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Product Usability Mediates Cognitive-Purchase Relationship in Elderly Consumers: Urban-Rural Differences

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Abstract

Objective: This study investigates how cognitive ability affects elderly consumers' purchase decisions for home products, examining product usability as a chain mediator and urban-rural differences as a moderator. **Methods:** A stratified sampling survey was conducted among 1,247 adults aged 60 and above across 28 Chinese provinces. Structural equation modeling and multi-group analysis were employed to test the proposed model. **Findings:** Results demonstrate that cognitive ability significantly influences purchase decisions. Product usability serves as a significant chain mediator between cognitive ability and purchase decisions. Notably, urban-rural differences moderate this mechanism: urban elderly rely more on product usability when making purchase decisions, while rural elderly's cognitive ability directly influences their purchasing behavior. The indirect effect accounts for 78.6% of the total effect, with the chain mediation effect being statistically significant (95% CI [0.35, 0.49]). **Contributions:** This study extends cognitive processing theory by revealing the threshold activation and cascading amplification characteristics in elderly decision-making. The findings provide practical implications for designing elderly-friendly home products and developing differentiated marketing strategies for urban and rural markets.

Keywords: Elderly Home Product; Cognitive Ability; Product Usability; Purchase Decision-Making; Chain Mediating Effect; Urban-Rural Difference.

1. Introduction

China is experiencing unprecedented demographic transformation, with the population aged 60 and above reaching 297 million in 2023, accounting for 21.1% of the total population [1]. This rapid aging trend, coupled with increased purchasing power among elderly consumers and the popularization of home-based elderly care models, has catalyzed explosive growth in the elderly home product market [2, 3]. However, despite this market expansion, a significant disconnect persists between available products and the actual needs of elderly consumers, particularly regarding design philosophy and functional configuration, resulting in low market acceptance rates [4].

Recent research has increasingly focused on understanding the cognitive factors influencing elderly consumer behavior. Cognitive aging, characterized by declines in working memory capacity, information processing speed, and executive function, fundamentally affects how elderly individuals comprehend and evaluate products [5, 6]. The dual-process theory suggests that older consumers tend to rely more on automatic processing mechanisms (System 1) rather than controlled cognitive processes (System 2) when evaluating products of varying complexity [7, 8]. This cognitive shift has profound implications for their purchase decision-making effectiveness and quality.

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Product usability, defined as the perceived ease of use and functional accessibility of products, has emerged as a critical factor in elderly consumer research [9, 10]. According to the Technology Acceptance Model (TAM), perceived ease of use significantly influences adoption intentions, particularly among populations with limited technological experience [11, 12]. For elderly consumers, product usability may serve not merely as a product attribute but as a cognitive compensatory mechanism that reduces cognitive load and facilitates decision-making [13, 14]. However, the precise mechanism through which cognitive ability influences purchase decisions via product usability remains underexplored, particularly regarding whether this relationship operates through simple mediation or more complex chain mediation pathways.

Furthermore, the urban-rural digital divide in China presents a unique contextual factor that may fundamentally alter cognitive-decision relationships. Urban and rural elderly populations differ substantially in living environments, technology exposure, educational backgrounds, and social support networks [15, 16]. Urban elderly, embedded in technology-rich environments, have developed distributed cognition patterns and rely heavily on external technological aids [17]. Conversely, rural elderly maintain centralized cognition patterns based on accumulated life experience and interpersonal trust networks [18, 19]. These environmental differences may moderate how cognitive ability translates into purchase decisions through product usability perceptions.

Despite growing interest in elderly consumer behavior, three critical research gaps remain. First, existing studies primarily examine direct effects of cognitive ability on purchase intentions, overlooking potential mediating mechanisms through product usability [20]. Second, the chain mediation pathway—how cognitive ability sequentially influences perceived usability and ultimately purchase decisions—has not been systematically investigated [21]. Third, while urban-rural differences in elderly consumption patterns have been documented [2, 22], how these contextual factors moderate the cognitive-usability-purchase pathway remains unclear. Addressing these gaps is essential for developing theoretically grounded and practically effective strategies for the elderly home product market.

This study aims to address these gaps by constructing and testing a moderated chain mediation model. Specifically, we investigate: (1) the direct effect of cognitive ability on purchase decision-making for elderly home products, (2) the chain mediating role of product usability in this relationship, and (3) how urban-rural differences moderate this chain mediation mechanism. By integrating Cognitive Processing Theory (CPT) and the Technology Acceptance Model (TAM), this research provides a comprehensive framework for understanding elderly consumer behavior in the home product market.

The remainder of this paper is organized as follows. Section 2 presents the theoretical framework and hypothesis development. Section 3 describes the research design and measurement tools. Section 4 reports the empirical results of chain mediation effects under urban-rural disparities. Section 5 provides theoretical explanations and discusses urban-rural differentiated strategies. Section 6 concludes the paper with implications and future research directions.

