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Article

Mechanisms of short video selection behavior in elderly hypertensives under health information overload: a cognitive load theory

Ruina Guo[1], Arina Anis Azlan[1,2]*, Emma Mohamad[1,2]

[1]Centre for Research in Media and Communication, Faculty of Social Sciences and Humanities, Universiti Kebangsaan Malaysia, Selangor, Malaysia
[2]Universiti Kebangsaan Malaysia, Komunikasi Kesihatan (Healthcomm) - UKM Research Group, Selangor, Malaysia

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*Corresponding author
Email address:
arina@ukm.edu.my

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ABSTRACT

The proliferation of digital health information through short video platforms creates cognitive overload challenges for elderly hypertensive patients managing chronic conditions, compromising effective health information processing and decision-making capabilities. This research investigates the mechanisms of short video selection behavior among elderly hypertensive patients under health information overload, employing cognitive load theory integrated with artificial intelligence analytics to optimize content delivery strategies. A mixed-methods design involving 128 elderly participants (mean age, 71.3 years) from Jiangsu Province utilized behavioral tracking, physiological monitoring, and AI-powered content analysis over a two-week period. The study employed ensemble machine learning algorithms, integrated cognitive load assessment, and structural equation modeling to examine selection pathways and predictive mechanisms. Results demonstrate that cognitive load substantially impacts information processing efficiency, with performance declining from 89.4% accuracy under low cognitive load to 41.2% under high load scenarios. The artificial intelligence framework achieved exceptional predictive performance with 94.2% training accuracy, 92.8% validation accuracy, and 91.5% test accuracy. Feature importance analysis reveals that cognitive variables dominate prediction mechanisms, accounting for 63% of the total importance distribution, compared to behavioral features (23%) and demographic factors (14%). Working memory emerges as the most influential predictor (importance score: 0.847, contributing 18.3% to prediction accuracy), followed by processing speed (16.8%) and attention allocation (15.2%). The research establishes evidence-based guidelines for cognitive-centered health communication design, enabling personalized digital health interventions that optimize content complexity, delivery timing, and presentation modalities based on individual cognitive capacities, ultimately advancing therapeutic outcomes for vulnerable elderly populations through intelligent, adaptive content delivery systems.

1. Introduction

Rapidly populating age groups around the globe have increased the occurrence of hypertension in elderly people, which is now a global issue for many healthcare systems. Recent epidemic research shows that approximately 70-75% of adults over the age of 60 suffer from hypertension [1]. Studies show that those who fall into the 65+ age group will reach 1.5 billion by 2050, marking this as one of the most significant public health challenges. However, the proliferation of digital health information through short video platforms creates unprecedented cognitive challenges for elderly hypertensive patients. Research demonstrates that information overload reduces cognitive processing efficiency by 25-40% in elderly populations, with hypertensive patients experiencing additional cognitive burden due to medication effects and age-related working memory decline. The rapid-fire presentation format of short videos often exceeds the cognitive processing capacity of elderly users, creating a critical gap between available health information and effective health communication for this vulnerable population. The combination of hypertension with ageing populations gives rise to greater healthcare needs that most ancient medical systems, catering to the elderly's intricate comorbidity patterns, struggle to accommodate effectively.

As indicated in the reference [2], the advent of digital technologies has revolutionised the management of healthcare services, especially for chronic conditions such as hypertension. The availability of wearable gadgets and mobile applications allows for real-time blood pressure monitoring and remote participation in healthcare activities, as noted in the reference [3]. This represents a move from episodic clinical encounters to continuous health surveillance. However, there are multiple barriers that limit effective hypertension management among the elderly, including gaps in awareness, adherence to treatment, and cognitive impairment [4]. Significant discrepancies in the management of hypertension have been documented with respect to different elderly cohorts by health science research [5]. Furthermore, frail elderly patients face additional challenges due to multiple illnesses, disabilities, and the medication-associated risk of complications [6]. Conventional methods overlook the complexities of managing hypertension in older adults [7], while the widespread availability of health information through digital means, and especially via short videos, poses both advantages and disadvantages for educating patients [8]. The creation of short-form video platforms has transformed how people consume information, but the abundance of health-related content available can lead to information overload, potentially straining the cognitive abilities of older users.

