attention (Manoharan et al., 2022). Using a combination of expert knowledge and mathematical techniques, DEMATEL creates a cause-and-effect matrix and can categorize the criteria into cause and effect groups, enabling decision-makers to identify the most prevalent and relevant criteria for the study and potential solutions to the problem (Taherdoost and Madanchian, 2023).

3.3.1. Step one: calculate the initial direct influence matrix Z

This measurement of the relationship between criteria requires that the degree considered by the experts, denoted by w_{ij} (*i.e.*, the degree to which factor i affects factor j), varies according to a five-level scale developed by Gabus and Fontela (1972) (*i.e.*, 0 = "no influence", 1 = "low influence", 2 = "medium influence", 3 = "high influence" and 4 = "very high influence"). As a result, a non-negative $n \times n$ matrix is obtained, the direct influence matrix Z of a given group of variables, elaborated as $Z = [a_{ij}]$ $n \times n$ and represented as shown in Equation (3).

$$Z = \begin{matrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{matrix} \begin{bmatrix} 0 & a_{12} & \cdots & a_{1n} \\ a_{21} & 0 & & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & 0 \end{bmatrix} \quad (3)$$

3.3.2. Step two: generate the normalized direct influence matrix X

Resulting from the normalization of the initial direct influence matrix Z through Equation (4), matrix X is generated, where λ, as we can see in Equation (5), corresponds to a normalization constant (Çipi et al., 2026; Lemos et al., 2022).

$$X = \frac{Z}{\lambda} \quad (4)$$

$$\lambda = \max\left(\max_{1 \leq i \leq n} \sum_{j=1}^{n} z_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^{n} z_{ij}\right) \quad (5)$$

3.3.3. Step three: construction of the total-ratio matrix T

After obtaining the normalized direct-ratio matrix X. The $n \times n$ matrix T can be obtained from Equation (6) (Lemos et al., 2022):

$$\mathrm{T} = \lim_{h \to \infty}\left(X^1 + X^2 + \ldots + X^h\right) = X(\mathrm{I} - X)^{-1} \quad (6)$$

3.3.4. Step four: evaluation of matrix T rows and columns

This step calculates the sums of the rows and columns of the matrix T, where the sum of the rows and the sum of the columns are represented by the vectors r and c, respectively (Sumrit and Anuntavoranich, 2013). Equations (7) and (8) make it possible to calculate the values of R and C:

$$R = \left[\sum_{j=1}^{n} t_{ij}\right]_{n \times 1} = \left[r_j\right]_{n \times 1} \quad (7)$$

$$C = \left[\sum_{i=1}^{n} t_{ij}\right]_{1 \times n} = \left[c_j\right]_{1 \times n} \quad (8)$$

3.3.5. Step five: determination of threshold value (α)

The threshold value (α) is calculated by averaging the elements of the matrix T, as defined in Equation (9) (Çipi et al., 2026; Sumrit and Anuntavoranich, 2013).

$$\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left[t_{ij}\right]}{N} \quad (9)$$

in which N is the number of factors in the matrix.

3.3.6. Step six: build an influence relation map (IRM)

The cause-effect diagram is constructed by mapping all the coordinate sets of ($r_i + c_i$, r_i-c_i) to visualize the complex interrelationships and provide information to assess which factors are the most important and how they influence the affected factors. In short, Quartile (Q)I has the most crucial influential factors, QII encompasses influential factors that can improve others, QIII has influential factors that are not very relevant and, finally, QIV encompasses important and influential factors that can be improved by others (Sumrit and Anuntavoranich, 2013) (see Fig. 1).

In this study, DEMATEL is particularly suitable because it allows for the modeling of complex interdependencies among barriers and opportunities associated with elderly interaction with AI systems. Unlike linear or independent evaluation approaches, DEMATEL captures feedback structures and causal loops, which are inherent in socio-technical systems and innovation adoption processes. This makes it especially appropriate for analyzing how factors such as trust, usability and autonomy influence each other dynamically.

The DEMATEL method offers several advantages compared to other techniques, including: (1) its ability to effectively identify mutual influences—both direct and indirect effects—among different factors, capturing the complex cause-and-effect relationships within the decision-making problem (Gil et al., 2026; Si et al., 2018); (2) its capacity to visualize the interrelationships between factors through an IRM, helping decision-makers clearly understand which factors mutually influence each other (Si et al., 2018); (3) its versatility, as it not only ranks alternatives but also uncovers critical evaluation criteria (Si et al., 2018); (4) its ability to enhance problem comprehension by illustrating the interdependencies between various system elements via causal diagrams (Ullah et al., 2021); and (5) its potential to model, map and improve satisfaction, offering deeper insights into interacting problems, factors and groups (Ullah et al., 2021).

However, the DEMATEL method also presents some limitations: (1) it ranks alternatives solely based on their interdependent relationships, potentially excluding other important criteria from the decision-making process (Si et al., 2018); (2) it does not account for the relative weights of experts when aggregating their personal assessments in group evaluations (Si et al., 2018); (3) it struggles to quantify the absolute degree of relationships between criteria or factors, which may hinder the decision-maker's ability to fully understand and classify cause-and-effect relationships (Aghelie et al., 2016); and (4) challenges arise when the information gathered is incomplete or subject to epistemic uncertainty (Aghelie et al., 2016).

Despite its limitations, the advantages of the DEMATEL method appear to outweigh the disadvantages. The method's ability to clearly identify and visualize complex cause-and-effect relationships, coupled with its flexibility in uncovering critical evaluation criteria and improving the understanding of interdependencies, makes it an invaluable tool in decision-making processes. Although it may not account for all criteria or expert weights in every situation, its capacity to handle intricate systems and provide actionable insights typically compensates for these drawbacks. As such, the DEMATEL approach remains highly regarded in the field of decision analysis.

In summary, the integration of the NGT, DEMATEL and neutrosophic logic is structured to ensure that each step directly contributes to answering the study's research questions. Specifically, the NGT is employed in the structuring phase to elicit and prioritize expert insights, thereby addressing the first research question (*i.e.*, What are the key barriers and opportunities for the elderly in adopting AI-driven technologies like RAs?). This step ensures a comprehensive definition of the decision problem based on collective expert knowledge. The DEMATEL method, applied in the evaluation phase and used in tandem with neutrosophic logic, contributes directly to the second research question (*i.e.*, How can the cause-and-effect relationships between these key barriers and opportunities be identified and analyzed?). DEMATEL facilitates the identification and quantification of the interdependencies among the criteria generated through NGT, while neutrosophic logic complements this process by managing uncertainty and indeterminacy in expert judgments, thereby strengthening the reliability of the causal analysis. Finally, insights derived from this integrated framework address the third research question (*i.e.*, How can participatory methods contribute to designing more inclusive AI solutions for the elderly?), by demonstrating how collective reasoning and interactive modeling can guide the design of inclusive, human-centered technological strategies.