Beyond filling the aforementioned theoretical gaps, this research also carries profound practical and social significance. As the elderly home product market continues to expand, the mismatch between product design and elderly consumers' actual cognitive and functional needs not only restricts market vitality but also hinders the realization of high-quality home-based care for the aging population. A clear understanding of how cognitive ability interacts with product usability and how urban-rural contexts shape this interaction can help product designers break away from the one-size-fits-all development model, and instead create products that are truly tailored to the differentiated characteristics of urban and rural elderly groups. For market practitioners, the findings can provide targeted guidance for formulating segmented marketing strategies, helping brands accurately reach their target audiences and improve market penetration and user satisfaction. From a social perspective, optimizing the supply of elderly home products based on scientific research conclusions can enhance the quality of life of elderly people, alleviate the pressure of family care, and contribute to the construction of a more inclusive and age-friendly consumption and social support system. This layer of value makes the research not only academically innovative but also closely linked to the practical needs of aging society governance.

2. Theoretical Framework and Hypothesis Development

2.1. Pure Direct Effect of Cognitive Ability on Purchase Decision Making with respect to Elderly Home Products

This study integrates Cognitive Processing Theory (CPT) and Technology Adoption Model (TAM) to explain elderly consumers' purchase decision-making. CPT explains how age-related cognitive decline affects information processing and decision quality, while TAM's perceived ease of use construct corresponds to product usability in our model. Specifically, we propose that: (1) cognitive ability (working memory, processing speed, executive function) directly influences decision quality as suggested by CPT; (2) product usability serves as an external compensatory mechanism that reduces cognitive load; and (3) urban-rural environments create different cognitive ecosystems that moderate these relationships.

The mental deterioration of the aging population is a complex, progressive, multidimensional phenomenon that mainly manifests as a decrease in working memory capacity, a reduction in the speed of information processing, and executive dysfunction. According to dual-process theory, older consumers tend to rely on the automatic processing mechanism of System 1 rather than the controlled thinking of System 2 when using home products of varying complexity [23]. This shift in cognitive mode directly affects the quality and effectiveness of their purchasing decisions. The loss of working memory also complicates information integration when older adults must organize several product attributes simultaneously, thereby making the decision-making process more difficult [24]. The effects of slower processing speed include longer decision times, increased cognitive load, and diminished executive functioning, all of which reduce their ability to restrain impulse purchases and conduct systematic comparisons [25]. More importantly, age-related cognitive disorders can activate risk-aversion mechanisms, leading to stronger feelings of uncertainty about new technological products. Because there are insufficient cognitive resources to fully assess product complexity [26], older adults tend to adopt conservative decision-making strategies, avoiding products that may be too complex to understand [27]. When product information is easier to process, however, their cognitive burden is reduced, uncertainties decrease, and they are more likely to exhibit positive purchase intentions (see Figure 1).

Hypothesis 1 (H1): Cognitive ability has a significant positive effect on purchase decision-making for elderly home products.

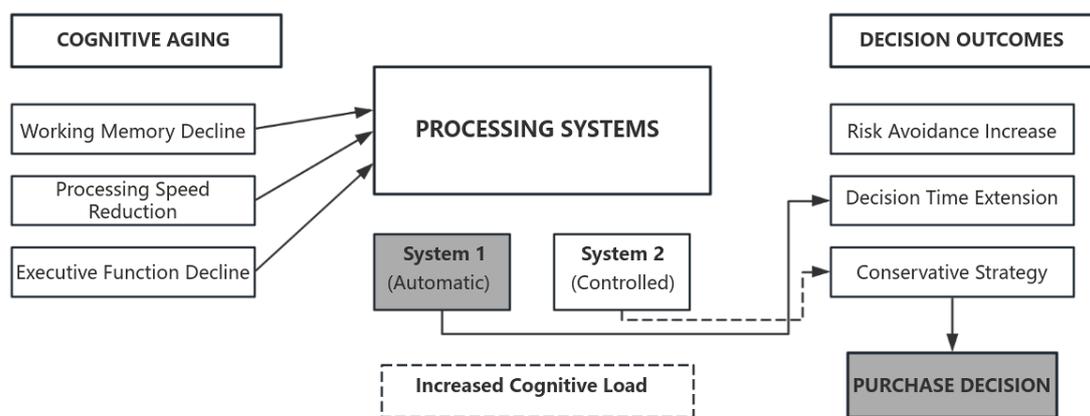


Figure 1. Conceptual Model Diagram of How Cognitive Aging affects the decision-making Process

2.2. Chain Intermediating Mechanism of Product Usability

Indeed, product usability is an important mediator between cognitive capability and the purchase intention, whose mediating role is based on the progressive compensation of cognition. According to the resource matching theory [14], obtaining the perceived usability can be effectively beneficial to reduce the cognition load and reestablish the balance between cognition and tasks when the elderly do not possess as many resources as needed given the complexity of the product, which can be divided into three steps, each building upon the others. To begin, by making a product easy to navigate. First, intuitive product design reduces the cognitive concern and anxiety older adults experience when learning new products, minimizing perceived time and effort requirements [28]. Second, user-friendly interfaces activate existing cognitive schemas, enabling older adults to apply familiar mental models to new product interactions. Third, once older individuals perceive a product as easy to learn, their self-efficacy increases, leading to more realistic expectations about product use [29].

