Multimodal Technologies and Interaction

Article

Designing Gamified Intergenerational Reverse Mentorship Based on Cognitive Aging Theory

Sijie Sun

Department of Philosophy, Autonomous University of Barcelona, 08193 Barcelona, Spain; 1583451@uab.cat

Abstract: With the intensification of population aging, elderly individuals face significant barriers in learning digital skills, leading to a widening digital divide. Based on Cognitive Aging Theory, this study proposes and validates an original paradigm called Structured Gamified Intergenerational Digital Reverse Mentorship to enhance digital literacy among the elderly. Cognitive Aging Theory suggests that due to declines in memory, attention, and executive function, older adults encounter challenges when learning new technologies, while gamified learning combined with intergenerational interaction can help reduce cognitive load and increase learning motivation. This study designed a collaborative gamified digital reverse mentorship application, "Digital Bridge", and employed a randomized controlled trial method, assigning 90 participants aged 60 and above into three groups: the traditional digital mentorship group (Group A), the independent gamified learning group (Group B), and the collaborative gamified digital mentorship group (Group C). Each intervention session lasted 30 min and was conducted in a controlled environment. Experimental results showed that Group C significantly outperformed Groups A and B in digital skill acquisition, user experience, and learning motivation ($p < 0.001$), indicating that the combination of gamified learning and intergenerational interaction effectively enhances learning interest, reduces learning anxiety, and improves skill transferability. This study provides a new approach to elderly digital literacy education and offers theoretical and practical support for the design of future age-friendly digital learning tools.

Keywords: cognitive aging theory; user experience design; age-friendly design; gamification design; digital literacy for older adults

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Academic Editors: Ana Manzano-León and José M. Rodríguez Ferrer

Received: 13 May 2025
Revised: 13 June 2025
Accepted: 16 June 2025
Published: 19 June 2025

Citation: Sun, S. Designing Gamified Intergenerational Reverse Mentorship Based on Cognitive Aging Theory. *Multimodal Technol. Interact.* **2025**, *9*, 64. https://doi.org/10.3390/mti9060064

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1. Introduction

As population aging intensifies, elderly individuals are facing increasingly severe challenges related to the digital divide, and significant barriers in using smart devices and digital technologies [1,2]. Although the Internet penetration rate among the elderly population has gradually increased, cognitive aging has led to a decline in learning capability, and the lack of age-appropriate learning resources continues to pose significant challenges in digital skill acquisition [1,3,4]. Therefore, it is of great practical significance to narrow the digital divide for the elderly, enabling them to better adapt to the digital society and benefit from the convenience and opportunities offered by digital technology.

Intergenerational digital reverse mentorship fosters the intergenerational transfer of digital skills through interactions between younger and older generations, and serves as a potentially effective intervention strategy. Research has shown that digital games can not only enhance the digital literacy among the elderly, but also improve memory, motor coordination, and cognitive function [5–7]. However, current digital reverse mentorship models largely rely on the support of family or community, and lack systematic and sustainable learning mechanisms. Therefore, they fail to meet the growing demand for digital skill acquisition among the elderly [8]. Moreover, existing digital skills training methods for the elderly primarily depend on offline courses or informal assistance from family members, lacking systematicity, engagement, and personalization, and mainly focusing on resolving specific operational issues rather than providing comprehensive support for enhancing digital literacy. Although the elderly show a strong interest in leisure and cognitive games [6,9], the market still lacks digital training tools specifically designed for the elderly, especially gamified products. Existing research predominantly focuses on adapting general applications for elderly users, but lacks targeted design tailored to their cognitive characteristics and learning needs. Therefore, it is of significant research value to develop a structured and gamified digital reverse mentorship program based on Cognitive Aging Theory to enhance digital literacy, optimize user experience, and increase learning motivation among the elderly.

Based on the theories of cognitive aging [10,11] and user experience design [12,13], the present study developed a gamified learning app for digital reverse mentorship tailored for elderly users. Cognitive Aging Theory suggests that the elderly face considerable challenges in performing complex tasks due to the decline in memory, attention, and reaction speed. Therefore, gamification design was employed to decompose complex digital learning tasks into simple and progressive micro-tasks, thereby gradually increasing the difficulty through level-based mechanisms. Additionally, instant feedback, virtual rewards, and social interactions were incorporated to reduce cognitive load, enhance engagement, and improve learning participation. Furthermore, based on user experience design theory, interface layout, operational processes, and interaction methods were optimized to align with the cognitive characteristics and usage habits of the elderly. Such system-supported design by theory not only improves the usability and attractiveness of the app, but also enhances the positive emotions and satisfaction of elderly users, providing them with an efficient and enjoyable digital learning experience and promoting digital skill acquisition and practical application.

The design was created using the ADDIE (Analysis, Design, Development, Implementation, and Evaluation) model [14], incorporating survey research, data analysis, prototype design, and experimental design to systematically evaluate the effectiveness of gamified digital reverse mentorship. A total of 90 participants aged 60 and above were recruited and randomly assigned to three different learning model groups. Then, the study evaluated user experience and learning motivation among elderly participants across different learning models using the UEQ-S (User Experience Questionnaire—Short Version) and the ARCS Model of Motivation scale while assessing learning outcomes through repeated task performance tests [15–17]. The primary objective of this study is to design an app and evaluate its effectiveness on gamified digital reverse mentorship interventions in enhancing digital literacy among older adults and to explore its potential in optimizing user experience and increasing learning motivation.

This study merges the application of Cognitive Aging Theory and user experience design theory in enhancing digital literacy among the elderly, offering new academic insights into intergenerational education and digital skills training. Practically, this study develops a gamified digital reverse mentorship learning app, filling the market gap in digital skills training tools for older adults while improving engagement.

The research findings provide scientific evidence for optimizing digital education for older adults and offer valuable references for governments, educational institutions, and social organizations in formulating digital inclusion policies. This, in turn, helps bridge the digital divide, fosters intergenerational interaction, and promotes social harmony.

2. Literature Review

2.1. Background Dimension: Older Adults' Digital Literacy and Intergenerational Digital Reverse Mentorship in the Context of the Digital Divide

The three-level model of the digital divide [18] reveals the core contradictions in the digital challenges faced by the elderly. After overcoming physical access barriers (first level), they encountered a "usage divide" (second level), characterized by difficulties in digital skill acquisition and insufficient intrinsic motivation, ultimately resulting in significant generational differences in digital resource acquisition outcomes (third level). The current research presents two opposing paradigms to explain this phenomenon: the individual deficiency paradigm emphasizes the limitations imposed by cognitive aging [19] and low self-efficacy [20], advocating for the improvement of cognitive reserves through repetitive training. In contrast, the structural constraint paradigm criticizes the imbalance in social resource allocation [21] and the lack of intergenerational support [22,23], calling for the reconstruction of technology empowerment networks. However, existing studies typically isolate the interaction between individuals and systems, failing to propose an integrated approach that combines cognitive intervention with social support.

Intergenerational Digital Reverse Mentorship offers an innovative solution to this issue. "Mentorship" generally refers to a structured relationship in which a more experienced individual (the mentor) provides guidance and support to a less experienced person (the mentee) in areas such as skills, experience, emotional development, and career advancement [24]. "Digital Reverse Mentorship," on the other hand, specifically refers to a mentorship model in the technological domain where younger, more tech-savvy individuals mentor older adults, thereby reversing traditional generational roles [25]. This mechanism not only facilitates technical learning, but also fosters emotional support and social connection. Research has indicated that technology transfer from younger to elderly individuals not only alleviates cognitive decline [26,27], but also reduces technology-related anxiety through emotional bonding [28], proving to be more effective than unidirectional teaching methods [29]. However, existing studies primarily focus on the social function of mentorship, while overlooking its potential as a systematic intervention tool. Therefore, this study introduced a gamified intergenerational mentorship model that integrates cognitive training within a social support network, simultaneously targeting individual cognitive deficits (e.g., decreased working memory) and structural support gaps (e.g., insufficient intergenerational interaction opportunities), thereby addressing a key gap in the intervention mechanisms of the digital divide.

Research on digital literacy of the elderly stems from a structural reflection on the digital divide, grounded in both Cognitive Aging Theory and social resource distribution theory. Cognitive Aging Theory [3] suggests that due to memory decline, attention deficits, and slower information processing speeds, the elderly experience severe cognitive overload in complex digital tasks, leading to "technological avoidance" [1]. Social resource distribution theory [18] highlights that low-income and low-education elderly populations are trapped in a "digital exclusion" cycle due to systemic resource deprivation, such as the lack of age-friendly tools and training opportunities. The data indicate that 25% of individuals aged 65 and above remain in a state of "digital isolation" [30,31], and digital skill deficiencies not only limit their access to health information [32], but also significantly correlate with worsening depressive symptoms [33]. Although the COVID-19 pandemic has accelerated the improvement of digital literacy among the elderly, skill growth remains uneven, and some groups still lack adequate technological support, highlighting the necessity for sustained intervention and structured learning. Additionally, the existing research primarily examines digital literacy barriers from physiological and psychological perspectives, neglecting the potential of intergenerational collaboration as an intervention strategy, thereby limiting an in-depth understanding of how collaborative learning enhances digital literacy among the elderly.