Importantly, this methodological integration reflects a coherent socio-technical and constructivist perspective, in which complex problems are understood as systems of interdependent elements shaped by both objective structures and subjective perceptions. While the exact combination of methods is novel in the elderly–AI domain, the underlying architecture is consistent with established MCDA practices in complex policy and systems research. This reinforces both the methodological rigor and the theoretical positioning of the present study.

4. Application and results

The MCDA process begins with a structuring phase aimed at defining the decision problem and identifying the criteria that will serve as the foundation for model development. To ensure a comprehensive perspective, a heterogeneous group of seven panel members was selected, each with several years of practical experience in the field of study. The panel size aligns with Bana e Costa et al. (2002) recommendation that panels typically comprise five to seven experts. This size is also consistent with MCDA and PSM guidelines recommending small, interactive groups to facilitate structured dialogue and collective learning (cf. Çipi et al., 2026; Gil et al., 2026; Vaz-Patto et al., 2024). The panel included individuals of varying ages, genders, roles and positions across different institutions, all operating within the domains of innovation, AI and elderly-focused initiatives, ensuring a breadth of expertise and perspectives. Experts were purposively recruited based on their

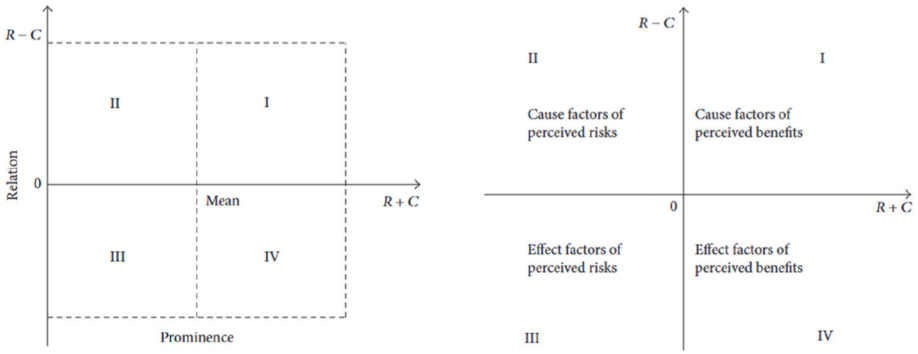


Fig. 1. Structure of a cause-effect diagram.
Source: Adapted from Si et al. (2018).

experience and decision-making responsibilities, and participation was voluntary and non-remunerated. Given the process-oriented nature of this study, representativeness was not a primary concern, as the emphasis was placed on understanding the decision-making process rather than statistical generalization (Bell and Morse, 2013; Gil et al., 2026). No personal, sensitive or health-related data were collected, and the study did not involve vulnerable individuals directly. Still, ethical approval for expert involvement was obtained in line with institutional guidelines for expert-based decision-support studies.

4.1. Structuring phase: Nominal Group Technique

The first session with the respective experts lasted about an hour and was held remotely (*i.e.*, via *Teams*). Initially, there was a brief introduction of each expert, followed by an overview of the study's subject and the methodology to be applied (*i.e.*, NGT). Next, the following trigger question was posed to stimulate brainstorming and drive the development of the analysis system: *"Based on your values and professional experience, suggest one or two initiatives or actions that would better integrate the elderly into the Age of AI"*. Participants were then informed about the expectations for the session, with the goal of identifying the most relevant criteria based on their individual perceptions.

To facilitate the process, they were given time to reflect on the proposed question. After this reflection, each expert was invited to share their ideas with the group in an orderly manner, explaining the importance of their contributions, without allowing for debates at this early stage. This format ensured that all participants had the opportunity to present their ideas without interference, preventing any one member from influencing the others. Once all the opinions had been shared, the debate stage began, during which the experts discussed the proposals with the aim of reaching a consensus, adjusting, complementing or excluding some of them.

Based on the consensus of the group, several ideas were identified. However, the group decided that it would be more beneficial to group these ideas into nine clusters, specifically: (1) *Mitigating social isolation* (*e.g.*, creating a humanoid robot that is empathetic, patient, creative and listens to the elderly; creating a digital persona; developing text-to-speech and speech-to-text technologies); (2) *Detecting, monitoring and responding to danger and cyber threats* (*e.g.*, in situations such as heart attacks, blood pressure issues, assaults, falls and fraud and installing devices or cameras to help monitor the elderly); (3) Supporting *the elderly to increase autonomy* (*e.g.*, developing appointment reminders for medication, drinking water, helping with cooking, cleaning the house and developing interfaces to create an adapted version for the elderly); (4) Supporting *the education of the elderly* (*e.g.*, in cognitive impact, by helping to study certain subjects such as 21st-century literature, keeping up with the news more quickly and offering voice workshops like learning to knit); (5) *Improving* support *devices for the elderly using AI* (*e.g.*, hearing aids, adapting the decibels to the elderly person's hearing issues and diabetes control); (6) *Increasing AI literacy among the elderly and those around them* (*e.g.*, providing more information to the elderly and their families about what technology is, its benefits and disadvantages and offering training actions to better integrate technology into their daily lives); (7) *Interaction between the elderly and technology* (*e.g.*, creating temporary initiatives to enable interaction between the elderly and technology through educational games and conversations); (8) *Robots that improve mobility and physical exercise* (*e.g.*, developing a physiotherapist robot to correct posture, guide specific exercises, tell them when to get up or rest and improve mobility); and (9) *Combating disinformation* (*e.g.*, fighting fake news on social networks and websites using AI). The criteria identified in the first session, using the NGT technique, allowed for the construction of a table to provide the decision-makers with a clearer and more organized view of the criteria identified by the group (see Table 1).

Table 1 presents the experience and knowledge of the experts chosen for the first group work session on the topic under study. It is worth noting that the nine clusters emerged organically from the structured negotiations and collective deliberations among the expert panel members, reflecting their professional judgments and domain-specific experience in innovation, AI and elderly-focused initiatives. This constructivist, participatory approach ensures that the clusters are contextually grounded and directly relevant to the practical challenges and decision-making realities in aging technology research. Rather than imposing predefined categories from the literature, this method allows for a nuanced, practitioner-informed structuring of the problem, capturing interdependencies and subtleties that may be overlooked in strictly literature-driven frameworks (cf. Bell and Morse, 2013; Çipi et al., 2026; Gil et al., 2026; Vaz-Patto et al., 2024). Consequently, the resulting nine clusters offer conceptual coherence and strong contextual relevance, aligning with the decision-makers' insights while maintaining strong relevance to the elderly-AI domain. Although there is an inherent degree of subjectivity in this process, as it relies on the experts' perspectives regarding the posed question, it can be reasonably concluded that the information gathered provides a clearer understanding of the criteria influencing initiatives aimed at better integrating the elderly into the AI era. Finally, after validating the clusters, the DEMATEL method was applied in a neutrosophic environment, as discussed in the next section.