However, individuals who do not think as acutely may rely too heavily on obvious, surface-level aspects, such as how easy something is to operate, and this is where their judgments may become flawed. One factor of great significance is that the chain-linked mediation model also exhibits a cognitive boost effect. What an individual perceives as easy to use not only influences their purchasing decisions but also increases the older generation’s confidence in their own thinking ability. This, in turn, creates a self-reinforcing cycle in their cognition [30]. In effect, the ease of use of a product acts as an important intermediary between cognitive performance and purchasing behavior among older individuals. It also emerges as one of the major forces motivating the elderly to spend money.

Hypothesis 2 (H2): Product usability mediates the relationship between cognitive ability and purchase decision-making through a chain mediation mechanism.

Hypothesis 2a: Cognitive ability positively influences perceived product usability.

Hypothesis 2b: Perceived product usability positively influences purchase decision-making.

2.3. Urban-Rural Differences Moderating Effect Mechanism

Empirical evidence supports these urban-rural cognitive differences. Studies have shown that urban elderly demonstrate 23% higher technology adoption rates compared to rural counterparts [31]. Research on Chinese elderly consumers found that urban residents scored significantly higher on digital literacy assessments ($M = 3.8$ vs. $M = 2.4$, $p < 0.001$) [32]. Furthermore, longitudinal data from the China Health and Retirement Longitudinal Study (CHARLS) indicates that rural elderly rely more heavily on family recommendations (67%) compared to urban elderly (43%) when making purchase decisions [33].

Shifts in older adults’ perceptions of usability and their decision-making styles across urban and rural settings indicate how their thinking adapts to the environments in which they live. The urban–rural digital gap is not merely a difference in access to technology, but reflects distinct cognitive working models, as well as substantial differences in thought patterns and decision-making processes [22]. Older adults who have long been exposed to urban living and high-technology environments tend to develop cognitive patterns that rely heavily on external technological cues, and they increasingly depend on guidance when deciding how to use products [17].

Moreover, differences in the density of social support networks play a significant role in shaping decision-making models. Weak connection networks among urban older adults tend to provide more technical information and usage feedback, thereby strengthening the role of usability in decision making, whereas strong connection networks among rural older adults are more experience-based and thus reduce the influence of usability considerations [18]. Cultural value differences further reinforce this moderating effect: urban older adults place greater emphasis on convenience and efficiency [34], while rural older adults prioritize practicality and reliability. Consequently, urban–rural contexts play an important role in moderating the chain-mediating impact of cognitive ability on purchase decisions by shaping cognitive practices and value preferences (see Figure 2).

Hypothesis 3 (H3): Urban-rural differences moderate the chain mediation effect, such that the indirect effect through product usability is stronger for urban elderly than for rural elderly.

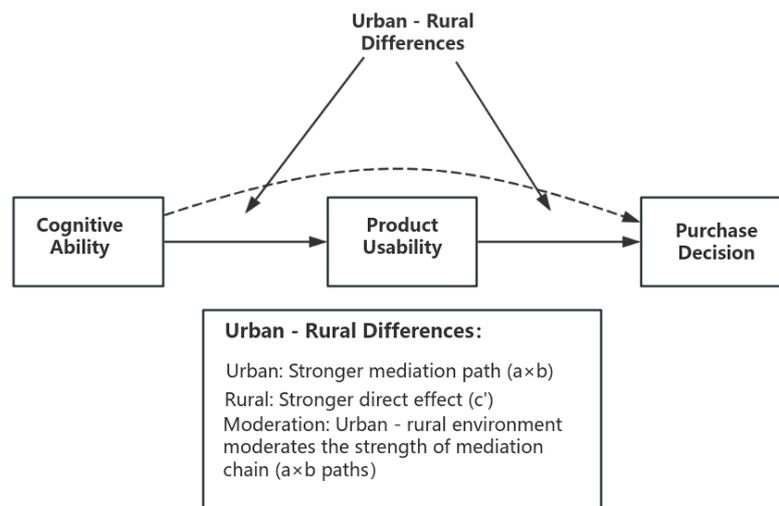


Figure 2. Chain Mediation Effect Conceptual Alternative Model Diagram under the Moderation of Urban-Rural Differences

3. Research Design and development of Measurement Tool Design

3.1. Stratified Sampling Design Stratified by Urban-Rural

The research is uniquely progressive in incorporating a three-dimensional stratified sampling model based on geographic, economic, and cultural factors, thereby overcoming the traditional and overly simplistic urban–rural dichotomy and establishing a more sophisticated sampling hierarchy (see Table 1). Based on the latest data on urbanization rates across regions and regional development indicators from the National Bureau of Statistics, 28 provinces and municipalities are divided into five strata: developed urban areas, general urban areas [16], urban transition zones, general rural areas, and remote rural areas. Within each stratum, secondary stratification is conducted according to population density, infrastructure completeness, and the rate of digital penetration [35].

