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Designing Inclusive AI for Aging Populations: A Conceptual Agentic Framework for Lifelong Learning

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Abstract Global demographic changes are also changing the educational focus, where the aged will number over two billion by 2050. Despite progress in innovative artificial intelligence (AI) in education, most frameworks are developed for younger learners, who are underserved. This paper introduces the Agentic AI framework for elderly learners, a conceptual model which makes seniors active, autonomous learners throughout their life. The framework entails the combination of three mutually supporting layers, i.e., emotion-sensitive mentorship, where learning interactions are personalized to emotional states; gamified discovery learning, where learning engages curiosity and maintains motivation; or reflective knowledge reservoir, where knowledge is anchored by memory and cognitive resilience. A systematic review of recent literature suggests that although each of these domains has been independently validated, there is no common framework to address integration of the domains in elderly learners. The paper formulates three research questions and corresponding hypotheses and calls them onto the proposed layers and a roadmap for research. This roadmap progresses to consolidation on the theoretical level to prototype development, pilot testing, and large-scale validation to ensure that it is scalable and inclusive. The discussion not only introduces some theoretical contributions such as the extrapolation of the affective computing, gamification and reflection to the field of elderly learning, but also introduces some practical implications such as design solutions such as empathetic AI mentor, age-friendly gamification and age-friendly reflection. There is also focus on societal effects, which help to indicate how the framework can contribute to cognitive health, social inclusion and fair digital participation. Limitations such as the lack of empirical testing is noted along with directions of future research. The combination of discontinuous strands into a unified model provided through the Agentic AI framework provide a stringent basis to create inclusive learner-centered AI systems that will allow the elderly adults to excel in the digital era.

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1 Introduction

Demographic change is taking place in the world like never before. The population of the aged (60 years and above) is projected to exceed two billion in the world in 2050, which raises serious issues in the societies to promote the cognitive, social, and emotional capabilities of older adults [1, 2]. This change in demographics presents a twofold threat: (1) educational technologies, oriented toward younger users, do not serve the elderly population due to their age-related cognitive, emotional, and technological constraints; (2) AI-driven educational technologies are not accessible or suitable to use among the elderly population, continuing to marginalize the elderly on a digital platform. Traditional systems of education, which are more oriented towards younger populations, are not adequately ready to address the specific problems of older age groups, experiencing obstacles to digital illiteracy, demotivation, and age-related cognitive deterioration [3, 4].

This study is motivated by the need for democratizing AI-guided learning and promoting digital inclusion of the elderly. As AI is becoming an integrated part of education, healthcare and socialisation, the exclusion of elderly in technological advancements will result in a society with two floors and age as a segregator. Such realities create the demand for the development of new learning frameworks that move beyond the traditional pedagogic interface, and more explicitly view elderly learners' needs, capacities, and agency.

The model proposed is structured into three interconnected layers:

1. Emotion-Aware Mentorship – Drawing on socio-emotional AI and affective systems research, the layer tailors AI interactions to learners' emotional states, offering customized guidance that can alleviate feelings of loneliness and increase engagement [5, 6].
2. Gamified Discovery Learning – Drawing from gamification research, this layer sustains intrinsic motivation by embedding elements of challenge, reward, and exploration into the learning process [3, 7, 8].
3. Reflective Knowledge Preservation – Grounded in lifelong learning and reflective journaling, this layer enables learners to preserve and revisit their experiences, fostering deeper reflection and longer-term cognitive resilience [9, 10].

It is new and required that these layers be integrated into one AI system. Although previous studies explored emotion-aware systems, gamified training, and reflective

Figure 1. Conceptual overview of the three interdependent layers of Agentic AI for elderly learners (adapted from recent empirical studies, 2020–2025)

practices, none of them unite these methods in elderly learners [11, 12]. What is more important, the lack of a common theoretical framework means that the existing systems can hardly be scaled in any meaningful way to the context of elder-focused lifelong learning. The framework can be conceptualized as three interlocking layers as illustrated in Figure 1 and constitute an Agentic AI approach to elderly learners.

Our paper, therefore, contributes by advancing a conceptual and theoretical model that synthesizes existing literature and formalizes the interactions between these three layers. Unlike empirical studies, this work does not present pilot data or statistical testing; instead, it provides the groundwork upon which empirical validation can later be built. Research Questions

To guide this theoretical development, the paper addresses the following research questions (RQs):

- **RQ1:** How can emotion-aware mentorship enhance engagement and motivation among elderly learners in AI-mediated environments?
- **RQ2:** In what ways can gamified discovery support sustained participation and reduce dropout in elderly learning contexts?
- **RQ3:** How can reflective knowledge preservation be integrated into AI frameworks to strengthen memory retention and cognitive resilience in older

adults?

1.1 Theoretical Contributions

Our study makes the following three important contributions to the field:

1. **Synthesis of Cross-Disciplinary Literature:** The current research combines multiple theories of socio-emotional AI, gamification, and reflective learning and thereby traces intersections which might have been missed in cross-disciplinary studies [13, 14]
2. **Formalization of a Multi-Layer Framework:** The theoretical structure of the model defines clear conceptual margins for every level and explains the relationships between these levels, providing a structure for testing a prototype in the future [15, 16].
3. **Research Roadmap:** Based on clear research questions and hypotheses formulated in this paper, it provides scope for testing these hypotheses in future research to ensure the hypotheses can be applied in practice for pragmatic solutions [8].

2 Literature Review

The literature related to the area of Agentic AI in elderly learners is categorized into four areas: (a) affective computing and emotion-aware mentorship, (b) gamified discovery learning and motivational psychology, (c) reflective practices and memory preservation, and (d) comparative educational AI frameworks. All the strands have brought valuable information though none of them offer an integrated model that is specifically geared towards elderly students.