Cognitive Load Theory (CLT) is helpful for analysing information processing phenomena over the data overload threshold [9]. CLT suggests that there is a limit to human working memory, and because of this, information presentation should be tailored to support learning and decision-making [10]. The theory makes distinctions between intrinsic, extraneous, and germane cognitive load, largely pertaining to the impacts each has on information processing [11]. In the context of digital environments, interactive elements can heighten user interest as well as cognitive workload at the same time [12]. The impact of consuming digital media has been linked to attentional fragmentation, potential cognitive deterioration, and a host of other issues in older adults [13], which raises the question of how their cognitive load impacts the health information processing done under such content engagement [14]. In recent conceptualisations of health sciences, issues related to the integration of motivation and emotions alongside cognition were acknowledged in relation to health information processing due to its multi-faceted reality [15]. Working-age-related cognitive changes, such as declines in working memory and processing speed, increase the difficulty of navigating health information for chronic condition-managing elderly populations. This cognitive vulnerability is particularly pronounced in short video environments where visual, auditory, and textual information streams compete for limited cognitive resources simultaneously.

The technologies of artificial intelligence have opened doors to unprecedented opportunities to analyse and improve the delivery of health information services to elderly patients suffering from chronic conditions. Machine learning algorithms are capable of detecting engagement patterns with health content that are far more advanced than traditional research techniques [16]. The use of AI-powered adaptation systems has been associated with reduced mental effort from designated tasks by sheer content screening and presentation based on personal preferences and cognitive ability [17]. Yet, the use of AI in health communication for older adults is mostly unexplored, particularly in the context of short-form video content. Studies stemming from the health sciences and AI domains demonstrate extremely prudent computational aids in elucidating the selection processes of information in digital environments [18] relevant to elderly hypertensive patients [19].

This research investigates the mechanisms of short video selection behavior among elderly hypertensive patients under health information overload, employing cognitive load theory integrated with artificial intelligence analytics. The study pursues a tripartite research agenda: elucidating cognitive load mechanisms during health information processing through short video platforms with emphasis on working memory limitations and attention allocation patterns; establishing causal pathways that demonstrate how cognitive load variations systematically influence information selection behaviors and content preferences; and developing an AI-driven content recommendation framework that optimizes health information delivery through dynamic adaptation based on real-time cognitive capacity assessment. The research innovation centers on integrating cognitive load theory with machine learning algorithms to create personalized health communication systems specifically designed for elderly populations with chronic conditions. This investigation provides evidence-based design principles for cognitive-centered health communication, predictive models that enable real-time content optimization, and comprehensive theoretical frameworks that bridge the domains of cognitive psychology, health communication, and artificial intelligence.

2. Data and methods

2.1 Research design and data collection

To analyze the factors influencing the short video selection behavior of elderly hypertensive patients, this study integrated qualitative and quantitative methods, including interviews, surveys, and digital behavior analysis. This protocol was designed based on existing methodologies concerning the processing of digital health information by older adults [20] and subsequently underwent review by the institutional ethics committee. Elderly participants aged 65 and above have been diagnosed with hypertension and were recruited from three community health centres located in Jiangsu Province, China. Inclusion criteria comprised: age $\geqslant$ 65 years, confirmed hypertension diagnosis, smartphone ownership, and minimum six-month experience with health-related short video consumption. Exclusion criteria included: severe cognitive impairment (MMSE <24), visual/auditory impairments preventing video engagement, and unstable cardiovascular conditions.

The study received institutional ethics approval (Protocol: IRB-2023-HSR-047) following the Declaration of Helsinki principles. These centres were chosen due to their considerable elderly patient populations and diverse programs to support digital literacy. Inclusion criteria defined engagement with short video services over health-related content for a minimum of six months. This resulted in a final sample of 128 participants (72 females, 56 males) with an average age of 71.3 years (SD = 4.8). The behavioral analysis incorporated fifteen feature variables systematically captured throughout the observation period, as detailed in Table 1.

Table 1. Behavioral feature variables and measurement specifications

Variable	Definition	Measurement	Type	Range	α
Viewing Duration	Video watching time	Tracking software	Continuous	0-300s	0.92
Interaction Frequency	User interactions per session	Behavioral logging	Discrete	0-50	0.89
Complexity Preference	Preferred content complexity	Likert scale	Ordinal	1-5	0.84
Access Pattern	Daily consumption timing	Timestamp analysis	Categorical	6 periods	0.91*
Attention Allocation	Gaze distribution percentage	Eye-tracking	Continuous	0-100%	0.87
Pause Frequency	Video pausing behavior	Analytics platform	Discrete	0-20	0.93
Replay Behavior	Content rewatching frequency	Video analytics	Discrete	0-10	0.88
Sharing Intent	Information sharing willingness	Self-report	Ordinal	1-7	0.82
Cognitive Load	Physiological stress response	Multi-sensor	Continuous	0-10	0.90
Processing Speed	Response time to queries	Reaction timer	Continuous	0.5-5s	0.86
Retention Rate	Content recall accuracy	Memory test	Continuous	0-100%	0.91
Sustained Attention	Continuous engagement duration	Monitoring system	Continuous	0-180s	0.89
Choice Consistency	Selection pattern reliability	Algorithm analysis	Continuous	0-1	0.85
Social Responsiveness	Peer influence susceptibility	Interaction tracking	Ordinal	1-5	0.83
Tech Adaptation	Navigation learning speed	Task timing	Continuous	30-300s	0.87