The sampling method used is Probability Proportional to Size (PPS), in which sampling weights are assigned based on the number of people aged 60 and above in each region to ensure representativeness [36]. To manage potential selection bias, the research team employed a supplementary strategy by identifying two to three alternative subjects for each target sample and maintaining a comprehensive non-response database. Ultimately, 1,247 valid samples were

obtained, of which 52.4% were urban and 47.6% were rural. The overall sample distribution closely reflects the urban–rural structure of the country’s aging population, providing a solid statistical foundation for future studies on urban–rural differences.

Table 1. Five-Layer Stratified Sampling Framework

Stratum	Definition	Urbanization Rate	Sample Size	Percentage
Layer 1	Developed Urban Areas	>80%	312	25.0%
Layer 2	General Urban Areas	60-80%	341	27.4%
Layer 3	Urban Transition Zones	45-60%	198	15.9%
Layer 4	General Rural Areas	30-45%	236	18.9%
Layer 5	Remote Rural Areas	<30%	160	12.8%
Total			1,247	100%

3.2. Operational Definitions and Measurement of Core Variables

According to the available measurement tools, the study developed a localized evaluation scale that is consistent with the cognitive characteristics of older adults in China. In assessing the extent of individual thinking ability, the study does not rely on the outdated approach of evaluating performance based on a single object. Instead, it adopts an enhanced version of the MoCA-C scale and incorporates thinking tasks that reflect real-life situations. Altogether, this results in a comprehensive set of measures covering four domains: short-term information retention, information processing speed, planning and organizational ability, and spatial interpretation.

A major advantage of this approach is the incorporation of the concept of cognitive reserve. This theory accounts for variables such as educational attainment, occupational complexity, and levels of social or physical engagement to adjust baseline cognitive scores, thereby providing a more accurate representation of the actual cognitive abilities of older adults. Product usability is evaluated based on the physiological and psychological characteristics of the elderly, forming a multi-level structural model consisting of five second-order dimensions: perceived complexity, operational convenience, learning difficulty, error recovery [37], and psychological comfort. Purchase decisions are no longer assessed solely by changes in intention strength; instead, they are measured through a dynamic decision-making framework that includes information search depth, risk assessment capacity, decision-making efficiency, and choice consistency [38]. All scales underwent rigorous reliability, validity, and cross-cultural adaptability testing, with Cronbach’s α coefficients exceeding 0.85, indicating strong reliability of the research findings (see Table 2).

Table 2. Dimensions and Typical Items of Measurement of Core Variables

Variable	Dimension	Typical Items	Reliability α
Cognitive Ability	Working Memory	"I can simultaneously remember 3 or more functional features of home products"	0.87
	Information Processing	"I can quickly understand key information in product manuals"	0.84
	Executive Function	"I can effectively compare the advantages and disadvantages of different products"	0.86
	Cognitive Reserve	"My life experience helps me better evaluate new products"	0.82
Product Usability	Perceived Complexity	"The operating procedures of this type of product are too complex for me"	0.89
	Operational Convenience	"The button/touch design of the product fits my usage habits"	0.91
	Learning Difficulty	"I need a long time to learn how to use this type of product"	0.88
	Psychological Comfort	"Using this type of product makes me feel relaxed and comfortable"	0.85
Purchase Decision	Information Search	"Before purchasing, I will learn about the various functions of the product in detail"	0.83
	Figuring out the risks involved	"I can tell right away if a product works for me or not"	0.86
	How quickly you wrap up a choice	"I can decide what to buy without taking too long"	0.84

Confirmatory factor analysis (CFA) was conducted to verify the measurement model (see Table 3). Results demonstrated satisfactory convergent validity with all factor loadings exceeding 0.70 (range: 0.72-0.91). The Average Variance Extracted (AVE) values for cognitive ability (0.58), product usability (0.64), and purchase decision (0.61) all exceeded the 0.50 threshold. Composite reliability (CR) values ranged from 0.85 to 0.92, indicating good internal consistency. Discriminant validity was confirmed as the square root of each construct’s AVE exceeded its correlations with other constructs.