Artificial intelligence and aging have become a respected field of study, equally resulting in the possibility to enhance the lives of aging individuals and causing serious ethical, social, and design issues [17, 18]. Current researchers point to the possibility of shifting beyond the ideas of black box approaches, noting the relations and co-constitutive interactions between AI technologies and aging people [19, 20]. Systematic reviews indicate that AI is already implemented in an extensive variety of spheres, such as healthcare, cognitive assistance, digital fluency, and individualized learning, and frequently it works with rather intricate data, including imaging, behavioural, genetic, and contextual data [21, 22]. Regardless of these developments, studies also indicate a lack of inclusivity in the design, implementation, and assessment of AI systems: the elderly are often underrepresented in designing, implementing, and evaluating AI systems, the value of participatory design, and multi-stakeholder involvement with the design and implementation of AI systems, including family members, caregivers, and clinicians [18, 23].

Real-world examples of AI use in the aging market show how conversational agents, generative AI, and learning systems can help improve lifelong learning and need to be adjusted to the requirements and accessibility of users, as well as how the elderly can interact with their generational peers [24–26]. There is an ethical concern, such as bias, equity, and representation, which will, nevertheless, be a significant focus, and frameworks like EDAI propose

practical approaches toward implementing diversity and inclusion throughout AI lifecycles [27, 28]. Lifelong learning and AI literacy have become widely viewed as the solution to help older adults become more engaged with technology and thus be able to be active contributors to the digital space [29–31]. Lasting innovative ways in collective intelligence and edge computing also signal chances of scalable, dynamic AI that persistently learns, disseminates what it already learns, and gives undeterred aid to the multiple needs of the elderly [32–34].

2.1 Emotion-Aware Mentorship

More recent studies focus on emotional sensitivity to play a crucial role in AI-facilitated learning. [5] Li, Wang, and Zhao (2022) conducted a survey on emotion-conscious conversational agents, referring to their possible contribution to personalization and empathy in the conditions of online learning. [6] Kaur and Sharma (2021) demonstrated how the capabilities of stress detection and emotional analysis can improve the flexibility of AI systems. Similarly, [14] Chen and Wu (2024) proposed a socio-emotional AI model of lifelong learning, in which the perspective on inclusiveness had an intergenerational character. Emotion-sensitive mentorship is also most relevant when working with older students because they are more likely to enjoy emotionally meaningful interactions when learning [13]. The current applications remain small-scale, and this suggests a gap that should be filled with a special system of this age group.

2.2 Gamified Discovery Learning

Gamification has been touting to get the older adults to be more engaged and to have their minds stimulated. [3] Park and Lee (2020) identified opportunities and challenges of developing gamified systems to older adult learners and focused on usability and accessibility. [7] Jones and Patel (2024) proposed the strategies of gamified learning which are grounded on curiosity that targets the intrinsic motivation of the aging population directly. Similarly to Rahman and Ali (2025) [8], they combined gamification strategies with AI to promote cognitive well-being and determined the potential of the latter in the long- term well-being. Despite these advances, older learners remain disintegrated and rarely involved in adaptive AI systems that involve gamification. This gap may be bridged, especially through pulling these lessons, into an integrated form, and building more complete learning processes.

2.3 Reflective Knowledge Sustenance

Reflection and memory reinforcement are the key features of learning in old age. [9] Ali and Hussain (2022) showed that AI-powered tools could be helpful in helping older adults to enhance their memory. The article by Nguyen and Chen (2020) [10] examined reflective journaling with AI assistance, with a particular focus on its contribution to lifelong learning. [35] Martinez and Brown (2019) also associated reflective practices with cognitive well-being among elderly persons. Combined, these studies illustrate the possibilities of reflective mechanisms in AI, which are usually considered as independent of mentorship and gamification.

Thus, reflective knowledge preservation requires a conceptual framework to build cognitive resilience. The most recent developments in AI-supported cognitive assessment showed that deep learning strategies may be used to track cognitive health in the elderly. [36] Laghari et al. (2023) created deep residual-dense models of medical pattern recognition, whereas [37] Yin et al. (2024) used attention to brain imaging classification, bringing up the role of AI in aiding cognitive surveillance in the aging population. Likewise, [38] Munir et al. (2024) showed that sparse regularized autoencoders can increase the predictive accuracy of healthcare analytics, which may be useful to monitor the cognitive patterns of elderly learners in the long term.

2.4 Comparative Educational AI Structures

Expansive studies of AI in education demonstrate a high level of development of personalization and scalability. [22] Murtaza, Aslam, and Hussain (2022) have reviewed personalized e-learning systems, whereas Nouman, Shaikh, and Rehman (2024) [39] present a personalized higher education system based on AI. [16] Singh and Kumar (2023) specifically concentrated on old learners and the need to include them. [12] [11, 12] Xu and Fang (2021) and Zhang and Lin (2020) emphasized the use of digital mentors in adult learning, but not seniors. Although these frameworks are useful, they emphasize more on youth or general adult education. As it can be summarized in Table 1, the literature highlights significant theoretical advancements, but it also indicates that emotion, gamification, and reflection are commonly researched independently of each other and not combined into one AI model to support elderly learners.

2.5 Synthesis and Gaps

The analysed research have unified on three lessons:

1. Mentorship that is sensitive to emotions enhances interaction, yet no use is made in the education of the aged.
2. Gamification enhances motivation and cognition and is not well integrated with AI platforms.
3. Reflective practices enhance memory and good health yet tend to be disconnected with the other processes.

According to the results of the critical literature review, we find a significant gap: No current system combines emotion-sensitive mentorship, gamified discovery learning, and reflective knowledge retention into a single, age-sensitive AI system, which facilitates agency among learners. Although the different domains have been investigated separately:

- There are emotion-sensitive systems which do not target the elderly (Li et al., 2022) [5].