Table 1
Identification of the *Clusters* formulated in the first session.

CLUSTERS	
C1	Mitigating social isolation
C2	Detecting, monitoring and responding to situations of danger and cyber-danger
C3	Supporting the elderly to increase their autonomy
C4	Supporting the education of the elderly
C5	Improving support devices for the elderly with the use of AI
C6	Increasing AI literacy among the elderly and those around them
C7	Interaction in activities between the elderly and technology
C8	Robot that improves mobility and physical exercise
C9	Combating disinformation

4.2. Evaluation phase: Neutrosophic logic and DEMATEL

The purpose of the second session was to conduct a more detailed analysis of the initiatives gathered during the previous session, continuing the evaluation phase with the application of the DEMATEL method in a neutrosophic environment. The DEMATEL method in this context allows for the representation of quantitative data in the study, ensuring that the influence of each criterion included in the analysis system is accurately determined. The session lasted one and a half hours and was conducted online via *Teams*. The main goal was to complete an influence matrix for the clusters identified in the previous session, enabling the analysis of the cause-and-effect relationships among them. The session began with a brief overview of the DEMATEL method and neutrosophic logic.

To facilitate the decision-makers' assessment of the degree of influence between criteria, a DEMATEL scale of 0 to 4 was used (*i.e.*, 0 = "no influence"; 1 = "low influence"; 2 = "medium influence"; 3 = "high influence"; and 4 = "very high influence"). Additionally, neutrosophic logic was applied, where experts expressed the probabilities, defined as percentages, of the evaluations being: true (*T*); indeterminate (*I*); or false (*F*). In other words, each cell in the matrix was assigned an *x*-value (*T*, *I*, *F*), with the sum of the neutrosophic values not needing to total 100%, thus allowing the experts to provide more nuanced and realistic opinions. Based on the clusters identified after the first session (see Table 1), the decision-makers filled in the matrix shown in Table 2, which includes the neutrosophic values assigned by the panel during the second group work session.

After the conclusion of the second session, the neutrosophic values were processed. This step ensured that the subjective evaluations from experts were quantitatively consolidated, facilitating the systematic

Table 2
Matrix of value-neutral initiatives.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	-	3 (0.8; 0.2; 0.15)	2.5 (0.7; 0.5; 0.1)	3 (0.8; 0.1; 0.1)	1 (0.7; 0.2; 0.3)	3 (0.7; 0.4; 0.2)	3 (0.6; 0.4; 0.1)	1 (0.7; 0.2; 0.3)	3 (0.8; 0.1; 0.1)
C2	1 (0.8; 0.5; 0.2)	-	3 (0.75; 0.1; 0.3)	0 (0.8; 0.15; 0.2)	0 (0.9; 0.1; 0.2)	1 (0.6; 0.5; 0.4)	0 (0.9; 0.1; 0.2)	0 (0.9; 0.1; 0.2)	1 (0.6; 0.5; 0.4)
C3	1 (0.8; 0.2; 0.2)	0 (0.85; 0.1; 0.1)	-	2 (0.7; 0.25; 0.3)	1 (0.8; 0.3; 0.25)	2 (0.8; 0.1; 0.1)	4 (0.9; 0.1; 0.1)	1 (0.8; 0.3; 0.25)	1 (0.8; 0.3; 0.25)
C4	1 (0.6; 0.4; 0.3)	2 (0.7; 0.2; 0.3)	4 (0.8; 0.1; 0.1)	-	0 (0.9; 0.1; 0.1)	4 (0.9; 0.1; 0.1)	4 (0.9; 0.1; 0.1)	0 (0.8; 0.1; 0.1)	4 (0.9; 0.1; 0.1)
C5	3 (0.8; 0.1; 0.1)	0 (0.9; 0.1; 0.1)	4 (0.8; 0.1; 0.1)	0 (0.9; 0.1; 0.1)	-	0 (0.9; 0.1; 0.1)	0 (0.9; 0.1; 0.1)	0 (0.9; 0.1; 0.1)	0 (0.9; 0.1; 0.1)
C6	4 (0.9; 0.1; 0.1)	4 (0.9; 0.3; 0.1)	4 (0.9; 0.1; 0.1)	4 (0.9; 0.1; 0.1)	0 (0.8; 0.2; 0.1)	-	4 (0.8; 0.1; 0.1)	2 (0.7; 0.2; 0.3)	4 (0.9; 0.05; 0.1)
C7	4 (0.8; 0.2; 0.2)	3 (0.8; 0.1; 0.2)	4 (0.9; 0.1; 0.1)	3 (0.8; 0.2; 0.1)	1 (0.7; 0.2; 0.3)	2 (0.7; 0.2; 0.2)	-	2 (0.7; 0.2; 0.2)	2 (0.7; 0.2; 0.2)
C8	1 (0.7; 0.3; 0.3)	0 (0.9; 0.1; 0.1)	3 (0.8; 0.1; 0.2)	0 (0.9; 0.1; 0.1)	0 (0.9; 0.1; 0.1)	0 (0.9; 0.1; 0.1)	3 (0.9; 0.1; 0.2)	-	0 (0.9; 0.1; 0.1)
C9	3 (0.7; 0.3; 0.3)	4 (0.8; 0.1; 0.2)	3 (0.8; 0.2; 0.2)	4 (0.9; 0.1; 0.1)	0 (0.9; 0.1; 0.1)	3 (0.8; 0.2; 0.2)	3 (0.8; 0.1; 0.1)	0 (0.9; 0.1; 0.1)	-

Note: C = cluster.

application of the DEMATEL method. In practical terms, these values were combined to generate the initial data required for the analysis. The calculations were performed using Equations (1) and (2) (see Section 3). The crispification process and the resulting values are shown in Table 3.

It is important to note that the crispification process maintains consistency with the scale used in DEMATEL and reflects the uncertainty captured by the original neutrosophic inputs. The denominator condition $S = 1$ confirms the proper normalization of the crispified values. The initial direct influence matrix was then completed (Table 4), incorporating the final crisp values. This matrix represents the quantified influence of each cluster on the others, forming the basis for the subsequent steps of the DEMATEL method. *Steps 2* to *6* of the DEMATEL method were applied as described in Section 3.3, including normalization, computation of total influence and identification of key relationships.

Beyond its computational role, Table 4 already reveals an emerging structural pattern within the system. In particular, clusters associated with capability-building and interaction (*e.g.*, C6 and C7) display consistently higher outgoing influence values, suggesting that the effectiveness of AI-based initiatives in ageing contexts is less dependent on isolated technological solutions and more on enabling conditions that support their use. From a theoretical perspective, this aligns with socio-technical and capability-based views of innovation, which emphasize that technology adoption is contingent upon users' skills, trust and contextual readiness rather than mere availability of technological artefacts. Table 5 presents the intermediate calculations, based on Equations (4) and (5) outlined in Section 3. These calculations are essential for normalizing the initial direct influence matrix (Step 2), as shown in Table 6.