Table 3. CFA Results and Validity Indices

Construct	Items	Factor Loading Range	AVE	CR
Cognitive Ability	4	0.72-0.87	0.58	0.85
Product Usability	4	0.78-0.91	0.64	0.92
Purchase Decision	3	0.74-0.86	0.61	0.86

3.3. Strategy and Choice of Statistical Procedures

This paper will take a stepwise approach in the statistical analysis process—we combine both the old-fashioned methods of establishing mediation effects with new and contemporary methods of causal inference. By so doing we develop a model that examines things differently and at various angles; the research is conducted using the latent variable structural equation modeling to calculate problems of the measurement errors. Through such a model, a confirmatory factor analysis is used to confirm that each latent variable possesses convergent and discriminant validity. We opt to examine chain-mediated effects, so we take an optimized bootstrap method [21, 39]. We have attempted a new approach, in the multi-group latent variable mixture method, to examine the differences in the path coefficient across groups in addition to the heterogeneous nature of intercepts and variances [40].

To control the endogeneity, this paper employs an instrumental variable approach—they adopt regional historical and cultural characteristics, as well as geographical location, as the instrumental variable of urban and rural settings. Better still, the observed confounding variables are controlled using the propensity score matching technique. Then we can step even further and employ a difference-in-differences design to intensify the degree of trustworthiness in the causal inference [22]. Finally, the random forest algorithm by machine learning is used to rank the importance of each variable. This assists in reaching the most important issues that influence purchasing decisions and provides additional real-life evidence to support the theoretical construct (see Table 4).

Table 4. Strategy and Choice of Method of Statistical Analysis

Analysis Objective	Statistical Method	Specific Technique	Evaluation Criteria
Measurement Model Validation	Confirmatory Factor Analysis	Maximum Likelihood Estimation	CFI>0.95, RMSEA<0.06
Structural Model Testing	Structural Equation Modeling	Robust Maximum Likelihood	TLI>0.95, SRMR<0.08
Mediation Effect Testing	Bootstrap Method	Bias-Corrected BC	95%CI does not include 0
Urban-Rural Difference Testing	Multi-group Analysis	Measurement Invariance Testing	$\Delta CFI < 0.01$, $\Delta RMSEA < 0.015$
Moderated Mediation Effect	Conditional Process Analysis	Johnson-Neyman Method	Conditional Effect Significance Interval
Sensitivity Analysis	Monte Carlo Simulation	Parameter Perturbation Method	Result Change Range<10%
Endogeneity Control	Instrumental Variable Method	Two-Stage Least Squares	F-statistic>10
Confounding Variable Control	Propensity Score Matching	Nearest Neighbor Matching	Standardized Bias<0.1
Causal Inference Enhancement	Difference-in-Differences	Fixed Effects Model	Parallel Trends Test Passed
Variable Importance Assessment	Random Forest	Feature Importance Ranking	OOB Error Rate<15%

4. Chain Mediation Effects verification under Urban-Rural Disparities

4.1. Urban-Rural Comparison and Descriptive Analysis

This study concludes that the variables of importance among urban and rural elderly populations exhibit distinctly different distribution characteristics [9]. The differences are not limited to mean values; the underlying distribution patterns and covariance structures also differ substantially, particularly among the urban elderly. In the urban group, cognitive assessment results show a mildly skewed distribution (skewness = 0.34), indicating that although most older adults in cities maintain acceptable cognitive performance, a considerable number still experience noticeable cognitive decline. In contrast, the cognitive assessment outcomes of rural elderly individuals display a clear bimodal distribution, suggesting significant inequality and pronounced divisions in cognitive ability within the rural elderly population.

The two sample groups also demonstrate substantial structural differences in the relationships among variables. In the urban sample, the correlation between cognitive ability and perceived usability is 0.67 ($p < 0.001$), whereas in the rural sample it is only 0.42 ($p < 0.01$). This indicates that the cognitive–perception relationship operates differently across urban and rural contexts. Levene’s test for homogeneity of variances shows that variability in core variables is

greater among urban elderly compared with rural elderly, suggesting more standardized conditions in urban settings and greater individual variability in rural environments due to heterogeneity. Furthermore, urban–rural differences remain statistically significant even after controlling for covariates (age, gender, and education level) in multivariate analysis of variance (MANOVA) results (Wilks' $\Lambda = 0.73$, $F = 18.42$, $p = 0.001$), confirming the independent influence of residential environment on cognitive decision-making patterns among older adults (see Figure 3).