Table 1. Literature Matrix of Key References Relevant to Elderly Learning and AI

Author(s)	Year	Focus	Population	Key Findings	Gap for Elderly Learners
[5] Li, Wang, & Zhao	2022	Emotion-aware conversational agents	General learners	Personalization and empathy in education	Limited elderly applications
[6] Kaur & Sharma	2021	Emotional AI and stress detection	Adaptive learning users	Stress analysis improves adaptability	Elderly-specific studies lacking
[3] Park & Lee	2020	Gamification opportunities & challenges	Elderly learners	Engagement and usability identified	Rarely integrated with AI
[7] Jones & Patel	2024	Curiosity-driven gamified learning	Seniors	Enhanced intrinsic motivation	Empirical validation still required
[9] Ali & Hussain	2022	Memory reinforcement via AI	Older adults	Assisted recall and reinforcement	No integration with gamification or emotion
[10] Nguyen & Chen	2020	Reflective journaling and AI	Adult learners	Supported lifelong learning	Not contextualized for seniors
[16] Singh & Kumar	2023	AI tutors for elderly inclusion	Elderly learners	Improved digital access	Broader emotional & reflective integration missing

- Seniors Seniors have been proposed to receive gamification, although it is seldom implemented together with adaptive AI (Park Lee, 2020) [3].
- The reflective practices are learned independently of emotional and motivational layers (Ali and Hussain, 2022) [9].

Lack of an offering of a fully integrated theoretical framework implies that the current systems would be unable to scale meaningfully in order to promote lifelong learning in aging populations. This gap is the reason behind the formulation of the Agentic AI framework in this paper.

Figure 2 shows that these three areas, namely emotion, gamification, and reflection, are discrete research lines without much indication of being incorporated into cohesive models. This drives the developed conceptual model of the Agentic AI.in this paper.

3 Theoretical Conceptual Framework

The conceptual framework proposed in this paper integrates three essential strands of recent research: emotion-aware mentorship, gamified discovery learning, and reflective knowledge preservation. As depicted in Figure 3, these layers are interdependent, working together to create an Agentic AI system that empowers elderly learners to participate actively, remain motivated, and retain knowledge.

3.1 Emotion-Aware Mentorship Layer

Emotion-sensitive mentorship has a basis on the principle that emotions play a vital role in learning process. [5] Li, Wang, and Zhao (2022) conducted a review of co nversational agent in education and found it to be more effective in personalizing learning interaction than neutral systems. [6] Kaur and Sharma (2021) also established that stress-detection and emotion analysis is able to improve the adaptability of AI so that learners are not overwhelmed but engaged.

Zimmermann and Meyer (2021) [13] claimed that emotionally adaptive environments support motivation and decrease the departure, especially in groups of vulnerable learners. When applied to aging students, this implies that emotional aware mentorship may be used to tackle the aspects of isolation and foster feelings of more trust and perseverance in the learning process.

The emotion-aware layer will therefore form the basis of empathetic, responsive AI mentors who are able to identify emotional behaviours and adjust based on them. Nevertheless, this area has not been applied extensively in older learners as it is highlighted in Table 2 since the theoretical base is well- grounded.

3.2 Gamified Discovery Learning Layer

Gamification uses the motivational design to make learning more of an exploration and an inquisitive process. According to Park and Lee (2020) [3], there are opportunities and challenges in the design of gamification tailored to the students of a specific age group, namely the elderly, and the accessibility of these should be viewed as crucial as entertainment. [7] Jones and Patel (2024) made a similar contribution by ensuring curiosity is the central force behind gamified systems and recommends the design of learning to focus on autonomy and intrinsic interest. [8] Rahman and Ali (2025) integrated the con-

Figure 2. Thematic clustering of existing studies motivating an integrated Agentic AI framework

cepts of gamification and AI through the cognitive health in which they hypothesized that integrated systems had the potential to enhance engagement and cognitive decline resistance. This supports the significance of gamified discovery among the aged, who require challenges stimulating, but not thought-provoking. Gamified discovery learning, therefore, offers the motivational nature of the framework. With the integration of elements of exploration, achievement and curiosity-based use of AI systems, older learners will be able to stay engaged. This is in line with the overall objectives of lifelong learning and in sympathy with the age-specific motivation hindrances.

3.3 Reflective Knowledge Preservation Layer

Reflective practices promote cognitive resilience are in the sense that the learner is able to process, revisit and internalize the knowledge. According to [35] Martinez and Brown (2019), reflection helps seniors to achieve cognitive well-being. [10] Nguyen and Chen (2020) revealed the way AI-assisted reflective journaling promotes lifelong learning. Equally, [9] Ali and Hussain (2022) established that AI memory reinforcement systems have the potential to assist the elderly and conserve information more. These results indicate that structured reflection is essential among the elderly learners especially when they are facing age-related cognitive deterioration. Nevertheless, the majority of AI systems are aimed at content delivery and assessment, but not reflective reinforcement. By incorporating reflective knowledge preservation in Agentic AI, it is guaranteed that the learning is not limited by the short-term results but to the long-term memory and well-being.

3.4 Integration Across Layers

Although all the layers were considered separately in previous studies, the integration is scarcely done. The significance of inclusive AI tutors was mentioned by Singh and Kumar (2023) [16], yet the authors did not discuss possible cross-over of emotional, gamified, and reflective processes. [11] Zhang and Lin (2020) suggested the use of digital mentors, but they did not include motivation- or reflection-related aspects.

The suggested Agentic AI framework will go a step further and bring together the three strands, unlike these isolated methodologies. The layers as illustrated in Figure 4 are inter-reliant as follows:

- Personalized support of Emotion-Aware Mentorship is given as a result of affective cues.