Intergenerational digital reverse mentorship, where the younger generation transfers digital skills to the elderly, offers a promising solution to this issue. Studies have shown that involving younger individuals in technology training for the elderly can foster a supportive learning environment and effectively meets their unique needs [34]. Moreover, integrating cultural sensitivity can enhance technology acceptance [35], while collaborative learning models provide personalized educational support and boost the confidence of the elderly in technology use [30]. However, current digital mentorship practices still have several limitations. Cota et al. (2015) and Marston (2013) pointed out that although informal family interactions can boost the technological confidence of the elderly, they rely on sporadic support and lack structured learning frameworks and systematic assistance [6,9,36]. Existing learning tools (such as tutorials and manuals) have dismal interactivity and contextual detachment [37], failing to encourage sustained participation. The elderly tend to prefer relaxed and interactive learning environments [38]. "Gamification" refers to the application of game elements (such as points, challenges, and real-time feedback) in non-game contexts to enhance user engagement, motivation, and learning outcomes [39]. In the context of digital literacy training, gamification can help reduce learning anxiety, increase enjoyment, and promote emotional involvement [40]. Cognitive games have been shown to improve their cognitive capabilities and learning motivation through task segmentation and instant feedback [5]. However, most market products focus on general cognitive training (such as Sudoku) rather than deep integration of digital skill development [41].

Although intergenerational collaboration programs such as Cyber-Seniors have demonstrated a certain success in higher education settings [42], their linear teaching models lack dynamic adaptability, and resource allocation disparities limit scalability [43]. More importantly, existing studies present several disjointed aspects: (1) the analysis of digital literacy barriers and intergenerational interaction theories remain separate, and have not formed an integrated framework; (2) intervention practices rely on informal settings, making it difficult to achieve sustainability [9]; and (3) technological design efforts focus primarily on interface simplification while neglecting cognitive load management and emotional motivation [1]. Despite the importance of addressing individual barriers, integrating intergenerational collaboration not only enhances the effectiveness of digital literacy interventions, but also fosters a more inclusive digital society.

In the present study, the "Structured Gamified Intergenerational Digital Reverse Mentorship" paradigm was proposed to overcome these limitations. Through progressive digital tasks (from basic operations to complex skills), a bidirectional intergenerational collaboration module (real-time voice/text guidance), and a multidimensional incentive system (points rewards, emotional feedback), a threefold intervention framework of "cognitive adaptation–emotional engagement–skill internalization" was constructed, and provided a scientific basis and practical solution for bridging the digital divide.

2.2. Theoretical Dimension: The Dual-Drive Framework of Cognitive Aging Theory and User Experience Design Theory

Cognitive Aging Theory and User Experience Design Theory play complementary roles in the digital skill learning process for the elderly. Cognitive Aging Theory focuses on the changes in cognitive function that occur with aging, particularly their impact on the execution of complex tasks [10,12]. Research has indicated that the elderly experience a gradual decline in controlled processing, working memory, and cognitive reserve, leading to increasingly challenging learning and operating in digital environments [44]. The changes in controlled processing make it more difficult for the elderly to adapt to new tasks, while slower processing speed and reduced short-term memory capacity increase the likelihood of errors or cognitive overload in attention-intensive tasks [45,46]. Additionally, the elderly have a diminished ability to filter out irrelevant information, making them more susceptible to distractions and thus reducing learning efficiency [47]. As cognitive reserve declines, they are more likely to feel anxious or frustrated when facing new technologies or complex operations [48,49]. Therefore, when designing digital learning tools, it is essential to provide adaptive support tailored to cognitive characteristics of the elderly to reduce cognitive load, enhance learning efficiency, and improve user experience.

User Experience Design (UXD) focuses on user needs, and emphasizes interaction experience, operational convenience, and emotional resonance to optimize product usability and accessibility [9]. Unlike traditional instructional design, UXD places greater emphasis on interactive fluidity, the integration of functionality, and emotional connection, ensuring a positive user experience before, during, and after product usage. For example, a digital reverse mentorship game for the elderly can incorporate personalized tutorials and step-by-step demonstrations to provide a progressive learning path based on users' initial proficiency level, so as to prevent frustration caused by steep learning curves [50]. Additionally, UXD prioritizes real-time feedback mechanisms, such as visual or auditory rewards upon task completion, to enhance users' sense of accomplishment and willingness to continue engaging. Designing a system that dynamically adapts to user needs can not only improve the usability of gamified applications, but also effectively promote the motivation of the elderly to explore digital technology proactively.

The integration of Cognitive Aging Theory and User Experience Design Theory has formed a framework of "Cognitive Adaptation–Emotional Drive–Skill Internalization", providing a dual-compensation pathway for digital skill learning for the elderly. First, in the cognitive adaptation phase, the system reduces initial learning barriers through segmented tasks, thereby decreasing cognitive load to enable the elderly to gradually become familiar with digital operations. Second, in the emotional drive phase, intergenerational social incentives (such as virtual badge sharing and collaborative tasks) are introduced to enhance user motivation by making the learning process more socially valuable and interactive. Finally, in the skill internalization phase, scenario-based simulation tasks (such as online shopping and social media interactions) reinforce skill transfer, allowing the elderly to flexibly apply their acquired digital skills in their daily life. Neuroscientific research supports this framework, as fNIRS (functional near-infrared spectroscopy) studies have shown that gamified learning activates both the dorsolateral prefrontal cortex (responsible for cognitive control) and the ventral striatum (involved in reward processing), indicating that gamification effectively enhances learning outcomes for the elderly [51].

In summary, Cognitive Aging Theory provides a theoretical foundation for cognitive support in digital skill learning, while User Experience Design optimizes interaction methods to enhance learning experiences and emotional engagement. The combination of these two theories overcomes the limitations of single-theory approaches. For instance, pure cognitive training may lead to low compliance due to its tedious nature [52], while isolated emotional incentives lack a physiological basis for cognitive improvement. Building on this theoretical framework, this study posits that a collaborative gamified model, by integrating cognitive adaptation mechanisms, intergenerational guidance, and contextualized task design, will outperform traditional mentorship and independent learning models in improving digital skill acquisition among older adults. Therefore, we propose Hypothesis 1 (H1) and Hypothesis 2 (H2):

H1: *The Collaborative Gamified Digital Reverse Mentorship model (Model C) is more effective in enhancing digital skill acquisition among older adults than the Traditional Digital Reverse Mentorship model (Model A) and the Independent Gamified Learning model (Model B).*

H2: *The Collaborative Gamified Digital Reverse Mentorship model (Model C) provides a better user experience than the Traditional Digital Reverse Mentorship model (Model A) and the Independent Gamified Learning model (Model B).*

2.3. Technical Dimension: The Integration of Gamification and Aging-Friendly Design

Aging-Friendly Design and Gamification Theory exhibit deep complementarity in the field of digital skills training for the elderly. The aging-friendly design holds a primary goal to reduce cognitive load for elderly users and promote them to adapt to and use digital technology, which is achieved through measures such as high-contrast visual encoding, simplified menu structures, and fewer interaction steps to optimize the user experience [53]. Although these measures have been proven to effectively enhance perceived ease of use (PEU), studies have indicated that optimizing the interface alone is insufficient to improve the learning motivation and skill retention of the elderly [1]. Based on the Technology Acceptance Model (TAM), research has suggested that the sustained learning of elderly users depends not only on perceived ease of use, but also on perceived usefulness (PU) and hedonic motivation (HM) [54] In other words, the elderly require not only easy-to-use interfaces, but also engaging and motivating learning experiences to sustain long-term use.

Compared with traditional aging-friendly optimizations, gamification strategies can reduce cognitive load while enhancing engagement and learning persistence. Gamification Theory enhances user retention by incorporating mechanisms such as task segmentation, instant feedback, and virtual rewards, ensuring that the elderly can maintain cognitive engagement throughout the learning process [7,55]. Task segmentation breaks down complex digital skills into progressive challenges, allowing elderly users to gradually adapt to and master new skills [6]. Instant feedback provides positive reinforcement during the learning process and increases self-efficacy [7,42], while virtual rewards (e.g., points and badges) leverage the goal-gradient effect [56] to boost motivation. However, most existing gamified applications for the elderly primarily focus on cognitive training (e.g., Sudoku, memory training) [57] and lack real-life application scenarios despite their ability to enhance cognition, thereby limiting the ability of the elderly to transfer learned skills into daily digital interactions [55,58]. In contrast, contextualized game design can strengthen the practical relevance of skill acquisition. For example, by simulating tasks such as online medical consultations, social media interactions, and digital payments, the elderly can learn digital skills in familiar environments and improve skill transfer and long-term retention [58]. Furthermore, neuroimaging studies suggest that contextualized game design can enhance functional connectivity between the hippocampus and prefrontal cortex, potentially delaying cognitive decline in the elderly [5,59]. Therefore, embedding gamification mechanisms into aging-friendly design not only lowers learning barriers, but also enhances learning motivation and long-term skill retention.

Based on aging-friendly design and gamification strategies, intergenerational interaction technologies further optimize digital learning experiences of the elderly. Research has indicated that teaching digital skills to the elderly by young individuals not only reduces their technology anxiety, but also enhances learning experiences through social interaction [27]. However, traditional intergenerational mentorship models typically rely on offline support from family members or volunteers and lack systematic and sustainable technological support, leading to individual learning discrepancies among the elderly [9]. To address this issue, recent studies have explored how technology can facilitate intergenerational interaction, such as real-time collaboration and remote guidance features, so as to enable younger users to provide digital assistance to the elderly at any time [28]. Additionally, gamified task-sharing and collaborative learning models allow younger and older participants to engage in learning tasks together, thereby facilitating knowledge transfer and increasing learning motivation for the elderly. The integration of artificial intelligence (AI) further optimizes the learning experience. For instance, intelligent recommendation systems can tailor learning tasks based on progress, provide personalized teaching suggestions, reduce frustration, and ultimately improve the digital skill mastery rate among elderly users.