The matrices *I*, *I-X* and *(I-X)-1*, presented in Table 7, were crucial for deriving the total influence matrix *T*, also shown in this table, which was computed using Equation (6) (see Section 3). Matrix *T* captures both direct and indirect influences among clusters, providing a comprehensive view of interdependencies within the system. It enables visualization and interpretation of the relationships between the criteria, with the sums in the row (*R*) indicating the total influence exerted by a cluster and the sums in the column (*C*) indicating the total influence received by a cluster.

Matrix *T* provides more than a mapping of interdependencies. It reveals the underlying logic governing the system. The prominence of C6 (*i.e.*, AI literacy) as the main driving factor suggests that digital inclusion in later life is fundamentally a knowledge- and capability-driven process. This finding challenges more technology-centric narratives often present in the AI policy discourse, where emphasis is placed on device development (*e.g.*, C5) rather than on user empowerment. Moreover, the strong influence flows toward clusters such as autonomy (C3) indicate that desired outcomes in the Silver Economy (*e.g.*, independent living) are not direct consequences of technological deployment, but rather emergent properties of a broader ecosystem of interactions.

Analyzing the *R* and *C* vectors allows for the identification of clusters with the highest driving power and the most affected clusters. For instance, C6—*Increasing AI literacy in the elderly and those around them*—exerts the greatest influence on other clusters ($R = 2.3606$), whereas C3—Supporting *the elderly to increase autonomy*—is the most influenced ($C = 2.2450$). This result has important implications when interpreted within the context of the Silver Economy. Specifically, it reinforces the notion that economic and social value creation in ageing societies depends not only on technological innovation but also on the capacity of older adults to meaningfully engage with such innovations. In this sense, AI literacy (C6) can be seen as a foundational enabler of participation, inclusion and co-creation, which are central pillars of the Silver Economy narrative.

A key part of this process is defining the threshold value (α), which is calculated from the average of the values in the *T* matrix presented in

Table 3
Neutrosophic crispification.

	Relationship under Analysis	DEMATEL scale (x)	Neutrosophic values (T, I, F)			Neutrosophic Crispification		
			T	I	F	Crispification Formula Numerator	Weight w Crispified	Final value in the matrix
MATRIX OF INITIATIVES	C1-C2	3.0	0.80	0.20	0.15	0.81516	0.01383	2.44547
	C1-C3	2.5	0.70	0.50	0.10	0.65843	0.01117	1.64609
	C1-C4	3.0	0.80	0.10	0.10	0.85858	0.01457	2.57574
	C1-C5	1.0	0.70	0.20	0.30	0.72920	0.01237	0.72920
	C1-C6	3.0	0.70	0.40	0.20	0.68909	0.01169	2.06726
	C1-C7	3.0	0.60	0.40	0.10	0.66834	0.01134	2.00501
	C1-C8	1.0	0.70	0.20	0.30	0.72920	0.01237	0.72920
	C1-C9	3.0	0.80	0.10	0.10	0.85858	0.01457	2.57574
	C2-C1	1.0	0.80	0.50	0.20	0.66834	0.01134	0.66834
	C2-C3	3.0	0.75	0.10	0.30	0.76726	0.01302	2.30179
	C2-C4	0.0	0.80	0.15	0.20	0.81516	0.01383	0.00000
	C2-C5	0.0	0.90	0.10	0.20	0.85858	0.01457	0.00000
	C2-C6	1.0	0.60	0.50	0.40	0.56411	0.00957	0.56411
	C2-C7	0.0	0.90	0.10	0.20	0.85858	0.01457	0.00000
	C2-C8	0.0	0.90	0.10	0.20	0.85858	0.01457	0.00000
	C2-C9	1.0	0.60	0.50	0.40	0.56411	0.00957	0.56411
	C3-C1	1.0	0.80	0.20	0.20	0.80000	0.01358	0.80000
	C3-C2	0.0	0.85	0.10	0.10	0.88098	0.01495	0.00000
	C3-C4	2.0	0.70	0.25	0.30	0.71569	0.01215	1.43138
	C3-C5	1.0	0.80	0.30	0.25	0.74669	0.01267	0.74669
	C3-C6	2.0	0.80	0.10	0.10	0.85858	0.01457	1.71716
	C3-C7	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C3-C8	1.0	0.80	0.30	0.25	0.74669	0.01267	0.74669
	C3-C9	1.0	0.80	0.30	0.25	0.74669	0.01267	0.74669
	C4-C1	1.0	0.60	0.40	0.30	0.63032	0.01070	0.63032
	C4-C2	2.0	0.70	0.20	0.30	0.72920	0.01237	1.45840
	C4-C3	4.0	0.80	0.10	0.10	0.85858	0.01457	3.43431
	C4-C5	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C4-C6	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C4-C7	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C4-C8	0.0	0.80	0.10	0.10	0.85858	0.01457	0.00000
	C4-C9	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C5-C1	3.0	0.80	0.10	0.10	0.85858	0.01457	2.57574
	C5-C2	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C5-C3	4.0	0.80	0.10	0.10	0.85858	0.01457	3.43431
	C5-C4	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C5-C6	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C5-C7	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C5-C8	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C5-C9	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C6-C1	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C6-C2	4.0	0.90	0.30	0.10	0.80851	0.01372	3.23406
	C6-C3	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C6-C4	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C6-C5	0.0	0.80	0.20	0.10	0.82679	0.01403	0.00000
	C6-C7	4.0	0.80	0.10	0.10	0.85858	0.01457	3.43431
	C6-C8	2.0	0.70	0.20	0.30	0.72920	0.01237	1.45840
	C6-C9	4.0	0.90	0.05	0.10	0.91340	0.01550	3.65359
	C7-C1	4.0	0.80	0.20	0.20	0.80000	0.01358	3.20000
	C7-C2	3.0	0.80	0.10	0.20	0.82679	0.01403	2.48038
	C7-C3	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C7-C4	3.0	0.80	0.20	0.10	0.82679	0.01403	2.48038
	C7-C5	1.0	0.70	0.20	0.30	0.72920	0.01237	0.72920
	C7-C6	2.0	0.70	0.20	0.20	0.76195	0.01293	1.52390
	C7-C8	2.0	0.70	0.20	0.20	0.76195	0.01293	1.52390
	C7-C9	2.0	0.70	0.20	0.20	0.76195	0.01293	1.52390
	C8-C1	1.0	0.70	0.30	0.30	0.70000	0.01188	0.70000
	C8-C2	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C8-C3	3.0	0.80	0.10	0.20	0.82679	0.01403	2.48038
	C8-C4	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C8-C5	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C8-C6	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C8-C7	3.0	0.90	0.10	0.20	0.85858	0.01457	2.57574
	C8-C9	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C9-C1	3.0	0.70	0.30	0.30	0.70000	0.01188	2.10000
	C9-C2	4.0	0.80	0.10	0.20	0.82679	0.01403	3.30718
	C9-C3	3.0	0.80	0.20	0.20	0.80000	0.01358	2.40000
	C9-C4	4.0	0.90	0.10	0.10	0.90000	0.01527	3.60000
	C9-C5	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000
	C9-C6	3.0	0.80	0.20	0.20	0.80000	0.01358	2.40000
	C9-C7	3.0	0.80	0.10	0.10	0.85858	0.01457	2.57574
	C9-C8	0.0	0.90	0.10	0.10	0.90000	0.01527	0.00000