Table 2. Mapping of Framework Layers to Theoretical Foundations and Identified Gaps

Layer	Supporting References	Core Contribution	Identified Gap for Elderly Learners
Emotion-Aware Mentorship	Li, Wang, & Zhao (2022); Kaur & Sharma (2021); Zimmermann & Meyer (2021) [5, 6, 13]	Emotion detection, stress adaptation, empathy	Few elderly-specific implementations
Gamified Discovery Learning	Park & Lee (2020); Jones & Patel (2024); Rahman & Ali (2025) [3, 8]	Motivation, curiosity-driven engagement	Limited integration into adaptive AI
Reflective Knowledge Preservation	Martinez & Brown (2019); Nguyen & Chen (2020); Ali & Hussain (2022) [9, 10, 35]	Memory reinforcement, reflective journaling	Often separated from emotional/motivational layers

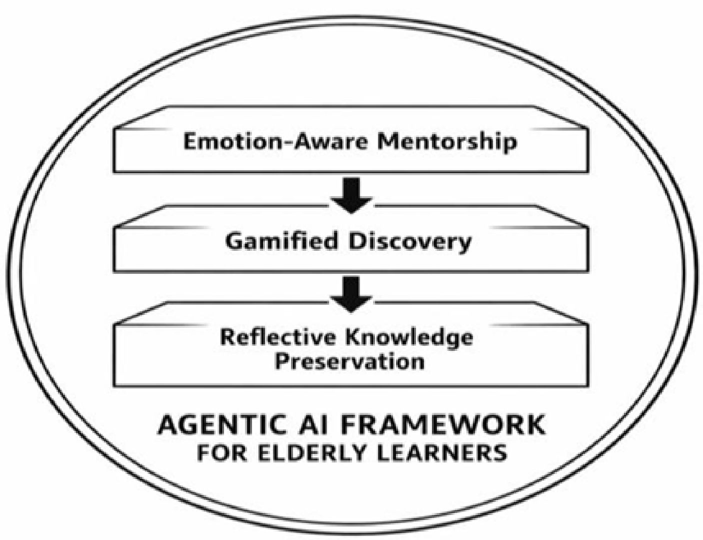

Figure 3. Conceptual overview of the Agentic AI framework for elderly learners

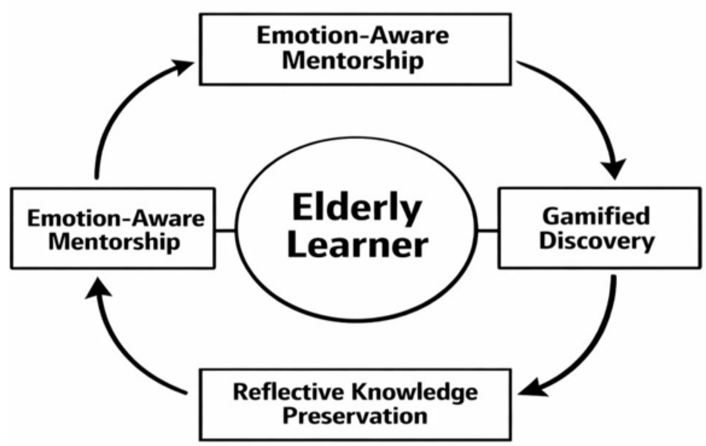

Figure 4. Interaction model of the three layers within the Agentic AI framework

- Gamified Discovery Learning provides incentive via learning and discovery.
- Reflective Knowledge Preservation is a process that strengthens knowledge with the help of memory and reflection cycles.

This combined form a feedback system that fosters activity, continuation and cognitive stamina among the elderly students.

4 Research Hypotheses and Roadmap

The Agentic AI framework for older learners is developed in this paper as a theoretical concept that bridges the current literature and future empirical investigation. Expanding on the research questions in the introduction, this section formulates detailed hypotheses and outlines a guide to their eventual verification. In formalizing these aspects, the framework sets out a concise research path for the progression of the discipline of AI within older learning environments.

4.1 Hypotheses

The model suggests three core hypotheses, aligned with the three interrelated layers of the model.

- H1 (Emotion-Aware Mentorship): Emotionally responsive AI mentorship will increase participation and decrease dropout for older learners [5, 6, 13](Zimmermann Meyer, 2021; Li, Wang, Zhao, 2022; Kaur Sharma, 2021).
- H2 (Gamified Discovery Learning): AI-mediated platforms with gamification will substantially amplify long-term motivation and engagement among older learners [3, 7, 8](Park Lee, 2020; Jones Patel, 2024; Rahman Ali, 2025).
- H3 (Reflective Knowledge Preservation): Guided reflection with AI assistance will enhance knowledge retention and cognitive strength in older learners [9, 10, 35](Martinez Brown, 2019; Nguyen Chen, 2020; Ali Hussain, 2022).

These hypotheses are not discrete suggestions but strongly interdependent, as each draws on a complementary literature thread. As outlined in Table 3, each research question (RQ) corresponds to a hypothesis (H) and corresponds to a particular framework layer. This correspondence shows how theoretical understanding is conveyed into testable pathways.

To facilitate empirical verification, the learner agency is modelled in terms of observable indicators which are aligned with each layer of the framework. The dimensions of autonomy, emotional regulation and reflective control that can be measured are summarized in Table 4, which may form the basis of quantitative and longitudinal analysis of agentic behaviour in old learning contexts.

4.2 Roadmap for Future Research

The research roadmap uses the vision of a rational path from theoretical formulation to empirical validation. This pathway helps to make sure that the conceptual contributions of the framework are reflected in the actual applications for elderly learners. The roadmap is comprised of four stages:

1. **Theoretical Consolidation (Current Work):** Synthesis of cross-disciplinary insights in order to establish the Agentic AI framework. This paper is the first stage, the theoretical rigor and research gap identification [15].
2. **Prototype Development:** Creating AI Agents with Emotional Responsiveness, Gamification Mechanisms & Reflective Journaling Features. This stage involves interdisciplinary efforts of computer scientists, gerontologists, and education specialists [12, 40].
3. **Pilot Testing with the Elderly:** Carrying Out Usability Studies on a Small Scale in Assisted Living Facilities, Community Centers or Online Pilot studies will help refine design, identify barriers as well as assess preliminary outcomes, such as engagement and satisfaction (Thakur, Sharma, Kapoor, 2021; Singh Kumar, 2023).
4. **Large-Scale Validation:** Implementing the system across different contexts in different parts of the world in order to test the long-term effects on motivation, memory and well- being. This will ensure the generalizability and support policy-level adoption [4].