In summary, traditional aging-friendly interface optimizations alone cannot fully meet the long-term digital learning needs of the elderly. Instead, integrating gamification mechanisms with intergenerational interaction offers a more effective approach by enhancing motivation, improving skill transferability, and fostering long-term retention of digital skills. In this study, a systematic and sustainable training model for the elderly was explored by incorporating gamification strategies into aging-friendly design, coupled with intergenerational collaboration, with the aim to help the elderly better adapt to digital environments and promote sustainable technology adoption. The combination of gamified learning and intergenerational collaboration is expected to foster both extrinsic and intrinsic learning motivations among elderly users, as supported by motivation theories and prior empirical findings. Hence, we formulate Hypothesis 3 (H3):

H3: *The Collaborative Gamified Digital Reverse Mentorship model (Model C) leads to higher learning motivation compared to the Traditional Digital Reverse Mentorship model (Model A) and the Independent Gamified Learning model (Model B).*

3. Materials and Methods

3.1. Research Design

This study adopts a design-based research methodology, systematically guided by the ADDIE instructional design model, to develop and evaluate a gamified intergenerational mentorship learning application, "Digital Bridge", with the aim of enhancing digital literacy among older adults. Rather than treating the application design itself as the primary research objective, this study focuses on evaluating the effectiveness of a collaborative gamified mentorship mechanism in a real-life learning context, grounded in both cognitive and user-experience theories.

Originally developed in the field of instructional design, the ADDIE model provides a structured process for creating effective and learner-centered educational programs. The ADDIE model consists of five stages, Analysis, Design, Development, Implementation, and Evaluation, as illustrated in Figure 1. This model is widely recognized as an effective methodological framework for developing training programs, ensuring scientific rigor, systematic organization, and practical applicability in instructional content [14].

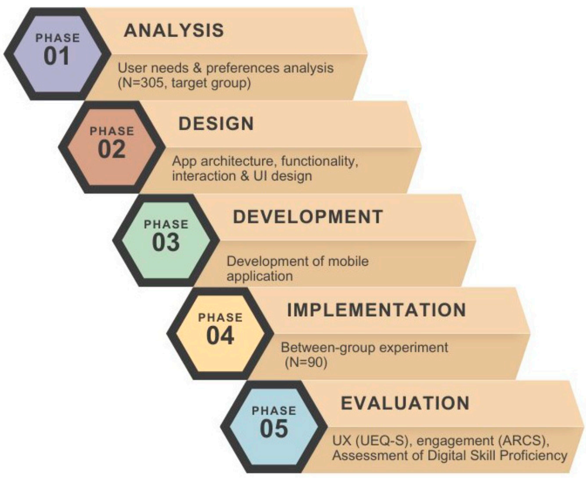

Figure 1. Mobile application development process using the ADDIE model.

3.1.1. Phase One: Analysis Phase

During the analysis phase, this study combined questionnaire surveys and focus group discussions to comprehensively understand older adults' digital skills status, needs, barriers, and preferences, providing data support and practical guidance for the design of the "Digital Reverse Mentorship" gamified application.

First, to ensure the scientific validity and content accuracy of the questionnaire, the research team consulted three gerontology professors (3), two design professors (2), two elderly university instructors (2), and one community center staff member (1). Based on their suggestions, a preference and needs assessment questionnaire was developed, covering six sections: basic information, current digital skills, digital skill needs, learning barriers, willingness for gamified learning, and open-ended suggestions.

Data collection was conducted in Taiyuan, Shanxi Province, China, via the "Wenjuanxing" online survey platform from November 15 to 5 December 2024, with 305 older adults (aged 60+) participating. All respondents provided written informed consent. To enhance comprehension, researchers explained each question during the survey process to ensure older participants could respond accurately.

To further explore user needs and ensure a multidimensional research approach, a focus group discussion was organized at a community center in Taiyuan, Shanxi Province. The discussion involved eight participants from diverse backgrounds, including older adults (2), family members (2), community center staff (1), elderly university instructors (1), experienced aging-friendly designers (1), and gerontology experts specializing in the digital divide (1). The discussion focused on the following key topics:

① How can gamification help older adults overcome learning barriers?

② How can game-based learning content and interaction be optimized to reduce learning anxiety, boost confidence, and promote intergenerational interaction?

③ What is the specific role and impact of younger individuals in assisting older adults with digital skill learning?

④ What is the current state of older adults' digital literacy, and what are the strengths and limitations of existing "digital reverse mentorship" models?

⑤ What is the potential of cognitive games in improving older adults' digital literacy and learning motivation?

The discussion followed an open-ended format, encouraging participants to share real experiences and insights. Sufficient background information was provided to facilitate meaningful dialogue. By incorporating perspectives from different stakeholders, the study refined the design direction of the gamified intergenerational digital mentorship application "Digital Bridge", ensuring that it meets the practical needs of older users while also achieving broader social and educational objectives, such as enhancing intergenerational interaction and improving the effectiveness and sustainability of digital skills learning.

3.1.2. Phase Two and Three: Design and Development Phase

Based on the findings from the analysis phase, including user needs exploration and focus group interviews, and guided by Cognitive Aging Theory and Aging-Friendly Experience Design, this study aimed to develop a "Digital Reverse Mentorship" application, "Digital Bridge", that balances practicality and engagement. The core design philosophy of this application is to accommodate older users' cognitive, emotional, and social needs by using gamification strategies to lower learning barriers, stimulate intrinsic motivation, and promote active intergenerational interaction. To achieve these goals, the application underwent comprehensive optimization in terms of workflow and structural design, UI (user interface) enhancements, interaction modes, and feedback mechanisms, creating a holistic digital literacy learning platform that combines education, entertainment, and social engagement to help older adults integrate into the digital world.

This study introduced "Intergenerational Digital Reverse Mentorship" as the core concept of the application, emphasizing the use of digital technology to bridge the intergenerational digital divide by enabling younger users to pass on digital skills to older adults while fostering mutual learning and interaction. Based on this concept, the application's functional design includes two user modes: the "Digital Learner" mode (for seniors) and the "Tech Mentor" mode (for juniors). It integrates four key modules: a digital skills learning module, an intergenerational interaction module (e.g., a "Call for Help" feature), a gamified reward system (including points, virtual achievements, and emotional rewards), and an optional AI voice assistant (providing game hints or acting as a virtual junior). The workflow design follows standard operational logic such as onboarding screens for first-time users, registration pages, and senior–junior binding pages, while ensuring a clear and progressive learning path from simple to complex and from basic to advanced content, with logical continuity between topics. The interface is simple and intuitive, tailored to the cognitive characteristics of older users, for example, by reducing the number of interactive elements per page and enhancing their visibility. A "Call for Help" function allows older users to request assistance from their junior counterparts when facing difficulties, who can then provide real-time guidance via voice or text, enhancing interactivity and collaboration. Additionally, a task challenge mechanism is introduced, encouraging older users to complete various digital skill challenges to earn achievement-based rewards, thereby boosting learning engagement and motivation.

In UI (user interface) and interaction design, this study optimized the layout based on Cognitive Aging Theory to make the application more intuitive, simplified, and user-friendly. The interface uses large fonts, high-contrast color schemes, and clear navigation structures to ensure that older users can browse and operate the app effortlessly. Additionally, for critical operations (such as payments and information submissions), confirmation dialogs were introduced to reduce the risk of errors and improve safety and reliability. To enhance learning interest and user experience, gamification-based interactions were further optimized. For instance, upon completing a task, users receive instant feedback (e.g., animated prompts, voice guidance), helping them track their progress and achievements while boosting confidence. At the same time, operation processes were simplified, reducing multi-level menus and improving touch interactions to ensure that tasks can be completed with minimal steps.

In the development phase, Android Studio was used as the primary development environment. Given the operational habits of older users, the application's interface interactions adopted a "tap-to-enter" navigation method, allowing users to easily access different functional modules without complex operations. Moreover, this study employed an iterative feedback loop model, collecting continuous user feedback throughout the development process to optimize operational fluency, interaction experience, and visual design. For example, early user testing revealed that some older adults were unfamiliar with swipe gestures, leading to an adjustment to a "single-tap confirmation" mode to reduce learning difficulty and error rates. Additionally, voice-assisted functions were incorporated into key learning tasks, further reducing cognitive load and improving interactive accessibility.

At present, the application has only completed the initial stage of basic development, with five levels created for testing purposes. Core features such as account registration, senior–junior pairing, interaction, and real-time communication have not yet been implemented. Therefore, during the testing phase of this study, each group used an Android device with the test version of the app installed. To simulate the guidance from juniors to seniors, a volunteer was assigned to observe the senior's gameplay in person. When the senior encountered difficulties and pressed the app's "Request Help" button, the on-site volunteer would provide prompts and guidance, simulating the app's intended intergenerational interaction functionality.

3.1.3. Phases Four and Five: Implementation and Evaluation

This study adopted a between-group experimental design to evaluate the effectiveness of the collaborative gamified digital mentorship application in improving digital literacy among older adults. The research focused on measuring digital skill acquisition and examining the impact of collaborative gamification on user experience and learning motivation.

First, a total of 90 older adults aged 60 and above were recruited from a senior university in Taiyuan, Shanxi Province, China. Participants were recruited after we obtained permission from the university administration. Recruitment was conducted through both online announcements and offline flyers distributed on campus. Inclusion criteria included: age $\geq$ 60 years, basic literacy skills, voluntary participation with signed informed consent, and confirmation in the pre-test that they had not yet mastered the seven digital skills involved in the experiment. To ensure the representativeness of the sample, recruitment considered factors such as educational background, digital skill levels, and smartphone usage experience. Exclusion criteria included: (1) individuals with severe cognitive impairment, mental disorders, or physical conditions that hinder learning, as well as those unable to complete a continuous two-hour learning task; (2) older adults who had participated in similar digital skills training in the past year. No participants dropped out during the experiment. To encourage participation, each participant received a small gift valued at approximately 30 RMB as a token of appreciation after completing the sessions.

Second, this study adopted a three-arm parallel randomized controlled trial (RCT) design, with participants randomly assigned to one experimental group and two control groups (N = 30 per group), each receiving a different learning intervention (Figure 2).