(*continued on next page*)

Table 3 (*continued*)

	Relationship under Analysis	DEMATEL scale (x)	Neutrosophic values (T, I, F)			Neutrosophic Crispification		
			T	I	F	Crispification Formula Numerator	Weight w Crispified	Final value in the matrix
Since $S = 1$, the conditions of the formula are respected.					Crispification Formula Denominator	**58.92630087**	**1**	

Table 4
Initial direct influence matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	SUM
C1	0.0	2.4	1.6	2.6	0.7	2.1	2.0	0.7	2.6	14.8
C2	0.7	0.0	2.3	0.0	0.0	0.6	0.0	0.0	0.6	4.1
C3	0.8	0.0	0.0	1.4	0.7	1.7	3.6	0.7	0.7	9.8
C4	0.6	1.5	3.4	0.0	0.0	3.6	3.6	0.0	3.6	16.3
C5	2.6	0.0	3.4	0.0	0.0	0.0	0.0	0.0	0.0	6.0
C6	3.6	3.2	3.6	3.6	0.0	0.0	3.4	1.5	3.7	22.6
C7	3.2	2.5	3.6	2.5	0.7	1.5	0.0	1.5	1.5	17.1
C8	0.7	0.0	2.5	0.0	0.0	0.0	2.6	0.0	0.0	5.8
C9	2.1	3.3	2.4	3.6	0.0	2.4	2.6	0.0	0.0	16.4
SUM	14.3	12.9	22.9	13.7	2.2	11.9	17.8	4.5	12.7	

Note: Ci = cluster i.

Table 5
Intermediate calculations.

Max	22.9	22.6
1/max	0.043674	0.044286
1/s	**0.043674**	

Table 7 (see Equation (9)). This threshold ($\alpha = 0.1504$) distinguishes significantly from insignificant influences, guiding the construction of the DEMATEL diagram of cause-and-effect relationships (*i.e.*, the IRM). Cells above α are considered highly influential (highlighted in green), while cells below α are less relevant (highlighted in red), enabling a clear visual representation of the cause-and-effect relationships. Additionally, the values of R + C and R–C, shown in Table 8, must also be considered. Fig. 2 illustrates the IRM, displaying the distribution of the nine clusters along the corresponding axes and the cause-and-effect relationships that have been established.

Considering that R + C represents the overall relevance of each cluster, factoring in both the influence it exerts and the influence it receives, the order of importance of the clusters is determined by the horizontal axis (*i.e.*, R + C). The highest value on this axis corresponds to a greater impact on the final system. In this context, C6—*Increasing AI literacy in the elderly and all those involved*—emerges as the most important cluster for the study (3.6617). In contrast, C5—*Improving* support *devices for the elderly using AI*—is the least relevant, with an R + C value of 0.8909.

Regarding R–C, this metric distinguishes clusters into cause groups (*i.e.*, positive values) or effect groups (*i.e.*, negative values), based on their position relative to the vertical axis of the diagram. As seen in Fig. 2, clusters C1, C4, C5, C6, C8 and C9 belong to the cause group, with C6 and C9 standing out as the clusters that most influence the others. The receiving factors (*i.e.*, those influenced by others and with a weaker relationship with them) are represented by negative values in R–C. These are clusters C2, C3 and C7, with C2 and C3—*Detecting, monitoring and responding to situations of danger and cyber-danger* and Supporting *the elderly to increase autonomy*—being the most influenced. In other words, these are the clusters most impacted by the system (see Fig. 2).

By analyzing the cause-effect diagram (see Fig. 2), it is possible to conclude the order of relevance of the criteria in the system: C6 > C7 > C4 > C3 > C9 > C1 > C2 > C8 > C5. Additionally, the analysis reveals that (1) C1, C4, C6 and C9 are driving factors (*i.e.*, they have a positive R–C value and have a strong impact on others): (QII) (2) C5 and C8 are independent factors (*i.e.*, they have low R + C values and have a weak impact on the system); (QIII); and (3) C2, C3 and C7 are impact factors (*i.e.*, they have negative R–C values and are the most influenced) (QIV), depending on their position in the diagram.

A more nuanced reading of the R–C results also highlights important tensions within the system. For example, while clusters such as monitoring and risk detection (C2) are essential for safety, their position as highly influenced factors suggests that their effectiveness depends on upstream conditions such as literacy and interaction. This raises potential trade-offs between protection and autonomy, as well as ethical concerns related to surveillance and data use. Similarly, the relatively low prominence of technology-focused solutions (C5) suggests that investments in advanced AI devices may yield limited systemic impact if not accompanied by parallel efforts in education and engagement. This finding challenges supply-driven innovation logics and supports more human-centered approaches to AI deployment.

Table 6
Normalized direct influence matrix or X-Matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	0.0000	0.1068	0.0719	0.1125	0.0318	0.0903	0.0876	0.0318	0.1125
C2	0.0292	0.0000	0.1005	0.0000	0.0000	0.0246	0.0000	0.0000	0.0246
C3	0.0349	0.0000	0.0000	0.0625	0.0326	0.0750	0.1572	0.0326	0.0326
C4	0.0275	0.0637	0.1500	0.0000	0.0000	0.1572	0.1572	0.0000	0.1572
C5	0.1125	0.0000	0.1500	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C6	0.1572	0.1412	0.1572	0.1572	0.0000	0.0000	0.1500	0.0637	0.1596
C7	0.1398	0.1083	0.1572	0.1083	0.0318	0.0666	0.0000	0.0666	0.0666
C8	0.0306	0.0000	0.1083	0.0000	0.0000	0.0000	0.1125	0.0000	0.0000
C9	0.0917	0.1444	0.1048	0.1572	0.0000	0.1048	0.1125	0.0000	0.0000

Note: Ci = cluster i.

Table 7
Intermediate calculation and matrix *T*.

I

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C2	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C3	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C4	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000
C5	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
C6	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000
C7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000
C8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
C9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

Note: Ci = cluster i.