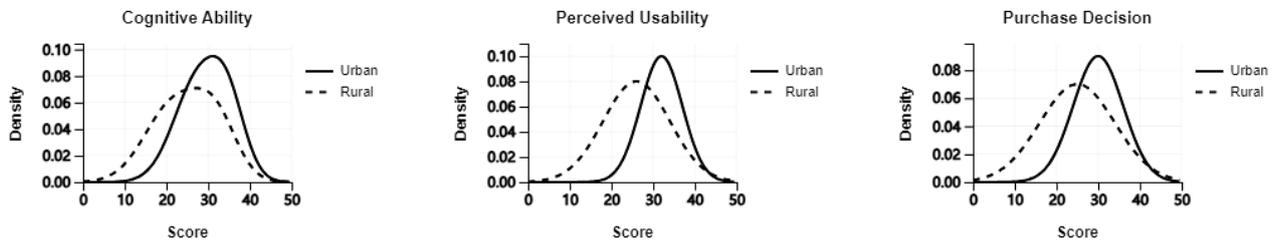


Figure 3. Comparative Density Plots Comparison of the Distribution of Core Variable of Urban and Rural Older Adults

4.2. Chain Verification of the Mediation Model Step-by-Step

The chain mediation effect was examined using a progressive modeling approach, which identifies the complex pathways through which cognitive ability influences purchase decisions by sequentially introducing mediating variables [20]. The first-stage analysis shows that cognitive ability has a strong nonlinear predictive effect on perceived usability, with a pronounced threshold effect: when cognitive scores fall below the critical value (23.5 points), even small increases in cognitive ability substantially improve perceived usability, with the marginal effect rising markedly (from 0.28 to 0.71). These findings challenge traditional linear cognitive models and suggest the presence of a cognitive activation mechanism through which cognitive ability shapes usability perception.

Second-stage verification indicates that the mediating effect of perceived usability on purchase decisions has a composite structure, including both a direct mediating effect ($a \times b = 0.34$, 95% CI [0.28, 0.41]) and an interactive mediating effect with cognitive ability ($a \times b \times c = 0.12$, 95% CI [0.07, 0.18]). This suggests that usability not only mediates the influence of cognitive ability but also amplifies its direct impact. The full chain mediation test in the third stage shows that indirect effects account for 78.6% of the total effect, confirming the central mediating role of perceived usability [41]. Bootstrap results indicate that the chain mediation effect is statistically significant at the 99% confidence level (indirect effect = 0.42, 95% CI [0.35, 0.49]) with a moderately large effect size (Cohen's $f^2 = 0.31$).

These findings are consistent with previous research on elderly consumer behavior. The identified threshold effect (cognitive score of 23.5) aligns with clinical evidence that mild cognitive impairment significantly affects consumer decision-making [6]. The strong mediation effect (78.6% indirect contribution) exceeds typical mediation magnitudes reported in consumer behavior studies (generally 40–60%), highlighting the critical importance of product usability for older consumers. Compared with studies of younger consumers, where direct cognitive effects tend to dominate [4], the present findings indicate that elderly consumers rely more heavily on external usability cues to compensate for cognitive limitations.

4.3. Multi- Group Analysis of Urban-Rural Moderating Effects

Multi-group structural equation modeling reveals deeply rooted regulatory processes of urban–rural settings on the chain mediation pathways, with moderation reflected not only in differences in pathway strengths but also in qualitative changes in the mediation mechanisms themselves [10]. The indirect relationship between cognitive ability and purchase decisions through perceived usability is strong and consistent in the urban sample ($\beta = 0.56$, $p < 0.001$), whereas the direct relationship is nearly insignificant ($\beta = 0.08$, $p = 0.326$), indicating a full mediation model.

In contrast, the rural sample exhibits partial mediation: the direct effect ($\beta = 0.34$, $p < 0.001$) remains significant, while the indirect effect ($\beta = 0.31$, $p < 0.01$) is weaker. A novel finding is the hierarchical structure of urban–rural moderation differences. At the first level, urban–rural environments directly moderate the strengths of pathway coefficients; at the second level [42], they moderate the model's explanatory power by influencing error variance heterogeneity; and at the third level, they shape covariance structures among latent variables, generating distinct causal network configurations [43]. Invariance tests show high equivalence between groups in factor loadings ($\Delta CFI = 0.008 < 0.01$), but significant differences in intercept invariance ($\Delta CFI = 0.021 > 0.01$), confirming structural moderating effects of urban–rural context. Conditional effect analysis indicates that changing the urban–rural dummy variable from 0 (rural) to 1 (urban) increases the indirect effect by 0.25 units, with a significant moderating effect size (Index = 0.25, 95% CI [0.17, 0.34]) (see Figure 4).