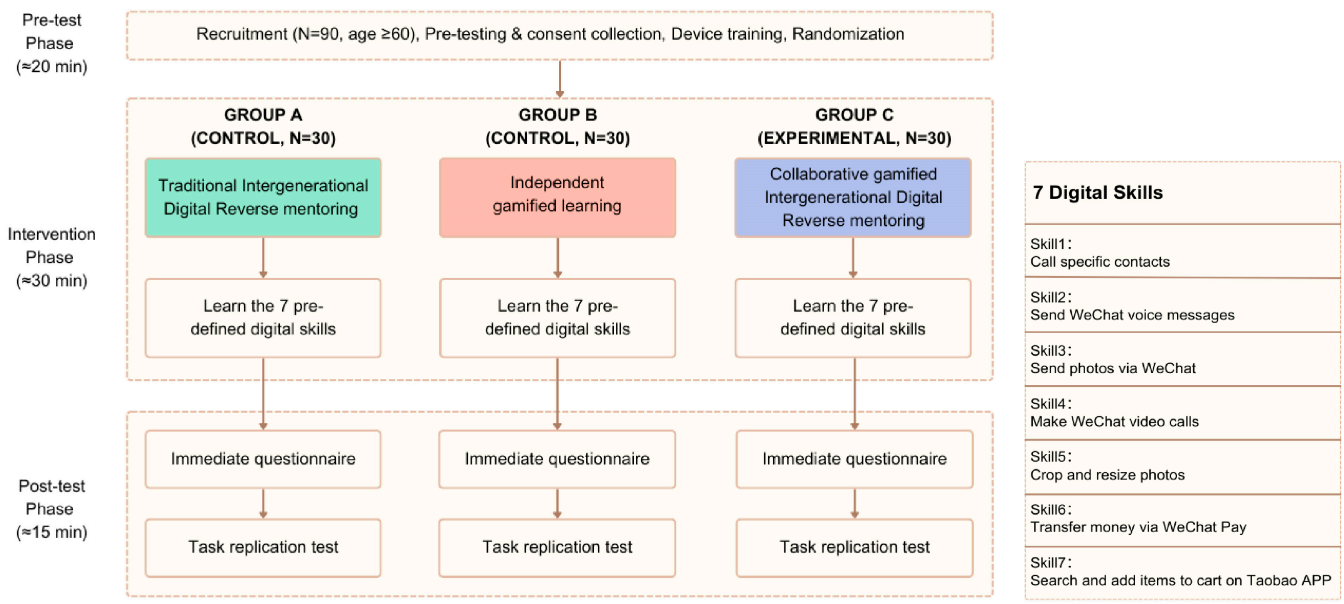

Figure 2. Experimental procedure diagram and seven digital skills.

Since intergenerational interaction was involved in the experiment, the "tech mentor mode" was carried out by trained staff members. All mentors completed a two-day standardized training program, which covered the digital skills instructional script, communication techniques, and strategies for supporting older adults in learning. After the training, mentors were required to pass a teaching simulation assessment to ensure consistency in instructional content and methods, as well as the ability to adapt flexibly to learners' progress.

The independent variable in this study was the three learning intervention modes (A/B/C models), characterized by differences in knowledge transfer medium (offline instruction/human–computer interaction/human–computer collaboration) and interaction dimension (one-way teaching/self-directed exploration/intergenerational collaboration). The dependent variables included:

① Digital Skill Acquisition: seven core digital skills (e.g., mobile payments, social media use) were selected based on the needs assessment and were evaluated using a dichotomous scoring system (1 = success, 0 = failure). Participants were required to perform skill-related tasks independently in a standardized environment, with double-blind observers recording accuracy.

② User Experience: measured using the User Experience Questionnaire—Short (UEQ-S), an eight-item scale divided into pragmatic quality (e.g., efficiency, clarity) and hedonic quality (e.g., attractiveness, innovativeness). Each item was rated on a 7-point semantic differential scale (e.g., "inefficient—efficient"), with scores ranging from 1 (negative experience) to 7 (positive experience). Mean scores for both dimensions were calculated separately to reflect user experience levels.

③ Learning Motivation: measured using the ARCS Model of Motivation (Attention, Relevance, Confidence, Satisfaction), assessed through a 16-item scale (4 items per dimension) on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), with a total score ranging from 16 to 80.

Experimental tasks were selected based on the needs assessment, covering high-frequency digital skills commonly required by older adults, including online shopping (76.7%), calling/messaging (73.4%), social media use (68.2%), photo/video editing (20.7%), and video chat (20.3%). Skills were selected based on a progressive difficulty principle, ensuring fairness and scientific rigor in comparing different learning models. All selected skills were confirmed through pre-testing to be unmastered by participants before the experiment, ensuring the reliability of results. The experiment was conducted in a standardized environment, with the venue set up as a quiet, comfortable, independent space to maintain consistent environmental conditions and lighting. All participants used the same model of Android smartphone, pre-installed with the standardized test application "Digital Bridge", and were provided with a uniform network configuration to minimize external factors influencing the results.

The experiment was divided into the pre-test phase, intervention phase, and post-test phase (as illustrated in Figure 2), with the following procedures:

① Pre-Test Phase: participants' baseline digital skills were assessed to ensure that none had prior knowledge of the seven experimental tasks. Additionally, this phase included device operation training to minimize the impact of unfamiliarity with the equipment.

② Intervention Phase: participants engaged in their assigned learning tasks according to group allocation. Researchers used a standardized observation record sheet to document learning duration, types and frequency of encountered issues, help-seeking behaviors, emotional responses, and learning strategies, ensuring comprehensive data collection.

③ Post-Test Phase: immediately after learning completion, the following assessments were conducted:

a. User Experience Measurement (UEQ-S).
b. Learning Motivation Measurement (ARCS Model of Motivation Scale).

c. Digital Skill Acquisition Assessment: participants performed skill-related tasks independently in a standardized environment, with double-blind observers recording their performance.

This study adopted an immediate testing approach to minimize the effects of short-term memory decay on test results. Additionally, all tests strictly followed a double-blind design, ensuring that both assessors and participants were unaware of their specific group allocation, thus maintaining data objectivity and experimental validity. Furthermore, all experiment staff underwent standardized training to ensure uniform instructional content and interaction methods across groups, adhering to a predefined teaching script to guarantee consistency in the experiment.

3.2. Data Analysis

To ensure the reliability and validity of the measurement instruments, this study conducted reliability and validity analyses on the User Experience Questionnaire—Short (UEQ-S), ARCS Motivation Model Scale, and Digital Skills Test. Internal consistency was assessed using Cronbach's α coefficient, while construct validity was evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE). Prior to analysis, all variables were preprocessed to ensure data suitability and robustness.

For data analysis, this study used R version 4.4.1 (2024-06-14 ucrt) and adopted non-parametric tests to ensure the robustness of the results. Since the data exhibited non-normal distribution (Shapiro–Wilk normality test $p < 0.05$), the Kruskal–Wallis H test was employed to compare differences among the three learning modes (Group A: Traditional Digital Mentorship, Group B: Independent Gamified Learning, Group C: Collaborative Gamified Digital Mentorship) in terms of user experience, learning motivation, and digital skill acquisition. For variables showing significant differences, Dunn's post hoc test was used for pairwise comparisons.

4. Results

This study conducted a systematic data analysis based on the ADDIE model, which encompasses five phases, Analysis, Design, Development, Implementation, and Evaluation, ensuring the scientific rigor and effectiveness of the developed digital learning intervention.

4.1. Findings from the Analysis Phase

During the needs assessment phase, a total of 305 older adults aged 60 and above participated in the questionnaire survey. The sample consisted of 52.46% male and 47.54% female respondents, with 68.2% aged between 61 and 75 years. The educational background of the participants was generally low, with 46.89% having only completed primary education or below and 28.53% having completed junior high school education. Regarding living arrangements, the highest proportion of participants lived with their children or relatives (33.77%), followed by those living with a spouse (30.49%), while 15.74% lived alone. The survey revealed that 69.5% of older adults regularly use smart devices, with smartphones being the most commonly used device (37.7%). However, their overall digital skills remained weak, indicating a significant demand for learning and notable learning barriers.

The findings showed that older adults' most frequently used digital skills were related to daily services and social functions, including online shopping (76.7%), calling/messaging (73.4%), and social media use (68.2%). However, only 15.1% of respondents considered themselves "highly proficient" in digital skills. In terms of learning demands, the most desired skills were photo/video editing (20.7%) and video chat techniques (20.3%), reflecting their high interest in recording life experiences and social interactions. Additionally, the demand for file transfer and printing (13.8%) highlighted practical operational needs in their daily routines (See Figure 3).

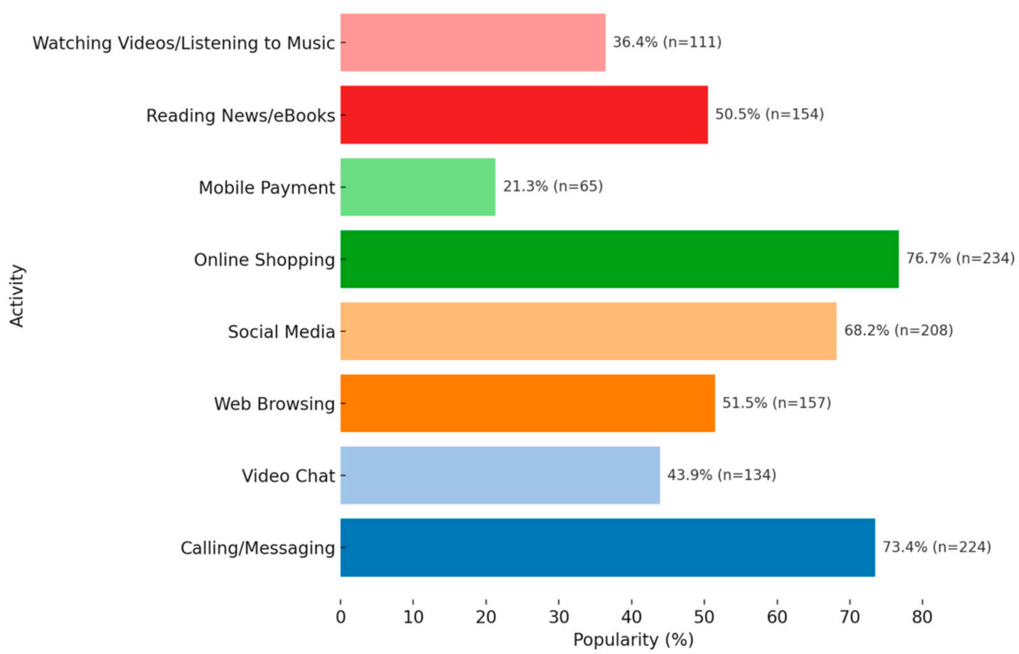

Figure 3. Primary activities using smart devices by the elderly.