I – X

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1.0000	−0.1068	−0.0719	−0.1125	−0.0318	−0.0903	−0.0876	−0.0318	−0.1125
C2	−0.0292	1.0000	−0.1005	0.0000	0.0000	−0.0246	0.0000	0.0000	−0.0246
C3	−0.0349	0.0000	1.0000	−0.0625	−0.0326	−0.0750	−0.1572	−0.0326	−0.0326
C4	−0.0275	−0.0637	−0.1500	1.0000	0.0000	−0.1572	−0.1572	0.0000	−0.1572
C5	−0.1125	0.0000	−0.1500	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000
C6	−0.1572	−0.1412	−0.1572	−0.1572	0.0000	1.0000	−0.1500	−0.0637	−0.1596
C7	−0.1398	−0.1083	−0.1572	−0.1083	−0.0318	−0.0666	1.0000	−0.0666	−0.0666
C8	−0.0306	0.0000	−0.1083	0.0000	0.0000	0.0000	−0.1125	1.0000	0.0000
C9	−0.0917	−0.1444	−0.1048	−0.1572	0.0000	−0.1048	−0.1125	0.0000	1.0000

Note: Ci = cluster i.

$(I - X)^{-1}$

	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1.1141	0.2198	0.2444	0.2326	0.0510	0.2000	0.2357	0.0719	0.2229
C2	0.0578	1.0296	0.1381	0.0377	0.0079	0.0558	0.0487	0.0131	0.0544
C3	0.1250	0.0899	1.1330	0.1555	0.0491	0.1525	0.2574	0.0678	0.1191
C4	0.1725	0.2102	0.3457	1.1666	0.0274	0.2824	0.3339	0.0570	0.2866
C5	0.1441	0.0382	0.1974	0.0495	1.0131	0.0454	0.0651	0.0183	0.0429
C6	0.3050	0.3058	0.3972	0.3340	0.0344	1.1753	0.3676	0.1220	0.3193
C7	0.2442	0.2213	0.3281	0.2337	0.0558	0.1865	1.1710	0.1083	0.1881
C8	0.0751	0.0414	0.1671	0.0502	0.0132	0.0436	0.1668	1.0217	0.0409
C9	0.2102	0.2683	0.2940	0.2878	0.0251	0.2310	0.2784	0.0495	1.1405

Note: Ci = cluster i.

Matrix *T*

	C1	C2	C3	C4	C5	C6	C7	C8	C9	*R*
C1	0.1141	0.2198	0.2444	0.2326	0.0510	0.2000	0.2357	0.0719	0.2229	1.5922
C2	0.0578	0.0296	0.1381	0.0377	0.0079	0.0558	0.0487	0.0131	0.0544	0.4431
C3	0.1250	0.0899	0.1330	0.1555	0.0491	0.1525	0.2574	0.0678	0.1191	1.1494
C4	0.1725	0.2102	0.3457	0.1666	0.0274	0.2824	0.3339	0.0570	0.2866	1.8822
C5	0.1441	0.0382	0.1974	0.0495	0.0131	0.0454	0.0651	0.0183	0.0429	0.6140
C6	0.3050	0.3058	0.3972	0.3340	0.0344	0.1753	0.3676	0.1220	0.3193	2.3606
C7	0.2442	0.2213	0.3281	0.2337	0.0558	0.1865	0.1710	0.1083	0.1881	1.7370
C8	0.0751	0.0414	0.1671	0.0502	0.0132	0.0436	0.1668	0.0217	0.0409	0.6200
C9	0.2102	0.2683	0.2940	0.2878	0.0251	0.2310	0.2784	0.0495	0.1405	1.7848
C	1.4479	1.4244	2.2450	1.5477	0.2769	1.3724	1.9247	0.5295	1.4147	12.1833

Note: Ci = cluster i; *R* = rows vector; *C* = columns vector.

These findings can also be interpreted in light of contrasting perspectives in the literature. While some studies advocate the transformative potential of AI to enhance autonomy and well-being among older adults, others caution that such benefits may be unevenly distributed due to persistent digital divides and socio-technical barriers. The present results support a more balanced view, suggesting that AI can indeed contribute to inclusion, but only when embedded within supportive ecosystems that address literacy, trust and accessibility concerns. Importantly, several sensitivity and robustness assessments were embedded throughout the model-building process and discussed with the panel members. As Belton and Stewart (2002) note, the interactive and iterative nature of PSMs and MCDA methods allows decision-makers to dynamically explore the consequences of input changes. These real-time explorations provided immediate feedback on how variations affected the model's outcomes, thereby reinforcing the model's reliability and transparency.

4.3. Consolidation, discussion and recommendations

After completing the structuring and evaluation phases, the final stage of the MCDA approach—*i.e.*, the consolidation and recommendations phase—was carried out. This session was held online via *Teams* and was attended by the Head of IT at the National Innovation Agency (ANI in Portuguese). ANI, under the supervision of the Portuguese Ministry of the Economy and the Ministry of Education, Science and Innovation, serves as a platform that ensures the alignment of research and development (R&D), innovation and technology-based entrepreneurship policies in the areas of science and the economy.

The session lasted 45 min and followed this structure: (1) an overview of the study, highlighting the main concepts and the methodologies applied; (2) a demonstration of the applicability of the techniques, specifically NGT and DEMATEL in a neutrosophic environment, alongside the respective results; (3) an analysis of the results, discussing the system's advantages and limitations; (4) an assessment of the system's potential applicability in a real-world context; and (5) suggestions for improvement and recommendations.

After presenting the framework, methodologies and results, the expert noted that he was unfamiliar with the applied methodologies. However, he acknowledged that: *"they are interesting methods for gathering information* […] *the combination of the methods and the work presented is very well structured and well justified, where the three interconnected methods present an advantage for the analysis system"* (in his words).

The expert agreed with the results, stating that: *"I must agree. It is a descriptive system, a very analytical system and very logical"* (in his words). However, he highlighted that: *"I don't consider it a statistical model and the results could easily be different, since it is based on the opinion and professional experience of experts"* (again in his words). In response, it was explained that these methodologies are not statistical in nature but belong to the realm of operational research/management science (OR/MS). It was also emphasized that despite the subjective component, these methods are scientific approaches widely recognized and used in organizations (Belton and Stewart, 2002; Gil et al., 2026; Vaz-Patto et al., 2024).

Regarding practical applicability, the expert noted that operationalization is context-dependent and not straightforward, given the breadth of the problem. Nevertheless, he suggested that: *"universities could adopt this system to develop projects for European or social funds.* […] *large tech companies* […] *such as Google and Microsoft"* could integrate it under a social responsibility logic.

When asked about the concrete benefits the elderly could derive from having a RA, he quickly responded: "support*, comfort, physical and emotional help"* (citing the interviewee's words). He further suggested that automation in data collection and processing could reduce human error and improve reliability. These functions were particularly valued due to their direct contribution to autonomy and daily health

management.