As illustrated in Figure 5, these four stages are sequential yet iterative, allowing feedback from each stage to refine subsequent phases. This stepwise approach moves systematically from concept � prototype � pilot � validation, providing both academic contributions and practical solutions for elderly learners.

5 Discussion and Implications

The Agentic AI model of elderly learners contributes to the theoretical literature and practical design by bringing together three important strands of research, including emotion-conscious mentorship, gamified discovery learning, and reflective knowledge preservation. Although each of the domains was examined separately, their combination into one, agentic model is a new input. In this segment, the discussion is further developed by expounding on the theoretical development, the design possibilities, the social effects and issues that need to be put in place so that the implementation can be successful.

5.1 Theoretical Contributions

The main input of the framework is the synthesis of the theory. The area of emotion-aware AI studies [5, 6, 13]

Table 3. Mapping of Research Questions to Hypotheses and Framework Layers

Research Question (RQ)	Hypothesis (H)	Framework Layer	Supporting References
RQ1: Emotion-aware mentorship and engagement	H1: Emotionally adaptive AI mentorship will enhance engagement and reduce dropout	Emotion-Aware Mentorship	Zimmermann & Meyer (2021); Li, Wang, & Zhao (2022); Kaur & Sharma (2021) [5, 6, 13]
RQ2: Gamification and sustained motivation	H2: Gamification integrated into AI will increase sustained participation	Gamified Discovery Learning	Park & Lee (2020); Jones & Patel (2024); Rahman & Ali (2025) [3, 7, 8]
RQ3: Reflection and cognitive resilience	H3: AI-supported reflection will improve memory retention and resilience	Reflective Knowledge Preservation	Martinez & Brown (2019); Nguyen & Chen (2020); Ali & Hussain (2022) [9, 10, 35]

Table 4. Operational Indicators for Evaluating Agency in Agentic AI Systems

Agency Dimension	Layer	Measurable Indicators	Example Metrics
Autonomy	Gamified Discovery	Voluntary task selection, exploration depth	% self-initiated tasks, session diversity
Emotional Regulation	Emotion-Aware Mentorship	Stress recovery, engagement stability	Affect shift score, disengagement recovery time
Reflective Control	Reflective Preservation	Depth of reflection, recall consistency	Reflection length, delayed recall accuracy
Sustained Agency	Cross-layer	Longitudinal engagement	Retention rate over 8–12 weeks

has been concerned with the issue of improving affective adaptability in educational settings to a significant extent. The research on gamification [3, 7, 8] has demonstrated that in the case of at least some research, it maintains motivation in the learners, yet it fails to connect it with emotional sensitivity or relativism. Reflective learning and memory reinforcement [9, 10, 35] are often viewed as the add-ons to learning, which is why they are not perceived as part of the design of learning.

The suggested framework of the Agentic AI integrates these strands focusing on the agency as the theoretical anchor. The elderly learners are placed as active and deliberate agents of their learning processes, as opposed to passive consumers of the content. This change has at least three ramifications:

1. **Reframing Affective Computing in Aging Situations:** Affective computing is a relatively well-known field, but when applied to elderly education, it takes on a different meaning, as a method of curing emotional weaknesses like isolation, anxiety, or disengagement.
2. **Application of Gamification Theories to Cognitive Resilience:** Gamification does not impose a motivational strategy only but a cognitive reinforcement strategy, which is consistent with cognitive resilience and curiosity-driven learning theories [7].
3. **Coming to make Reflection a Central Process:** Reflection, instead of being peripheral, is hypothesized as a component of learning structure, which facilitates cognitive reinforcement and identity-forming in elderly learners.

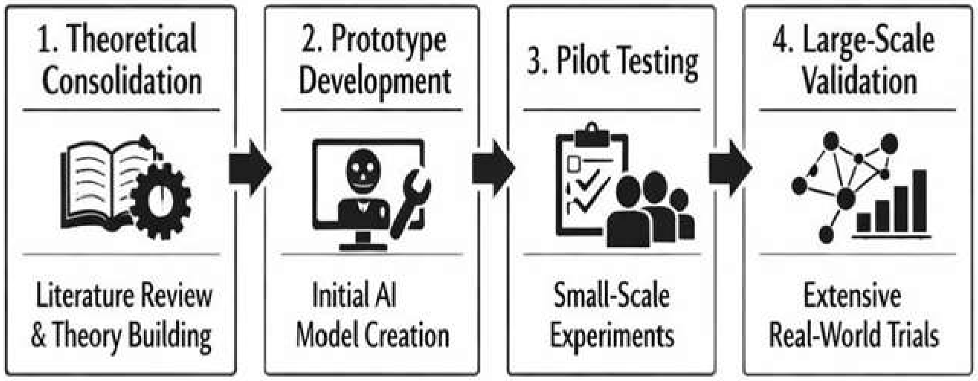

Figure 5. Research Roadmap for the Development and Validation of the Agentic AI Framework

5.1.1 New Additions of the Agentic AI Framework.

This framework contributes to the advancement of the field in three important ways making it stand out among the current research on AI-in-education:

1. **First Integrated Framework with the Elderly:** Unlike the previous studies that involved emotion sensitive systems [5], gamification [3], or reflective practices [10] separately, this article is the first to combine all three dimensions in specific studies on aging populations. The current systems of AI education focus on young people or adult learners in general [22, 39], which means that elderly individuals are an add on aspect of their design, instead of the main priority.
2. **Theoretical vs. System-Driven vs. Learner-Driven Agency:** The theory is a fundamental change of design the paradigm of AI to move towards agentic empowerment (learner initiates, controls and reflects on learning), as opposed to system-based algorithmic optimization (determinism of best learning paths). This re-framing based on gerontological theories of active aging operationalises agency using three quantifiable dimensions of autonomy, emotional self-regulation and reflective control (Table 4). There is no framework available with such operational metrics on an elderly learner agency.
3. **Testable Hypotheses + Roadmap of Action. This structure contains:**
4.
   - Three hypothesis that are formal, testable (Section 4.1)
   - Empirical validation operation indicators (Table 4)
   - Algorithms of concrete implementation (Section 6.3)
   - Four stage research roadmaps between theory to large scale validation (Figure 5)

Such rigor of theory combined with operationalization creates a clear lineage on the way to an actual implementation, unlike a solely theoretical contribution.