However, older adults faced significant barriers when learning digital skills. The most prominent concern was the fear of making mistakes that could damage devices or lead to financial losses (88.5%), followed by difficulty understanding technical terms (58.0%) and lack of patient guidance from family or friends (46.6%). These barriers indicate that older adults commonly experience psychological anxiety and a lack of environmental support when learning digital skills, necessitating tailored learning tools to lower entry barriers (See Figure 4).

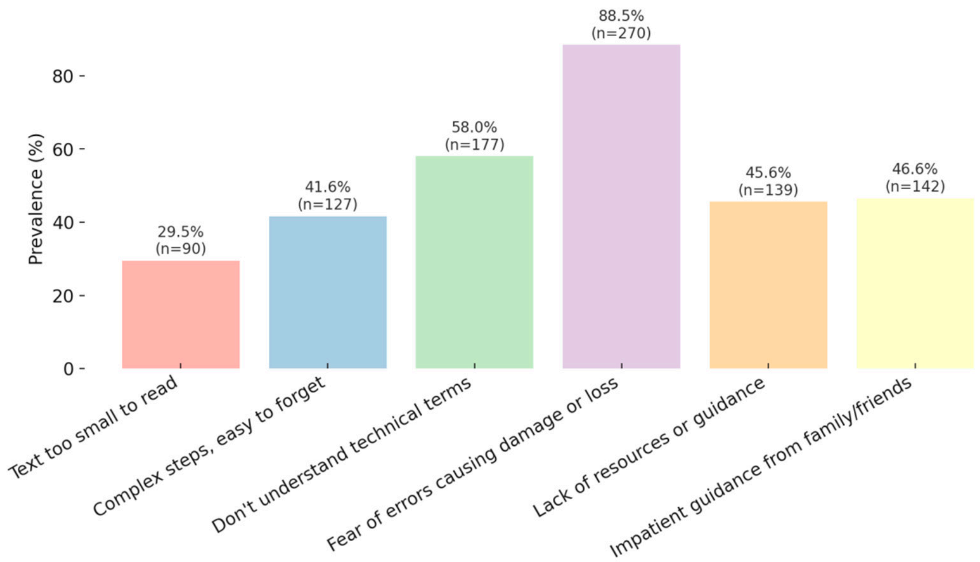

Figure 4. Main difficulties older adults face in learning to use smart devices.

Additionally, survey data showed that older adults had a high acceptance of gamified learning products, with reward mechanisms (89.5%), interactivity (73.4%), and personalized settings (71.5%) being key motivators (See Figure 5). Open-ended suggestions further revealed that older adults prefer digital learning tools with a simple and intuitive interface, instructional videos or image-based tutorials, and real-life scenario-based training. These insights provided valuable references for subsequent gamification design.

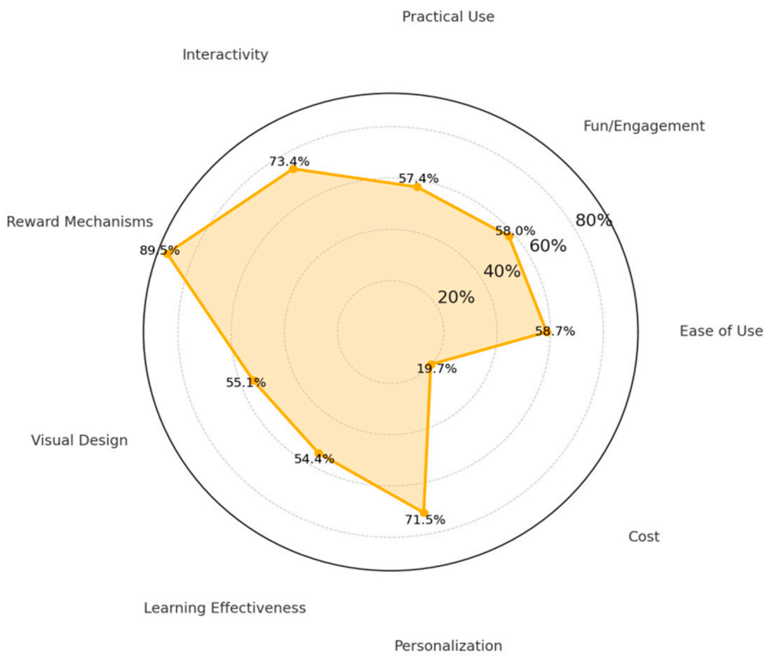

Figure 5. Factors influencing the elderly's willingness to use digital learning products.

The focus group discussions with participants provided valuable insights into the core functions and design strategies of the "Digital Reverse Mentorship" gamified learning application. Participants emphasized that gamification elements could significantly reduce learning barriers for older adults. One participant remarked, "Breaking down complex tasks into smaller, progressive steps makes learning less overwhelming and more manageable." Others highlighted the importance of cognitive load reduction, suggesting that a structured, step-by-step learning approach would help older users retain information more effectively.

Regarding motivation, several participants pointed out that point-based rewards, virtual achievements, and emotional reinforcement mechanisms could make the learning experience more engaging. One participant shared, "Seeing progress through points and badges would keep me motivated to continue learning."

For instructional content, the discussions underscored the need for real-life scenarios to enhance practical understanding. A participant explained, "If I see how these digital skills apply to everyday tasks, like online banking or video calls with family, I'd be more confident in using them." Additionally, participants stressed the importance of a simple and intuitive interface, with optimized navigation and confirmation dialogs for critical actions. As one participant put it, "I worry about making mistakes, so having a clear confirmation before taking an action would make me feel much safer using the app.".

These discussions confirmed that designing with older adults' needs in mind—by simplifying tasks, providing motivational reinforcement, and ensuring usability—would enhance the effectiveness of the gamified learning experience.

In summary, during the needs assessment phase, this study conducted a comprehensive analysis of older adults' digital learning needs, barriers, and expectations through questionnaire surveys and focus group discussions. By integrating participant's feedback, this study clearly defined the design direction for the gamified digital mentorship application. The findings provided strong data support and theoretical foundations for designing and optimizing gamified learning tools, ensuring that the final product not only meets the practical needs of older adults, but also enhances intergenerational interaction and promotes long-term digital skill development.

4.2. Results from the Design and Development Phases

In the design phase, this study, based on findings from the needs assessment and focus group discussions, and guided by Cognitive Aging Theory and Aging-Friendly Experience Design, developed a Collaborative Gamified Digital Mentorship Application "Digital Bridge". This application aims to enhance older adults' digital literacy, promote intergenerational interaction, and reduce learning barriers through gamification strategies, thereby increasing user motivation and digital skill acquisition. The following sections summarize the design research findings in four key areas: game framework, functionality design, UI design, and interaction design.

In terms of game framework and functionality design, the application consists of four core modules: Digital Skills Learning Module, Intergenerational Interaction Module, Reward Mechanism, and AI Voice Assistant. The Digital Skills Learning Module covers 12 fundamental skills, such as making phone calls, sending text messages, and using social media. Task design is closely aligned with the daily life scenarios of older users, helping them understand the practical significance and application of these operations. The Intergenerational Interaction Module innovatively introduces the "Call for fresh Help" feature, allowing younger users to guide older users in real-time via voice or text, facilitating intergenerational knowledge transfer and collaboration. The Reward Mechanism employs a point-based system and virtual achievements (such as badge collections) to provide multi-dimensional incentives, enhancing user motivation and a sense of accomplishment. Additionally, the AI Voice Assistant offers voice navigation and real-time operational prompts, further reducing learning complexity and enabling older users to complete digital skill training more independently.

In terms of UI design, this study strictly adhered to aging-friendly design principles, optimizing visual accessibility and operational convenience. The visual design employs font sizes of at least 18 pt and high-contrast color schemes, ensuring that interface elements are clearly visible, thus reducing accessibility barriers caused by age-related vision decline. The interface layout, while ensuring functionality completeness, adopts a hierarchical navigation structure, ensuring that core functions (such as digital skills learning and intergenerational interaction) are placed in top-level menus, allowing users to quickly and intuitively locate target functions, minimizing confusion and frustration caused by complex pathways. For example, a secondary confirmation mechanism is implemented in key task steps to prevent accidental errors, thereby improving interaction security. Additionally, the system provides real-time visual and auditory feedback, ensuring operational visibility and predictability, thus enhancing users' learning experience and confidence.