Following the consolidation and presentation of the results, further discussions were held with a group of five elderly individuals, all aged around 90 years, to gain deeper insights into their perceptions and potential acceptance of the proposed technological solution. These interviews, conducted in person, focused on understanding their openness to adopting a RA and the potential benefits they saw in integrating such a system into their daily lives. During the discussion, four out of the five elderly participants expressed a strong willingness to adopt a RA, particularly for practical purposes such as receiving medical advice, managing medication schedules and assisting with physical tasks like operating a wheelchair. They highlighted the potential convenience and support that a RA could provide, especially in helping them manage their health and ensuring they adhered to important routines, such as taking pills at the correct time. These functions were particularly valued due to their direct impact on autonomy and daily health management.

The elderly participants also appreciated the idea of maintaining an ongoing relationship with a RA, viewing it *"not just as a tool for specific tasks but as a form of companionship"* (citing one of the interviewees). The ability to interact with the system for various needs, including emotional support, was seen as a significant benefit. This was particularly important for those who, due to age-related limitations, might experience feelings of isolation or difficulty with physical tasks. Overall, responses indicated strong acceptance, conditional on usability and personalization. Most of the participants expressed interest in further exploring such solutions. These insights emphasize the potential for RAs to enhance the lives of elderly individuals, offering them not only practical assistance but also emotional comfort in their daily routines.

Critically engaging with alternative perspectives further enhances our understanding of these findings. While several studies emphasize the potential of AI-based tools such as RAs to promote inclusion and autonomy in later life (cf. Cruces et al., 2024; José et al., 2024), other research highlights persistent barriers and socio-technical inequalities that may limit these benefits (cf. Szewczyk, 2018; Weck et al., 2022a). Factors such as digital literacy, perceived risk, algorithmic transparency and trust can produce ambivalent or even contradictory outcomes, where AI solutions intended to empower older adults may inadvertently reinforce exclusion if not carefully tailored to users' cognitive, emotional and ethical needs. This highlights the need for co-design approaches involving older adults, ensuring alignment with user values and capabilities. Nevertheless, it is worth noting that this study is process-oriented and while it does present some inherent limitations—such as the subjectivity of expert opinions and the specific focus on the Portuguese context—the outcomes can be adapted and applied with significant advantages to different contexts. The use of NGT, combined with the DEMATEL method in a neutrosophic environment, provides a robust framework for tackling complex, multi-dimensional problems, especially in areas such as integrating the elderly into the RA ecosystem.

The applicability of the system is flexible, as it can be tailored to the unique needs of other countries or regions, with adjustments made to reflect local conditions, resources and priorities. The system's design emphasizes process improvement over representativeness, allowing for iterative updates and refinements based on evolving contexts and data (Bell and Morse, 2013). While limitations regarding the subjectivity of expert opinions are acknowledged, the methods used are well-established in OR/MS and are proven to provide meaningful, actionable insights in decision-making processes.

Given these factors, the system holds substantial promise for being adapted to other sectors and geographical contexts. Its process-driven approach ensures that it can remain relevant and valuable across different settings, continuously evolving to meet the specific needs and challenges of diverse stakeholders. The flexibility of this system positions it as a valuable tool for addressing complex social and technological challenges, not just in the integration of RAs into elderly care but also in broader applications within innovation, technology and entrepreneurship.

Building on the insights derived from the empirical analysis, the proposed decision-support system notably differs from and advances existing multi-criteria frameworks applied in the fields of AI policy and gerontology. Specifically, it distinguishes itself in three main ways. First, it adopts a constructivist and participatory orientation, combining NGT, DEMATEL and neutrosophic logic to capture expert knowledge interactively and transparently. This contrasts with many existing models in AI policy or gerontology, which typically rely on pre-defined criteria or quantitative datasets and therefore lack a process-oriented perspective (cf. José et al., 2024; Weck et al., 2022c). Second, by operating within a neutrosophic environment, the model explicitly accommodates the uncertainty and indeterminacy inherent in expert judgments—an aspect often neglected in traditional multi-criteria analyses (cf. Gil et al., 2026). Third, the integrated framework is designed to map the causal architecture of barriers and opportunities that affect the digital inclusion of the elderly and the adoption of RAs. This causal orientation supports both diagnostic and prescriptive insights, offering policymakers and practitioners a structured mechanism to prioritize interventions. Together, these features result in a system that moves beyond descriptive evaluation toward interactive policy learning and decision support, aligning with current calls in the AI and aging literature for more adaptive and human-centered analytical tools (cf. José et al., 2024).

Notably, the findings can be positioned in relation to established technology adoption frameworks frequently used in AI and elderly-focused research, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). While these frameworks primarily emphasize individual-level determinants of adoption—such as perceived usefulness, ease of use and behavioral intention—the results of this study extend these perspectives by revealing the systemic, multi-level conditions that shape such perceptions among older adults using RAs. The cause-and-effect structure identified through the proposed framework shows that factors related to ethics, trust, accessibility, governance and digital literacy operate as upstream drivers that condition individual acceptance and sustained use of AI-based RAs. In this sense, the results complement rather than contradict TAM and UTAUT, by embedding individual attitudes within a broader socio-technical and policy context. This constructivist, systems-oriented perspective offers a richer understanding of elderly-AI adoption, capturing interdependencies and feedback effects that are typically overlooked in linear adoption frameworks, and providing decision-makers with actionable insights that go beyond individual acceptance toward long-term inclusion and societal impact.

From a holistic perspective, the results provide clear managerial and policy-relevant insights for the design and governance of AI-based RAs in aging societies. The identification of cause clusters highlights leverage points where interventions are likely to generate systemic effects. For example, the prominence of C6 (*i.e.*, AI literacy) as a driving factor suggests that interventions in training and education are not merely complementary but foundational, with cascading effects across the system. Consequently, policymakers should prioritize targeted interventions such as publicly funded digital literacy programs, certification frameworks for trustworthy AI systems and regulatory mechanisms ensuring transparency and informed consent.

Furthermore, from a managerial perspective, the findings indicate that technology developers and service providers should adopt human-centered and inclusive design principles, ensuring transparency, explainability and ease of use for elderly users. For public authorities, the framework supports the formulation of coordinated policies that align technological innovation with social inclusion goals, including investment in training programs, regulatory safeguards for data protection and mechanisms to promote informed consent. Dependent clusters, in turn, signal areas where supportive measures and complementary policies are required to reinforce adoption and long-term impact.

From an implementation perspective, based on the identified causal

Table 8
Inter-Cluster interactions.