5.1.2 Theory Agency as the Core Theoretical Construct.

The concept of agency in this framework is the ability of the learner to start, control, and cognate about learning behaviour in an AI-mediated condition. Based on the theory of agentic AI (Viswanathan, 2025) and gerontological models of active aging, the agency is measured on three levels: (i) autonomy (self- directed choices), (ii) emotional self-regulation (emotion-aware adaptation), and (iii) reflective control (deliberate meaning-making). Against the background of traditional adaptive systems that optimize the learning pathways through an algorithmic approach, Agentic AI focuses on the intentionality of its learners, which places the elderly user in the role of a co-director and not a passive receiver of instructions. This specifically grounds the agency on theory instead of connotations. As summarized in Table 5, this framework bridges the gap between isolated theoretical contributions and integrated, testable constructs.

6 Practical Implications

As a design, the framework is informative to developers of AI education systems:

- **Future of Human-Computer Interaction:** Designing Emotion-Aware Interaction Systems - Andy Adamatzky, Tonio Buonancore, and Fabio Ziboli - In "Future of Human-Computer Interaction", the authors provide an overview of the future of human-computer interaction. For example, conversational agents could help to slow down the pace of explanation or encourage when signs of disengagement are noticed [5, 13].
- **Gamified Discovery Learning:** Systems must make use of age-specificially adaptive-challenge or knowledge-quest systems that use curiosity, which are age-appropriate in the seniors [3, 7]. The design has to focus on accessibility (larger fonts, simplified interactions) as well as motivation. The systems should be able to use age-relevant adaptive-challenge mechanisms that should exploit curiosity at the same time being accessible. The recent systematic reviews of serious games in healthcare show that the consideration of age-relevant design is crucial in determining the quality of experience in virtual/augmented reality environments [41]. The design should aim at accessibility (big font, simplified interactions, etc.) and motivational factors [3, 7].
- **Reflective Knowledge Preservation:** AI tutors have the option to add journaling prompts, recap quizzes, or memory tasks to make the seniors review important concepts [9, 10].

Together, all those strategies help to motivate elderly learners to perceive themselves as competent and active participants in digital education. This is especially important in the bridging of the digital divide that is documented in aging societies [2].

6.1 Societal and Policy Relevance

The framework has implications beyond individual learning outcomes. Globally, aging populations present challenges for healthcare, social inclusion, and lifelong learning systems [1]. By empowering seniors with agentic AI tools, several societal benefits can be realized:

1. C**ognitive Health:** Reflection and gamification can mitigate risks of cognitive decline, delaying the onset of memory-related impairments.
2. **Social Inclusion:** Emotion-aware mentorship fosters digital participation and reduces isolation, particularly for seniors living independently [16].
3. **Lifelong Learning Systems:** Integrating Agentic AI into community centres, universities of the third age, or digital literacy programs can expand educational equity.

As illustrated in Figure 6, the framework creates ripple effects, moving from personal benefits (motivation, resilience) to broader societal outcomes (social inclusion, healthy aging).

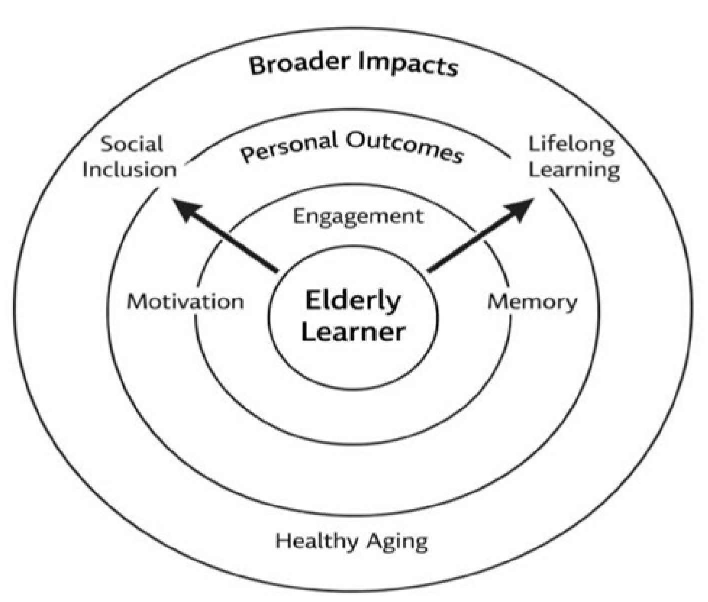

Figure 6. Impact Pathways of the Agentic AI Framework for Elderly Learners

6.2 Comparative Perspective with Existing Models

Most AI in education frameworks are aimed at individualization and scalability for youth or for general

Table 5. Theoretical and Practical Implications of the Agentic AI Framework

Dimension	Theoretical Implication	Practical Implication
Emotion-Aware Mentorship	Extends affective computing theories into aging education contexts.	Guides design of AI mentors that recognize stress, boredom, or motivation drop in seniors.
Gamified Discovery Learning	Positions gamification as a cognitive resilience strategy.	Enables creation of age-appropriate learning games that encourage sustained engagement.
Reflective Knowledge Preservation	Formalizes reflection as a cognitive reinforcement mechanism.	Supports AI tools that prompt elderly learners to revisit, record, and retain knowledge.
Integrated Agentic AI	Proposes a unified framework that consolidates isolated strands.	Provides roadmap for scalable prototypes targeting elderly inclusion in digital education.

adult populations [22, 39]. While valuable, they miss age-specific needs like slower cognitive processing, memory reinforcement and the importance of affective connection.