In terms of interaction design, this study focused on the core objectives of reducing cognitive load and optimizing user experience, employing four key design strategies. First, simplifying navigation paths, using an intuitive menu structure, and clear task flow to reduce operational difficulty and cognitive burden. Second, an instant feedback mechanism, where the system immediately provides success prompts accompanied by dynamic celebratory animations after task completion, enhancing the sense of achievement and learning motivation. Third, progressive task difficulty, where tasks follow an easy-to-difficult learning path—initial tasks focus on basic operations (e.g., answering a phone call), while more complex tasks (e.g., using mobile payments) are gradually introduced as users gain proficiency. This ensures users stay within an optimal challenge zone, preventing frustration due to excessive difficulty. Lastly, the "Call for Help" function, which optimizes the guidance process for younger users, supporting both voice intercom and text prompts to ensure efficient and engaging intergenerational collaboration. When older users encounter operational difficulties, they can instantly request help from their paired younger user, who can provide real-time assistance through voice or text instructions, effectively solving problems while strengthening emotional bonds through intergenerational interaction (see Figure 6).

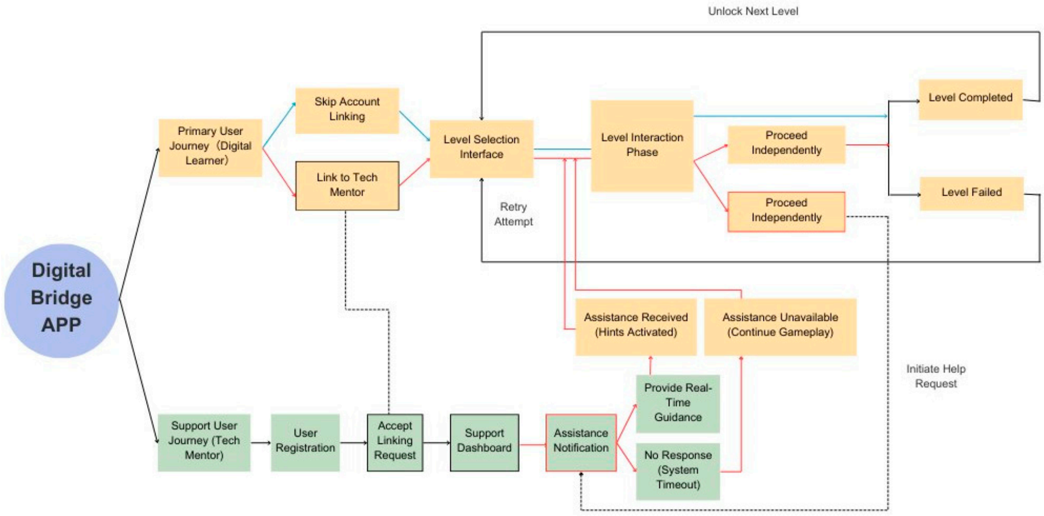

Figure 6. "Digital Bridge" Intergenerational Digital Mentorship Gamified Application process diagram. This game consists of digital learner mode (A) and tech mentor mode (B), with elders as the primary players while younger users assist them upon receiving a help request. The game flow and key interaction design are as follows: After entering the game, users must select either Elder or Younger identity. Elders can choose to play independently or bind with a younger user, enabling them to send help requests during the game. Once bound, when a younger user receives a help request, they can choose to assist the elder. If they choose to help, they will receive a prompt guiding them through the task. If the elder successfully completes a level, they unlock the next one, but if they fail, the next level remains locked.

Through these design strategies, the application is expected to effectively reduce cognitive load, improve operational ease and the learning experience, and establish an interactive and practical digital skills learning environment, enabling older users to integrate more smoothly into the digital society. Ultimately, through systematic design and development, this study aims to build a digital learning platform that aligns with older users' cognitive characteristics, meets their emotional needs, and promotes intergenerational interaction. (see Figures 7 and 8).

Through these design strategies, the application effectively reduces cognitive load, enhances ease of operation and learning experience, and establishes an interactive and practical digital skills learning environment, enabling older users to integrate more easily into the digital society. Ultimately, through systematic design and development, this study successfully built a digital learning platform that aligns with older users' cognitive characteristics, meets their emotional needs, and promotes intergenerational interaction. At the same time, the application's design fully integrates aging-friendly principles and gamification strategies, offering an intuitive, user-friendly, and emotionally engaging learning experience, laying a solid foundation for subsequent user testing and effectiveness evaluation.

Figure 7. "Digital Bridge" Application Primary User Flow (A) Elder Mode Interface, from left to right: Character Selection Page, where users choose between "I am an elder" and "I am a junior" to enter the game; Bind Younger User Page, prompting the elder to bind with a junior by providing a unique binding code ("Please tell the junior the binding number: 123321"); Home Page (Level Selection Page), where users begin learning tasks from the beginner level and select from Level 1 to Level 3, with a prominent "Start" button to proceed; Task Execution Page (Skill Task: "Call specific contacts"), displaying a task goal ("Goal: Save contact number") with instructions like "Open dial page, click 'Add Contact'" and an option to "Call the junior" for help; and Level Completion Page, which shows feedback upon successfully completing a task ("Score + 1", "Level passed successfully") with options to return home or continue to the next level.

Figure 8. "Digital Bridge" Application Support User Flow (B) Tech Mentor Mode Interface. From left to right: Bind Elderly User Page, where the junior user enters the elder's binding number and sets their own name, confirming the connection to assist the elder. The labels read "I am a junior," "Enter elder's binding number," and "Confirm binding"; Home Page (Always Ready to Help the Elderly), showing that the junior is ready to assist the elder in learning. Levels such as Level 1, 2, and 3 are displayed, along with a button labeled "View Assistance Records"; and Task Execution Page, where the junior sees the task goal ("Goal: Save contact number") and prepares to provide real-time guidance. A banner at the bottom reads: "You are currently in observer mode, assisting the elder to complete the task.".

4.3. Results from the Implementation and Evaluation Phases

In the implementation and evaluation phase, this study conducted a randomized controlled trial (RCT) to assess the effectiveness of the Collaborative Gamified Digital Mentorship Application. A total of 90 older adults aged 60 and above were recruited and randomly assigned to three groups: the Collaborative Gamified Digital Mentorship Group (C Group), the Traditional Digital Mentorship Group (A Group), and the Independent Gamified Learning Group (B Group). Data collection focused on three core indicators: digital skill acquisition, user experience (UEQ-S), and learning motivation (ARCS) (see Figure 9).

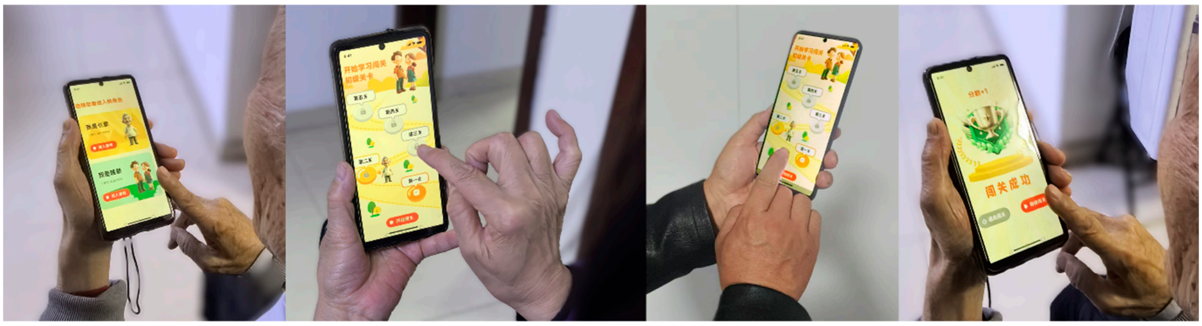

Figure 9. Trial scenarios for older adult users. This image presents a sequence of four real-life photos showing elderly users interacting with the "Digital Bridge" application. In the first photo, the user is on the role selection screen, choosing "I am an elder" to begin. The second photo shows the user navigating the level selection page, preparing to start a digital skill training task. In the third photo, the user is actively performing the task, such as making a phone call, as part of the guided activity. The final photo displays the completion screen with a "Level Passed" message, highlighting the user's success and reinforcing a sense of accomplishment. This series visually demonstrates the practical engagement of older adults with the app in real-world settings.

First, in the correlation analysis of group variables, gender, education level, and smartphone proficiency showed no significant differences ($p > 0.05$). Additionally, there was no significant association between group assignment and these variables, indicating that there were no systematic differences in baseline demographic characteristics among the groups. The random assignment was reasonable, making it suitable for further group comparisons (see Table 1). This is also supported by the association analysis results presented in Table 1, where all *p*-values were greater than 0.05 and effect sizes (Cramer's V) were small, indicating no systematic bias across gender, education, or smartphone proficiency among the groups.

Table 1. Results of categorical variable association analysis.

Variable 1	Variable 2	Statistic	Value	*p*-Value	Effect Size
Group	Gender	$\chi^2(2)$	1.71	0.425	0.138
Group	Education Level	Fisher's Exact		0.296	0.231
Group	Smartphone Usage Proficiency	Fisher's Exact		0.226	0.240
Gender	Education Level	Fisher's Exact		0.853	0.128
Gender	Smartphone Usage Proficiency	Fisher's Exact		0.462	0.206
Education Level	Smartphone Usage Proficiency	Fisher's Exact		0.200	0.256

Note: effect size is measured using Cramer's V.

Second, experimental results showed that different learning modes had significant differences in user experience, learning motivation, and digital skill acquisition. Specifically, the Collaborative Gamified Digital Mentorship Model (C Group) outperformed both the Traditional Digital Mentorship Model (A Group) and the Independent Gamified Learning Model (B Group), confirming its effectiveness in improving digital literacy among older adults. As shown in Table 2, Group C not only had the highest average scores across all dimensions, but also the smallest standard deviations, indicating more consistent and reliable outcomes. C Group had the highest scores across all evaluation metrics: User Experience (UEQ-S): 5.59 ± 0.33, Learning Motivation (ARCS): 5.75 ± 0.19, Skill Acquisition (Skills): 6.23 ± 0.94. A Group and B Group showed significantly lower scores: A Group (UEQ-S: 3.83 ± 0.55, ARCS: 3.99 ± 0.30, Skills: 2.97 ± 2.39), B Group (UEQ-S: 3.90 ± 0.44, ARCS: 4.14 ± 0.28, Skills: 2.87 ± 2.05). The small difference between A Group and B Group suggests that traditional teaching and independent game-based learning had comparable effects (see Table 2).