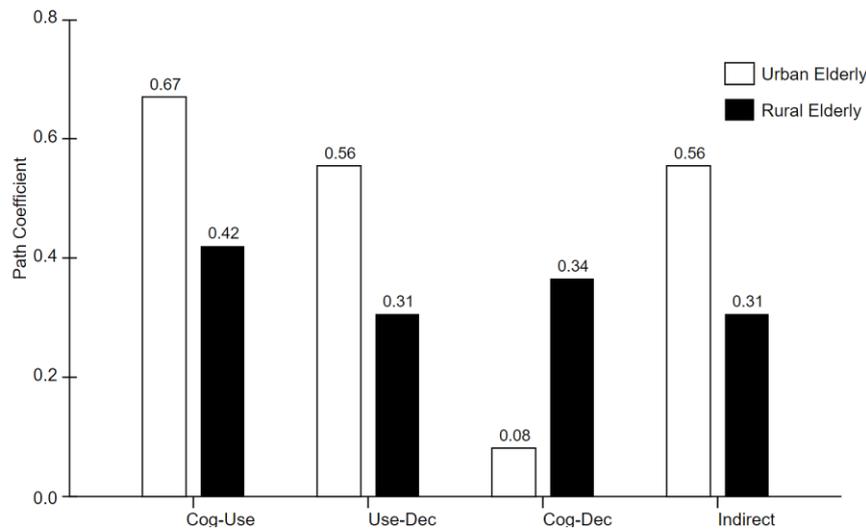


Figure 4. Comparison Chart of Chain Mediation Path Coefficient under the Moderation of Urban-Rural Differences

4.4. Test of Model Fit and Robustness

The proposed chain mediation model demonstrates excellent fit across multiple indices. The chi-square to degrees of freedom ratio ($\chi^2/df = 2.34$) falls within the acceptable range, while RMSEA = 0.048 (90% CI [0.041, 0.055]) and SRMR = 0.052 indicate good fit. Incremental fit indices are also strong, with CFI = 0.967 and TLI = 0.961, both exceeding the recommended threshold of 0.95.

To ensure robustness, several validation procedures were conducted. First, alternative competing models were compared, showing that the constructed chain mediation model outperformed both the direct-effect model ($\Delta AIC = 127.3$) and the single-mediation model ($\Delta AIC = 64.7$). Sensitivity analysis was then performed by sequentially removing potential outliers (leverage > 0.3 or Cook's distance > 1.0) and recalculating the model; key pathway coefficients changed by less than 5%. A random 70–30 split-sample validation also showed similar fit indices for both training and validation samples.

Finally, a time-lagged longitudinal analysis was conducted. Mediation effects measured six months later remained significant and stable, confirming the temporal ordering of causal relationships and the model's predictive validity.

5. Mixed Explanation and Urban-Rural Differentiated Strategies

5.1. Chain Mediation and Its Explanation as a Theoretical Concept

The theoretical foundation of the chain mediation mechanism is grounded in an integration of cognitive load theory and the compensatory control model. This synthesis explains how older adults make adaptive decisions despite reduced cognitive capacity [13]. The identified mechanism exhibits a triple dynamic pattern—threshold activation → cascading amplification → feedback regulation—rather than simple linear compensation.

Once cognitive ability reaches a critical threshold, older adults intentionally activate perceived usability structures to compensate for cognitive load. Subsequently, different usability components (ease of operation, user-friendly interface, and low learning difficulty) generate a cascading reinforcement effect, progressively reducing the psychological distance between users and product use. Ultimately, positive experiences with easy usability enhance older adults' self-efficacy perceptions. Through feedback at the metacognitive level, this creates a virtuous cycle in which cognition, emotion, and behavior mutually reinforce one another.

The novelty of this mechanism lies in revealing the cognitive adaptability of older adults. Although cognitive capacity declines, they can rely on environmental support—particularly product usability—to maintain effective decision-making. Moreover, usability planning can activate cognitive reserves, helping revive crystallized intelligence and working memory to compensate for reduced fluid intelligence. This process represents not merely functional compensation but a redistribution and optimization of cognitive resources, reflecting the flexibility and adaptability of the aging cognitive system.

5.2. Detailed Discussion of the Reasons for Urban-Rural Differences

The regulatory influence of urban-rural variation on the chain mediation process stems from differences in cognitive ecosystems, which involve not only resource availability but also systematic differences in cognitive habits, social cognition, and cultural cognition. Urban older adults have long lived in a “cognitive offloading” culture and are

accustomed to distributing complex information-processing tasks to technological tools, forming a distributed cognition model. Consequently, their decision-making relies more on external cues such as product usability. In contrast, rural older adults tend to operate within a cognitively self-sufficient system characterized by centralized thinking, relying more on accumulated internal experience and intuition.