By contrast, the Agentic AI framework has three differences:

- **Target Population:** It explicitly puts the elderly learners at the centre of attention, which is not the case in the current frameworks which cater for them as an afterthought.
- **Integration:** It brings together the emotional, motivational and reflective dimensions, whereas most models currently emphasize on content delivery and adaptive pacing.
- **Agency:** It moves from the focus of personalization (system driven) to learner-driven autonomy (gerontological theories of active aging).

The other applicable comparative area is the intelligent personal assistant. [40] Pinto, Tavares, and Costa (2021) used a systematic review of AI assistants in elderly care to determine essential factors that establish success such as emotional responsiveness, simplicity, and personalization. Nevertheless, their discussion showed that the majority of the current assistants are concentrated on the surveillance of health or help with daily tasks excluding the empowerment of education. In contrast with the latter, the Agentic AI framework takes a more explicit approach to cognitive resilience and lifelong learning, instead of trying to provide assistive care only.

Toe analysis highlights the novelty of the proposed framework and justifies the theoretical advancement. In an effort to situate the proposed framework in the context of past research in AI-in- education, a brief comparison of the Agentic AI framework and past AI systems developed for the purpose of personal learning and for seniors is provided in Table 6.

6.3 Challenges and Limitations

Although the framework has much promise, there are several issues that will need to be addressed during future implementation of the framework:

1. **Technological Barriers:** The elderly may have difficulty using technology, which means that AI technology should be simple and easy to use (Thakur, Sharma, Kapoor, 2021).
2. **Emotional Overload:** Over-sensitivity to the feeling may lead to annoying interaction. The process of balancing response and the freedom of the learners to have autonomy can never be emphasised enough in this regard. This has been made increasingly.
3. **Risks in Gamification:** Inappropriate use and implementation of gamification could come across as devaluing or paternal if implemented for seniors. Age-appropriate adaptation is a very important aspect.
4. **Reflection Fatigue:** Although reflective thinking is

Table 6. Comparison of Agentic AI Framework with Existing AI-in-Education Models

Dimension	ITS / Personalized AI [22] (Murtaza et al., 2022)	Elderly Digital Tutors [16] (Singh & Kumar, 2023)	Agentic AI Framework (This Study)
Target Population	General / Youth	Elderly	Elderly (Primary)
Emotional Awareness	Limited	Basic	Emotion-aware, adaptive
Gamification	Optional	Rare	Core motivational layer
Reflection & Memory	Minimal	Absent	Central design component
Learner Agency	System-driven adaptation	Guided	Learner-initiated, reflective
Cognitive Resilience Focus	No	Partial	Explicit objective
Ethical Framing	Implicit	Limited	Explicit safeguards

a key to the development of intellectual resilience, excessive writing or memory work may prove to be tedious if performed in a judicious manner [10].

5. **Ethical Considerations:** Care needs to be taken with the issues of privacy, autonomy, and consent, particularly where the system is concerned with the analysis of emotional or behaviour-related data.

Overcoming these challenges will be a key factor in reaching the moral and ethical standards and functional efficiency of Agentic AI.

6.4 Toward an Inclusive Research Agenda

Finally, the framework suggests directions for a broader research agenda:

- **Interdisciplinary Collaboration:** Integrating expertise from AI, gerontology, psychology, and human-computer interaction.
- **Cross-Cultural Validation:** Validation done across various cultures and socioeconomic levels to guarantee inclusivity [4].
- **Longitudinal Studies:** Exploring beyond the short-term usability to the long-term effects on cognitive well-being.
- **Policy Integration:** Promoting governments and institutions to integrate Agentic AI in lifelong learning strategies for an ageing population.

In such an agenda, the potential roles of Agentic AI extend from mere innovation to transformation itself.

6.5 Ethical Risks and Mitigation Strategies

In view of the sensitivity that can be linked with emotion-aware and adaptive AI systems when working with elderly users, the ethical risks can no longer be ignored. The main ethical issues related to Agentic AI are highlighted in Table 7 below, along with strategies that can be used to address them.

The issue of ethical design assumes a crucial role in the use of AI among the geriatric population due to the vulnerability associated with autonomy, consent, and emotional well-being. The involvement of transparency, control, and minimal inference of emotional well-being eliminates the associated dangers of dependency and over-personalization.

7 Conclusion and Future Directions

Thus, our paper introduced the Agentic AI approach for elderly learners, which is a conceptual approach of the combination of emotion-aware mentoring, gamification-based discovery learning, and reflective knowledge preservation. In contrast to existing AI-based frameworks which emphasize the needs of young learners or the general adult population [22, 39], the Agentic AI approach emphasizes the needs of elderly learners as active agents in their educational process. The framework provides the following three main contributions. Firstly, it integrates cross-disciplinary literature to provide theoretical support to elderly-oriented AI-learning systems. The integration of cross-disciplinary literature is supported by references from 2021 to 2024, indicating its relevance to present day. Secondly, it provides a multi-layer conceptual framework comprising affective, motivational, and reflective processes. Thirdly, it presents a research road map to develop testable hypotheses.

7.1 Limitations

Although the framework holds a lot of promise, several issues will have to be addressed during future implementation:

1. **Technological Barriers:** The elderly may find it difficult to operate technology, which means that

Table 7. Ethical Risks in Agentic AI for Elderly Learners and Mitigation Strategies

Risk	Description	Mitigation Strategy
Emotional Surveillance	Over-inference of affective states	On-device processing, opt-out controls
Dependency Formation	Over-reliance on AI mentors	Scheduled autonomy prompts
Data Privacy	Sensitive emotional data misuse	Differential privacy, consent dashboards
Infantilization	Gamification is perceived as patronizing	Age-sensitive design validation
Cognitive Manipulation	Excessive nudging	Transparent decision logic

AI technology has to be simple and user-friendly (Thakur, Sharma, & Kapoor, 2021).