Table 2. Descriptive statistics of anxiety scale scores by group (mean ± SD).

Group	UEQ-S	ARCS	Skills
A	3.83 (±0.55)	2.98 (±0.24)	2.97 (±2.39)
B	3.90 (±0.44)	3.11 (±0.23)	2.87 (±2.05)
C	5.59 (±0.33)	3.66 (±0.52)	6.23 (±0.94)

Note. Data are presented as mean ± SD.

Further analysis of scale reliability and validity confirmed the measurement instruments' robustness. Cronbach's α values: UEQ-S: 0.78, ARCS: 0.91, Skills: 0.85. These values indicate high internal consistency. Construct validity tests (CFI > 0.90, TLI > 0.90, RMSEA < 0.08) showed a good model fit, supporting the individual validity of the measurement tools. Additionally, the Shapiro–Wilk normality test results showed that UEQ-S, ARCS, and Skills scores in C Group failed the normality test ($p < 0.05$). The Levene's test for homogeneity of variance indicated that ARCS and Skills scales showed significant variance differences among groups ($p < 0.05$). Therefore, non-parametric tests were used to ensure robustness of the results (see Table 3).

Table 3. Homogeneity of variance and normality tests.

Variable	Group	Shapiro–Wilk W	Shapiro *p*	Levene Test	Levene *p*
ARCS	A	0.9658199	0.432	F(2, 87) = 5.02	0.009
ARCS	B	0.9456768	0.129	F(2, 87) = 5.02	0.009
ARCS	C	0.8959594	0.007	F(2, 87) = 5.02	0.009
Skills	A	0.8656595	0.001	F(2, 87) = 7.48	0.001
Skills	B	0.9346811	0.065	F(2, 87) = 7.48	0.001
Skills	C	0.7777873	<0.001	F(2, 87) = 7.48	0.001
UEQ-S	A	0.9715425	0.582	F(2, 87) = 2.83	0.064
UEQ-S	B	0.9573003	0.264	F(2, 87) = 2.83	0.064
UEQ-S	C	0.9259038	0.038	F(2, 87) = 2.83	0.064

Note: The Shapiro–Wilk test reports the W statistic and exact *p*-value, while the Levene test reports the F-value and degrees of freedom.

To further evaluate the central tendency and dispersion of the data, this study calculated the median and interquartile range (IQR) for each group (see Table 4). The analysis results indicate that Group C had the highest median scores in UEQ-S (5.6250), ARCS (3.9375), and Skills (6.5), with the smallest IQR, suggesting that the learning outcomes in Group C were the most stable and consistent. In contrast, Groups A and B had lower median scores, and the IQR of Skills scores was larger (Group A: 4.00, Group B: 2.75), reflecting greater individual variability in adaptation under traditional teaching and independent game-based learning modes. This indicates that the collaborative gamified mentorship model not only led to better outcomes on average, but also produced more stable learning results with less variation, which is critical when designing inclusive interventions for elderly learners.

Table 4. Median and interquartile range (IQR) for each group.

Group	Median_ UEQ-S	IQR_ UEQ-S	Median_ ARCS	IQR_ ARCS	Median_ Skills	IQR_ Skills
A	3.6875	0.625	2.96875	0.296875	2	4
B	3.875	0.375	3.0625	0.359375	3	2.75
C	5.625	0.34375	3.9375	1.046875	6.5	1

The Kruskal–Wallis H test results (see Table 5) further confirmed significant differences among the three groups across all measured indicators (UEQ-S: $\chi^2(2) = 59.39$, $p < 0.001$; ARCS: $\chi^2(2) = 60.99$, $p < 0.001$; Skills: $\chi^2(2) = 36.51$, $p < 0.001$). Dunn's post hoc test (see Tables 6–8) indicated that Group C scored significantly higher than Groups A and B ($p < 0.001$), while there was no significant difference between Groups A and B ($p > 0.05$). This finding highlights that simply using gamified content without intergenerational support may not be sufficient for improving outcomes. The interactivity and social reinforcement in Group C appear to be key differentiators. Additionally, Group C had the highest median and the smallest IQR, indicating a more concentrated data distribution and more stable learning outcomes. In contrast, the Skills scores in Groups A and B showed greater dispersion (IQR = 4.00 and 2.75, respectively), suggesting that older adults exhibited higher variability in adaptation under independent learning and traditional teaching modes.

Table 5. Kruskal–Wallis test results.

Variable	Chi_Squared	df	*p*_Value
UEQ-S_total	59.39197	2	<0.001
ARCS_total	28.23301	2	<0.001
Skills_total	36.50690	2	<0.001

Table 6. The results of Dunn's post hoc test—UEQ-S_total.

Comparison	Z_Value	*p*_unadj	*p*_adj	Significance
A—B	−0.556889	0.578	1.000	ns
A—C	−6.935124	<0.001	<0.001	***
B—C	−6.378235	<0.001	<0.001	***

Note: *** $p < 0.001$; ns indicates non-significant (no statistical significance).

Table 7. The results of Dunn's post hoc test—ARCS_total.

Comparison	Z_Value	*p*_unadj	*p*_adj	Significance
A—B	0.1175083	0.906	1.000	ns
A—C	−5.1728633	<0.001	<0.001	***
B—C	−5.2903715	<0.001	<0.001	***

Note: *** $p < 0.001$; ns indicates non-significant (no statistical significance).

Table 8. The results of Dunn's post hoc test—Skills_total.

Comparison	Z_Value	*p*_unadj	*p*_adj	Significance
A—B	−1.491985	0.136	0.407	ns
A—C	−5.162467	<0.001	0.000	***
B—C	−3.670482	<0.001	0.001	***

Note: *** $p < 0.001$; ns indicates non-significant (no statistical significance).

Moreover, the results suggest that there may be a strong relationship among user experience, learning motivation, and digital skill acquisition. In the Collaborative Gamified Digital Mentorship group (Group C), participants not only achieved significantly higher scores on the UEQ-S and ARCS scales, but also demonstrated better mastery of digital skills. This indicates that a positive user experience and stronger learning motivation may jointly contribute to improved learning outcomes. Specifically, a good user experience such as a clear interface, intuitive operation, and timely feedback can help reduce cognitive load during the learning process, thereby enhancing older adults' willingness to participate and their engagement. Higher learning motivation reflected in interest in the content, confidence, and satisfaction further drives active task completion and continuous practice, leading to better skill acquisition. In contrast, Groups A and B showed relatively lower scores in both user experience and learning motivation, with poorer overall performance in skill acquisition and more dispersed data distribution. This suggests that in the absence of interaction or motivational mechanisms, learning outcomes among older adults are more susceptible to individual differences, resulting in greater variability. Therefore, optimizing user experience and enhancing learning motivation are key strategies for improving the effectiveness of digital skills training for older adults.

5. Discussion

5.1. Effectiveness of the Intergenerational Digital Mentorship Model

Based on Cognitive Aging Theory, this study developed a Collaborative Gamified Digital Mentorship Application and evaluated its effectiveness in improving digital skill acquisition, user experience, and learning motivation among the elderly. The experimental results demonstrate that the Collaborative Gamified Digital Mentorship Model (C Group) significantly outperforms the Traditional Teaching Group (A Group) and the Independent Gamified Learning Group (B Group) across all three dimensions ($p < 0.001$), indicating that a model combining intergenerational interaction and gamified learning can effectively reduce learning anxiety, enhance skill acquisition, and increase learning motivation and engagement among the elderly.

In the present study, intergenerational interaction played a crucial role, as interactions between older and younger users provided real-time feedback and support, so as to reduce technical barriers and boost learning confidence [60]. Particularly in a gamified environment, elderly users actively participated in tasks, received immediate feedback, and engaged with the reward mechanism, which helps them stay motivated and enhance their digital skills [7]. Additionally, the introduction of gamified learning provides an immersive learning experience to make the learning process more interactive and enjoyable, ultimately increasing learning motivation. These findings confirm that combining intergenerational interaction with gamified learning not only leads to more effective skill acquisition, but also improves attitudes toward digital learning of the elderly.

5.2. Skill Acquisition and Learning Experience

In this study, the elderly in C Group exhibited superior skill acquisition, significantly outperforming the other two groups. The combination of intergenerational interaction and gamified learning provided more effective learning support. Through intergenerational collaboration, the elderly received timely assistance and guidance from younger users, which reduced cognitive load during learning and enabled them to acquire digital skills more quickly and accurately. In contrast, the Traditional Teaching Model (A Group) and Independent Gamified Learning Model (B Group) lacked interactive support, making older users feel more isolated and confused during the learning process, ultimately impacting their skill acquisition.

Regarding user experience, the elderly in C Group scored significantly higher in both usability and enjoyment compared to A Group and B Group. Collaborative learning and aging-friendly game design effectively enhanced user experience, making the learning process more seamless and enjoyable. Intergenerational interaction not only provided social support, but also fostered emotional connections, giving the elderly a greater sense of belonging and emotional engagement during learning. Additionally, gamified design elements (such as task breakdown, immediate feedback, and reward mechanisms) increased learning enjoyment, allowing the elderly to better appreciate the learning process, and thereby improving their overall experience.

Another key finding of this study is the significant improvement in learning motivation. C Group achieved the highest learning motivation scores, indicating that the combination of gamification and intergenerational interaction effectively stimulates the elderly's interest in learning. The elderly often struggle with low learning motivation, but gamification elements, task feedback, and intergenerational support in this study successfully enhanced their interest and engagement, providing valuable insights for the design of future educational programs for the elderly.