	R	C	R + C	R–C
C1	1.5922	1.4479	3.0401	0.1443
C2	0.4431	1.4244	1.8676	−0.9813
C3	1.1494	2.2450	3.3944	−1.0956
C4	1.8822	1.5477	3.4299	0.3345
C5	0.6140	0.2769	0.8909	0.3371
C6	2.3606	1.3724	3.7330	0.9881
C7	1.7370	1.9247	3.6617	−0.1877
C8	0.6200	0.5295	1.1495	0.0904
C9	1.7848	1.4147	3.1995	0.3701

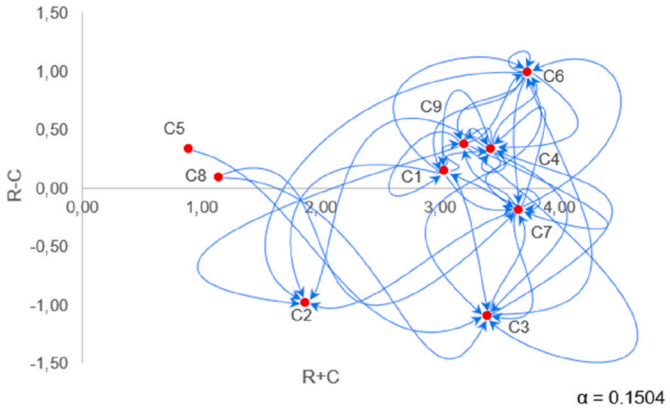


Fig. 2. Influence map.

structure derived from the DEMATEL analysis, the proposed framework can be operationalized through a three-step pathway: (1) Diagnosis, where stakeholders (*e.g.*, policymakers, firms or service providers) map their specific context using the identified clusters and construct an influence map based on the DEMATEL structure; (2) Prioritization, where interventions are ranked using the driving power (R–C) values, enabling decision-makers to identify high-leverage factors (*e.g.*, AI literacy, trust and interaction) and allocate resources accordingly; and (3) Intervention design and monitoring, where targeted actions (*e.g.*, digital literacy training programs, user interface redesign, certification schemes for trustworthy AI systems) are implemented, accompanied by performance indicators and iterative feedback mechanisms to continuously refine policies and system design.

Overall, the proposed decision-support system functions as a practical learning and prioritization tool, enabling decision-makers to translate complex cause-and-effect structures into actionable strategies that enhance autonomy, well-being and social participation among older adults using RAs.

5. Conclusion

This study aimed to answer the following research questions: What are the key barriers and opportunities for the elderly in adopting AI-driven technologies like RAs? How can the cause-and-effect relationships between these key barriers and opportunities be identified and analyzed? How can participatory methods contribute to designing more inclusive AI solutions for the elderly? The outcomes address these questions by offering a process-oriented, multi-criteria decision support system to facilitate the integration of elderly individuals into the digital landscape through the adoption of RAs. By combining NGT and DEMATEL techniques within a neutrosophic framework, the study provides a novel approach that captures both objective and subjective elements, offering a nuanced understanding of challenges and solutions in this context.

The novelty of this study lies in its methodological approach, which merges established decision-making techniques with neutrosophic logic, enabling the capture of uncertainty and indeterminacy inherent in human reasoning. Additionally, the study's constructivist approach, involving active participation from experts and interviews with the elderly, provides deeper insights into the acceptance and perception of AI-based RAs, addressing end users' readiness and concerns.

Theoretical contributions of this study include the application of an MCDA system to a relatively unexplored context—*i.e.*, AI-based RAs for the elderly—extending knowledge in decision support systems and aging research by accounting for both technological and human factors. In addition, this study extends socio-technical systems and technology adoption frameworks by demonstrating how elderly inclusion in AI-enabled ecosystems can be modeled through an integrated MCDA approach. By operationalizing trust, usability, autonomy and engagement as causally interrelated constructs, the study bridges the gap between conceptual adoption theories and structured decision-support modeling in complex socio-technical environments.

From a practical perspective, the decision-support framework offers actionable guidance for policymakers and AI developers. Based on the identified cause-and-effect relationships, policymakers can prioritize interventions with the highest systemic impact, such as digital literacy programs, ethical oversight of AI systems and inclusive technology design. For example, a national-level intervention could involve the development of publicly funded "AI literacy for seniors" programs delivered through community centers and healthcare institutions, combined with certification labels for RA systems that meet transparency and usability standards.

The framework further supports stakeholder-specific strategies: regulators can define compliance and data protection standards; technology developers can align product features with elderly needs; and service providers can tailor adoption initiatives to vulnerable subgroups. For AI developers, in particular, the study highlights key design principles: (1) prioritizing accessibility to accommodate varying levels of digital literacy and physical abilities; (2) minimizing cognitive load through clear presentation and avoidance of unnecessary complexity; (3) ensuring simplicity and intuitiveness, with step-by-step guidance and consistent navigation; (4) safeguarding safety and trust via transparent data handling, consent mechanisms and protection of sensitive personal information; and (5) incorporating emotional and social features, such as empathetic responses or socially supportive interactions. As a result, the framework developed also provides a structured implementation logic, enabling stakeholders to move from diagnosis to prioritized intervention and continuous policy learning.

Societally, the study contributes to improving the perception of AI-based RAs among older adults, fostering a more inclusive approach to technological advancement. While context-specific, the framework serves as a flexible learning mechanism, enabling adaptation across different institutional and cultural environments and supporting continuous refinement based on feedback from elderly users and expert stakeholders.

However, the study has some limitations. The reliance on a single expert panel emphasizes the context-dependency of the results and the time-intensive nature of group sessions, particularly for DEMATEL application, posed challenges in terms of participant fatigue and availability. While these limitations constrain the scope, they do not diminish the study's value in offering actionable insights into integrating the elderly into the RA-driven AI era.

Looking forward, several avenues for future research emerge. Replicating the study with different expert panels, applying alternative PSMs or MCDA techniques and conducting cross-cultural or international studies could refine the decision-making system and provide deeper insights into RA adoption among elderly populations. Comparative studies could reveal how social, cultural and technological contexts shape integration strategies and inform global best practices.

In summary, this study provides an integrated MCDA-based decision-support framework that operationalizes socio-technical complexity in

elderly-AI adoption through a constructivist and participatory design. It contributes theoretically by extending socio-technical and technology adoption perspectives, methodologically by integrating NGT, DEMATEL and neutrosophic logic, and practically by offering actionable pathways for policymakers and AI developers to enhance inclusion, autonomy and well-being in aging societies.

CRediT authorship contribution statement

Roxana R. Iordache: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Validation, Visualization, Writing – original draft. **Fernando A.F. Ferreira:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – review & editing. **Neuza C.M.Q.F. Ferreira:** Data curation, Formal analysis, Funding acquisition, Methodology, Validation, Visualization, Writing – review & editing. **Marina Dabić:** Formal analysis, Funding acquisition, Investigation, Resources, Visualization, Writing – review & editing. **João J.M. Ferreira:** Formal analysis, Funding acquisition, Investigation, Resources, Validation, Writing – review & editing.

Declaration of competing interest

The authors of this paper have directly participated in the planning and execution of the study and have read and approved the final version submitted. The contents of this manuscript have not been previously published.

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Data availability

The authors do not have permission to share data.

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