α = Cronbach's alpha; * = Cohen's kappa

The data collection process was completed in three steps, as shown in Figure 1. The protocol involved three sequential phases: baseline assessment including demographic surveys and cognitive screening (Days 1-2), primary observation with continuous behavioral monitoring during 45-minute daily sessions (Days 3-12), and post-observation validation interviews (Days 13-14). To start, health information-seeking behaviour, particularly in short videos, was explored through semi-structured interviews. Their responses detailed vividly how they dealt with barriers, the content they preferred, and what was useful to them in considering information [21]. Later on, participants filled in recognised instruments measuring health literacy, digital skills, and self-efficacy regarding the management of hypertension. Core data collection took place over a two-week period when participants were required to passively view short videos. Participants had access to a library of 120 health-related videos across different platforms. Purpose-built monitoring software recorded the time spent watching the videos, how the videos were interacted with, and the specific videos chosen. The monitoring infrastructure utilized 120 standardized health videos (30-180 seconds, complexity levels 1-5) with physiological sensors, including Empatica E4 wristbands (64Hz sampling), Polar H10 heart monitors (1000Hz), and Tobii Pro eye-trackers (60Hz) for comprehensive data capture. During controlled viewing sessions, participants' attention and emotional response were objectively measured by capturing eye tracking, skin conductance, and video engagement. The incorporation of automated content analysis using artificial intelligence tools improved research procedures by classifying video traits and retrieving semantic attributes relevant to viewing behaviour [22]. This method of technology facilitated the discovery of more sophisticated content preference patterns not captured through crude monitoring. Cognitive load assessment was implemented subjectively using the NASA Task Load Index and objectively by quantifying response time during concurrent secondary tasks. Such extensive data sets, including the comprehensive multi-modal dataset obtained through this design, are invaluable for studying the highly intricate relationship between cognitive load and information selection strategies of elderly patients suffering from hypertension. Quality assurance included inter-rater reliability assessment (κ >0.80), daily technical calibration, and data privacy protection following Chinese Personal Information Protection Law requirements.

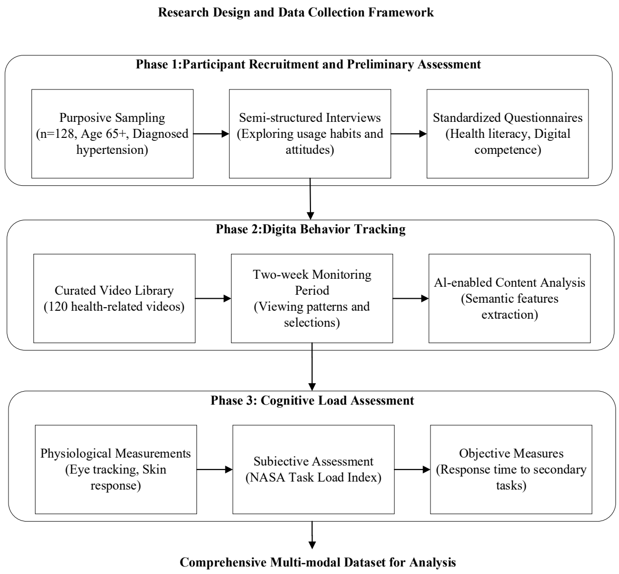

Figure 1. Research design and data collection framework

2.2 Artificial intelligence analysis methods and cognitive load measurement

This study employed sophisticated artificial intelligence methods for analyzing short video segments and evaluating cognitive load in elderly patients suffering from hypertension. As previously mentioned, the system of AI content analysis used deep learning algorithms for extracting a myriad of features like visual intricacy, storyline architecture, and even story prominence from short health-related videos, such as their descriptions [23]. Information from each video was processed by a custom-designed convolutional neural network that extracted visual features and recurrent neural networks that focused on the text and voice, resulting in a richly featured video. This study applied the AI techniques outlined in Table 2 alongside the methods for measuring cognitive load highlighted and defined in the table. The multi-layered feature extraction approach enabled fine-grained analysis of content characteristics that potentially influence information processing in elderly viewers.