5.3. Comparison with Existing Research

The findings of this study align with the existing literature and further expand the application of gamified learning in the education of the elderly. For example, Cota et al. (2015) and Marston (2013) found that the elderly show strong interest in puzzle-based games, and this study further confirmed that gamification elements (such as task segmentation, instant feedback, and reward mechanisms) can enhance learning motivation and optimize learning experience. Additionally, the elderly engage more actively in digital skill learning in the interactive learning environment with immediate feedback and rewards [6,9].

Xie et al. (2022) suggested that intergenerational interaction effectively reduces technology anxiety in the elderly, and this study further found that intergenerational collaboration not only improves skill acquisition, but also enhances emotional belonging and social connectedness [27]. Intergenerational interaction helps the elderly overcome challenges in the learning process, thereby strengthening emotional bonds between younger and older generations [61,62]. This social support not only improves learning outcomes, but also increases the social participation of the elderly, allowing them to exert greater social value and achieve emotional fulfillment in digital learning [63,64], which aligns with the core principles of the Ethics of Care with the emphasis on interpersonal relationships, emotional connections, and mutual dependence [65]. From the perspective of the Ethics of Care, digital reverse mentorship is not merely a transfer of knowledge, but also an intergenerational responsibility, a means of fulfilling needs, and a form of emotional support.

This study also validates the positive impact of gamified learning on the elderly, demonstrating that gamified design provides continuous learning incentives, which are challenging to achieve in traditional teaching and independent game-based learning models. Additionally, this study provides empirical evidence that gamified learning not only enhances skill acquisition, but also improves overall learning experiences by increasing motivation to make learning more engaging, and fostering emotional connections.

In addition, this study conducted a comparative analysis of the UEQ-S and ARCS scores with findings from the related literature, further validating the effectiveness of the system while identifying areas for potential improvement. The UEQ-S results indicated high scores in the pragmatic dimensions (such as efficiency and clarity), suggesting that the system interface was smooth and functionally sound. However, scores in the hedonic dimensions (such as novelty and stimulation) were relatively lower. Compared to the study by Maskeliūnas et al. (2023), where the FGPE+ platform reported high scores in stimulation and attractiveness (M = 4.11, SD = 0.51), our results suggest that enhancing visual engagement and interactivity could further improve the emotional experience [66]. Similarly, Lampropoulos et al. (2020) emphasized that combining augmented reality with gamification significantly enhances the hedonic aspects of learning, offering a promising direction for future design enhancements [67].

In terms of learning motivation, this study recorded high scores in the "Relevance" and "Satisfaction" dimensions of the ARCS scale, which aligns with the findings of Kumar et al. (2023), who reported a strong positive correlation between relevance and learner engagement (r = 0.727) in a biomedical VR education system [68]. However, the "Confidence" dimension received comparatively moderate ratings, which is consistent with the ARCS+G model proposed by Fazamin et al. (2023) [69]. That model recommends integrating gamified motivational strategies—such as goal setting, progress tracking, and achievement badges—to reinforce learners' self-efficacy. These comparisons suggest that the present system demonstrates notable strengths in usability and relevance, but still holds room for improvement in emotional stimulation and confidence-building mechanisms.

5.4. Research Limitations and Future Directions

First, the research sample was primarily drawn from a senior university in Taiyuan, a specific region in China, which may affect the external validity of the findings. Moreover, this study only involved 90 participants. Future research should expand the sample size and include elderly individuals from diverse social strata, cultural backgrounds, and residential areas to enhance the generalizability of the results. For example, older adults from different communities, urban and rural settings, and various cultural environments may exhibit significant differences in their acceptance of and response to gamified learning. Therefore, further studies are needed to verify the broader applicability of intergenerational interaction and gamified learning.

Second, this study primarily focused on short-term learning outcomes and did not track long-term skill retention and cognitive function changes among the elderly. While this study demonstrated that the Collaborative Gamified Digital Mentorship Model can effectively improve digital skill acquisition in the short term, future research can extend the study period to observe long-term effects, such as the sustainability of learning outcomes and skill retention. Since Group C outperformed the other groups, future studies can further analyze the specific characteristics or intervention measures within Group C to identify the key factors contributing to the significant learning improvement. These could include the frequency of intergenerational interactions or the optimization of game tasks, which is conducive to refining the core mechanisms and optimizing intervention strategies, so as to make them applicable to a broader population of the elderly. In addition, future research is recommended to comprehensively consider the impact of multiple factors, such as cognitive abilities, health status, emotional state, learning motivation, and habits of using digital devices in individuals. It is also advisable to expand the application scenarios by implementing this intervention model in settings such as home environments, community education centers, senior activity venues, or online learning platforms, so as to enhance its practicality and scalability.

Additionally, Group A (traditional teaching) and Group B (independent game-based learning) share relatively similar learning outcomes in this study, suggesting that these two intervention methods may have limited effectiveness in improving digital literacy among the elderly. Future research may consider adjusting experimental designs or intervention approaches, such as introducing more interactive teaching models, optimizing learning content, or incorporating enhanced motivational mechanisms to improve learning outcomes and increase engagement and persistence among the elderly.

Moreover, it is important to consider the potential limitations of the measurement tools used in this study, such as the UEQ-S (User Experience Questionnaire-Short Version) and the ARCS (Attention, Relevance, Confidence, Satisfaction) model. These scales may have inherent constraints in assessing user experience and motivation, particularly when the elderly are engaging with gamified learning applications. Future research should critically evaluate whether these frameworks fully capture the cognitive and emotional responses of elderly learners. Additionally, this study used the Chinese versions of these scales, and it is necessary to assess whether the translation has been appropriately validated to ensure conceptual equivalence with the original instruments. Translation and cultural adaptation processes may introduce subtle variations in meaning, thereby potentially impacting the validity and reliability of the results. Future studies should conduct validation studies on these localized versions to confirm their suitability for assessing user experience and learning motivation in the Chinese-speaking elderly population.

Finally, this study mainly examined skill acquisition and learning experience, while it did not explore the impact of gamified learning on memory, attention, and executive function in the elderly. To comprehensively assess the effectiveness of gamified learning, future studies should integrate neuropsychological assessment tools to systematically evaluate the impact of gamified learning on cognitive capabilities such as memory, attention, and executive function in the elderly. Additionally, this study has a relatively small sample size. Future research should incorporate effect size analysis (e.g., Eta-squared or Epsilon-squared) to assess the practical significance of intergroup differences and provide more precise statistical conclusions, which will contribute to a more comprehensive understanding of the role of gamified learning in enhancing digital literacy among the elderly, and providing a stronger theoretical and practical foundation for subsequent research and applications.

6. Conclusions

This study demonstrates that the Collaborative Gamified Digital Mentorship Model is an effective strategy for improving digital literacy among the elderly, enhancing skill acquisition, optimizing user experience, and increasing learning motivation. The experimental results indicate that learning models combining gamification and intergenerational interaction are more effective than traditional teaching and independent game-based learning in enhancing digital skills, optimizing user experience, and boosting learning motivation. Gamification elements, such as task segmentation, instant feedback, and reward mechanisms, not only optimize user experience, but also increase learning engagement, while intergenerational interaction provides emotional support and a sense of social belonging, thereby achieving more positive and enjoyable learning.

The present study suggests that the combination of gamified learning and intergenerational interaction provides multidimensional support, which not only facilitates skill acquisition, but also enhances the interest and enthusiasm of the elderly for digital learning. Future educational product designs should leverage these findings by integrating gamification strategies and intergenerational collaboration to improve the effectiveness of digital skills training for the elderly.

The theoretical significance of this study lies in providing a new perspective for the application of Cognitive Aging Theory in digital education and validating the effectiveness of integrating gamified learning with intergenerational interaction. Thes findings expand the boundaries of research on education and digital literacy among the elderly, and provide theoretical support for the future development of more interactive and aging-friendly digital education products. In practical terms, this study proposes a feasible intervention strategy that not only helps bridge the digital divide among the elderly, but also promotes intergenerational interaction and provides greater social support for their learning. Additionally, this study provides practical guidance for optimizing digital skills training programs for the elderly, particularly in incorporating gamification and social interaction to enhance learning outcomes and satisfaction.

Future research should further explore long-term intervention effects, cultural adaptability, and more refined personalized learning strategies to develop a more sustainable digital literacy education system for the elderly. Moreover, it should incorporate virtual reality (VR), voice assistants, and other intelligent technologies to optimize digital training programs for the elderly, so as to enhance learning immersion and interactivity. By leveraging artificial intelligence and big data analysis, learning tasks can be dynamically adjusted in terms of difficulty and content, thereby enabling personalized learning support and optimization tailored to the individual needs and progress of elderly learners, finally improving learning effectiveness and continuity.

In conclusion, this study provides practical guidance for enhancing digital literacy among the elderly, improving the access to technology design, and developing future educational products, as well as lays a foundation for building a more inclusive and sustainable digital education system for the elderly. Future research should further explore personalized gamified learning, long-term intervention effects, and the integration of social support networks to drive innovation in digital education for the elderly, thereby ensuring that a wider range of such advancements benefit the elderly population worldwide.

Funding: The author(s) declare that financial support was received for the research, authorship, and/or publication of this article. This research was funded by the China Scholarship Council (File No. 202208390037).

Institutional Review Board Statement: The studies involving humans were approved by Research Ethics Committee (CERec) of the Autonomous University of Barcelona (20241115CSH) on 15 November 2024.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to privacy reasons.

Acknowledgments: I sincerely thank Elena Bartomeu Magaña and Haoran Li, Ruijie Zhang, and Xi Chen for their guidance and support during the data analysis process. Their insights and resources were invaluable in helping me face this challenge and ultimately complete the work independently. I would also like to thank all participants for their support.

Conflicts of Interest: The author declares no conflicts of interest.

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