2. **Emotional Overload:** Sensitivity to emotion - too much, and the emotion may be annoying to interact with. The process of balancing response and the freedom of the learners to have autonomy can never be emphasised enough in this regard. This has increasingly been made
3. **Risks in Gamification:** The inappropriate use and implementation of gamification could be perceived as devaluing or paternal when gamification is used for seniors. Age appropriate - this is a crucial aspect Reflection Fatigue While the use of reflective thinking is helpful for developing intellectual resilience, too much writing or memory work might be tedious if done judiciously [10]
4. Ethical Considerations: Consideration needs to be given to the issues of privacy, autonomy, and consent, particularly where the system involves the analysis of emotional or behaviour- related data (Krishna et.al, 2024)

Overcoming these challenges will be a crucial factor towards helping achieve the moral and ethical standards as well as the functional efficiency of Agentic AI.

7.2 Future Research Directions

The proposed model provides a fertile land for future studies. Three key directions are proposed:

- AI for Senior Living: Design and Evaluation of an AI System to Implement Three Layers of Senior Living Services, with Usability Testing in the Context of Elderly Learning Scenarios (Prototyping, 2021) by Thakur, R., Sharma, P. & Kapoor, M.| Singh, S. & Kumar, H.
- The longitudinal studies: examining the long-term effect of Agentic AI to cognitive resilience, motivation and memory in seniors.
- References Cross-Cultural Validation: Performing the application of the model in a diverse range of cultural or economic contexts/tools to promote its inclusivity and generalizability [12, 40] Table 8, presents the summary of Contributions, Limitations, and Future Research Directions.

7.3 Agentic AI Framework Operationalization.

Operationally, the framework may be implemented as a modular AI system comprising: (i) an affect sensing component (speech/text analysis), (ii) a gamified task engine with difficulty level adjustment mechanism, and (iii) a reflective memory component, which contains learner narratives. The decision orchestration element utilizes a lean agent manager, which places more emphasis on learner-initiated action as opposed to system-stimulated action, thereby maintaining agency.

The pseudo-code of the core decision orchestrator, which organizes the three layers of the framework, is shown in Algorithm 1.

7.4 Closing Statement

It is a time when the world faces dual forces of an aged and technology-driven revolution, and the education system also needs to develop to cater to the requirements of the young and old alike. When viewed as a crucial turning point towards reaching this particular objective, the Agentic AI approach developed and explained within this research shows a big step towards a new and better world for senior adults to become successful active participants of a lifelong education process and towards the making of a new revolution within the field of AI and technology education for the elderly as well as the young generation alike.

8 Adherence to Ethical Standards

It is stated that there is no conflict of interest among all the authors. Moreover, all the individual participants

Table 8. Summary of Contributions, Limitations, and Future Research Directions

Dimension	Contribution	Limitation	Future Research Direction
Theoretical Framework	Integration of emotion, gamification, and reflection into Agentic AI	No empirical testing conducted	Build prototypes and pilot systems
Practical Relevance	Blueprint for designing elderly-centred AI systems	Contextual boundaries in design focus	Test across cultural and socio-economic contexts
Societal Impact	Potential for lifelong learning, social inclusion, cognitive resilience	Generalizability not yet validated	Conduct longitudinal studies on impact

Algorithm 1. The agentic AI Decision Orchestrator of Elderly Learners (Algorithm 1).

Input:

- Continuous monitoring of E is the emotional state of the learner.
- Difficulty in current task D (easy, mediocre, challenging)
- Reflection history R (historical journals of learners)
- Learner preference P (learner-initiated vs system-guided)

Outcome: Adaptive learning response (next system response)

1. Initialize learner profile
2. Continuously monitor emotional state E
3. Assess the suitability of task difficulty D
4. Adjust mentorship strategy based on E and D
5. Select discovery activity aligned with learner preference P
6. Allow learner to initiate or follow guided exploration
7. Capture interaction outcome and update reflection history R
8. Reinforce learning through reflective prompts
9. Update learner profile using E, D, R, and P
10. Iterate to support sustained learner agency

who were involved in the study gave informed consent.

Note: It is a strictly conceptual and theoretical study. None of the human subjects were explicitly involved in data collection. The designs and synthesis of published literature are used to make all theoretical constructs and designs of frameworks. Empirical validation research can only be done in the future, whereby the relevant ethical approval of the institutional review boards and the informal consent of the elderly subjects are acquired.

Declarations

Data Availability

The authors developed a dataset, which is used in this study and available publicly in Elsevier Mendeley Data repository under the name A Bilingual Synthetic Dataset of Elderly Emotional Wellbeing and Agentic AI Support in Low-Resource Contexts (Version 1), with the DOI: 10.17632/n957vf24sp.1.

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Consent for Publication

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Competing Interests

The authors declare that they have no competing interests.

Author Contributions

P.B. (Priha Bhatti) developed the conceptualization and original draft. Validation was provided by Z.A. (Dr. Zubair Ahmad). Formal analysis was contributed by P.B. and F.Z. (Fahim Uz Zaman). Investigation was carried out by P.B. and Z.A. Resources were provided by P.B., Z.A., and F.Z. Visualization was prepared by P.B. and F.Z. Supervision was carried out by Z.A. Project administration was handled by P.B., Z.A., and F.Z. All authors reviewed and approved the final manuscript.

AI Assistance Disclosure

The authors state that the following were the only purposes to use artificial intelligence tools: ChatGPT (OpenAI, GPT-4) and Grammarly Premium.

1. Language editing: Grammar, sentence structures, and clarity.
2. Formatting services: Reference style check and Table formatting.
3. Technical perfection: Coherence checks in the use of terminologies.

Critical Clarification: No AI tool was utilized:

- Formulation of research questions or hypotheses.
- Conceptual framework or theoretical contribution development.
- Literary analysis or interpretation.
- Development of research arguments or academic knowledge.
- Creation of referenced academic material.

The authors did all the conceptual frameworks, theoretical contributions, research design, literature synthesis and scholarly arguments by traditional academic research means. The authors examined and checked all AI-generated material and can fully warrant the accuracy, validity, and integrity of the final publication.

Compliance with Ethical Standards

It is declared that all authors do not have any conflict of interest. Furthermore, informed consent was obtained from all individual participants included in the study.

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