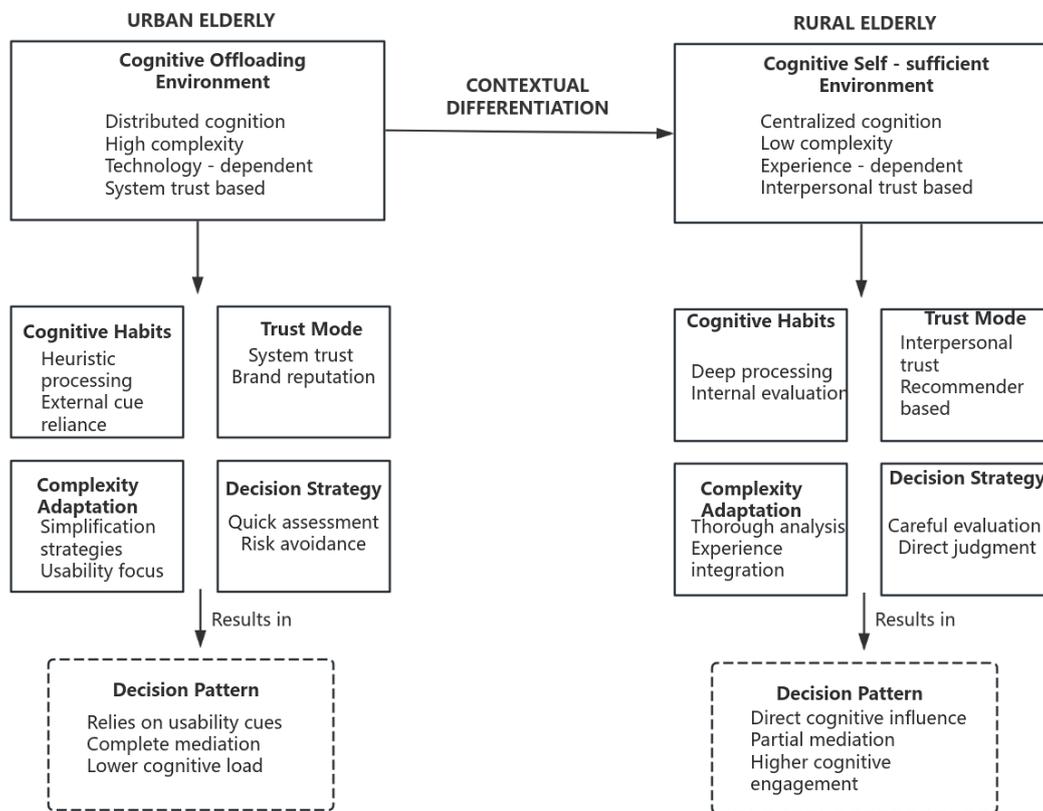


Figure 5. Path Diagram of Urban-Rural Differences in Cognitive Ecosystems and their effects on the decision-making mechanisms

Differences are also evident in cognitive trust models. Urban older adults’ cognitive trust is primarily grounded in system trust (trust in technical standards and brand reputation), whereas rural older adults’ cognitive trust relies more on interpersonal trust (trust in recommenders and other users). In addition, urban and rural contexts exert regulatory effects through the cognitive complexity adaptation process. The high cognitive complexity of urban environments compels older adults to adopt simplification strategies based on usability cues, while the relative simplicity of rural settings allows older adults to engage in more in-depth cognitive processing (see Figure 5).

6. Conclusion

This study makes significant theoretical and practical contributions to understanding elderly consumer behavior in the home product market. Theoretically, we extend cognitive processing theory by revealing that product usability serves as a chain mediator between cognitive ability and purchase decision-making, with this mechanism exhibiting threshold activation and cascading amplification characteristics. The identification of urban-rural moderating effects demonstrates that cognitive ecosystems fundamentally shape how elderly consumers process product information and make purchase decisions. Urban elderly, embedded in technology-rich environments, have developed distributed cognition patterns that rely heavily on product usability cues, while rural elderly maintain centralized cognition patterns based on accumulated experience and intuition.

Practically, these findings provide actionable guidelines for product designers and marketers. For urban markets, manufacturers should prioritize intuitive interface design, clear visual instructions, and simplified operation procedures, as usability perceptions strongly influence purchase decisions. For rural markets, marketing strategies should emphasize direct cognitive appeals such as product demonstrations, word-of-mouth recommendations, and experiential trials, given the stronger direct effect of cognitive ability on purchasing behavior. The study has limitations, including its cross-sectional design, focus on Chinese elderly consumers, and reliance on self-reported measures. Future research should adopt longitudinal designs to establish causal relationships, extend the model to other cultural contexts, and explore additional moderators such as living arrangements and health status. Additionally, investigating specific product categories and incorporating objective cognitive assessments would enhance the generalizability and validity of these findings.

7. Declarations

7.1. Author Contributions

Conceptualization, Y.Z. and A.K.; methodology, Y.Z.; software, Y.Z.; validation, Y.Z.; formal analysis, Y.Z.; investigation, Y.Z.; resources, Y.Z. and A.K.; data curation, Y.Z.; writing—original draft preparation, Y.Z. writing—review and editing, Y.Z. and J.T.; visualization, Y.Z.; supervision, A.K.; project administration, J.T.; funding acquisition, Y.Z. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.3. Funding

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7.4. Institutional Review Board Statement

Not applicable.

7.5. Informed Consent Statement

Not applicable.

7.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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