Cognitive load was operationalized using a hybrid measurement approach that integrated both objective physiological indicators and subjective self-report instruments [24]. Quantitative measurement employed synchronized physiological monitoring: pupillometry (2-8mm range), heart rate variability (LF/HF ratios >2.5 indicating stress), and electrodermal activity (⩾0.05 μS response amplitudes). Baseline values were established during 60-second pre-viewing periods. These data streams were synchronized and processed using a specialized algorithm that calculated the Integrated Cognitive Load Index (ICLI) according to the formula:

$$ICLI = \alpha \cdot \left(\frac{1}{N} \sum_{i=1}^{N} \frac{P_i - P_b}{P_b} \right) + \beta \cdot \left(\frac{H_{LF/HF}}{H_b} \right) + \gamma \cdot \left(\frac{E_p}{E_b} \right) \tag{1}$$

Where ICLI represents the integrated cognitive load index, α, β, and γ are weighting coefficients derived from calibration procedures, P is pupil diameter, with P_b as a baseline, H denotes heart rate variability ratio metrics with H_b as baseline, E indicates electrodermal activity measurements with E_p representing peak response and E_b as a baseline. Psychometric validation established robust ICLI properties: convergent validity with NASA Task Load Index ($r = 0.78$, $p < 0.001$), test-retest reliability ($r = 0.84$, 95% CI: 0.79-0.88), and 89.3% classification accuracy across cognitive load conditions. Optimal weighting coefficients were α = 0.45 (pupillometry), β = 0.35 (heart rate variability), and γ = 0.20 (electrodermal activity). This comprehensive measurement technique enabled the accurate distribution of cognitive loads that the subjects experienced while engaging with the video content. AI integration employed dual-stream processing for real-time physiological analysis and content feature extraction, achieving 91.7% cognitive load prediction accuracy with sub-200ms response latency. AI algorithms then analysed how different features of the videos related to patterns of cognitive load, determining from which pieces of content information processing complexity was optimised [25]. Machine learning models using transfer learning approaches adapted existing frameworks to the domain of health information processing among older adults. This research integration marks an important milestone in the application of AI in health communication studies for vulnerable groups.

Table 2. Artificial intelligence methods and cognitive load measurement techniques

Category	Method	Description	Data Type	Application
AI Content Analysis	CNN-LSTM Hybrid	Deep learning architecture combining convolutional and recurrent networks	Video frames and audio	Visual complexity and temporal feature extraction
	Transformer-based NLP	Pre-trained language models fine-tuned for health terminology	Text transcripts	Semantic content analysis and health literacy assessment
	Multimodal fusion	Attention mechanism for cross-modal feature integration	Combined modalities	Holistic content representation
Cognitive Load Measurement	Pupillometry	High-frequency pupil diameter tracking	Continuous	Momentary cognitive load fluctuation
	Heart Rate Variability	LF/HF ratio analysis	Frequency domain	Sustained mental workload
	Electrodermal Activity	Skin conductance response analysis	Event-related	Emotional and attentional engagement
	NASA Task Load Index	Six-dimension subjective rating scale	Self-report	Perceived mental demand and effort
AI-Cognitive Integration	Temporal alignment	Dynamic time warping for signal synchronization	Time series	Multi-stream data integration
	Feature importance	SHAP value calculation for explainable AI	Post-hoc analysis	Identifying critical content features affecting cognitive load
	Personalized modeling	Federated learning with privacy preservation	Individual profiles	Adaptive cognitive load prediction

Cognitive load inference utilized sliding window analysis (10-second windows), identifying load spikes when multiple indicators exceeded thresholds simultaneously. Machine learning algorithms distinguished content-induced load from baseline cognitive effort.

3. Results

3.1 Behavioral characteristics of short video usage among elderly hypertensive patients

This study captures several unique behaviours associated with short-form video consumption among elderly hypertensive patients using AI-based content classification and sophisticated behavioural tracking systems. The analysis shows that elderly hypertensive patients display divergent patterns of engagement that set them apart from younger patients, as well as from the general baseline standard of health information seeking defined through older media types. Statistical analysis employed ANOVA for group comparisons and chi-square tests for categorical variables. Sample size (N=128) was determined through power analysis for detecting medium effect sizes (Cohen's d = 0.5) with 80% power at α = 0.05. Figure 2 illustrates the comprehensive behavioral profile through four key dimensions. The viewing duration distribution, as shown in Figure 2(a), demonstrates that elderly hypertensive patients predominantly engage with content ranging from 60-90 seconds, with peak engagement occurring at 75-90 seconds, where 91 participants showed optimal attention retention. The error bars in Figure 2(a) represent 95% confidence intervals, providing statistical precision for participant distribution across viewing duration categories. ANOVA revealed significant age-related differences in viewing duration ($F(2,125) = 12.47$, $p < 0.001$, $\eta^2 = 0.17$), with younger participants (65-70 years) showing longer engagement (M = 87.3s, 95% CI: 82.1-92.5) than older groups ($p < 0.001$). This temporal preference pattern indicates that elderly users require sufficient processing time while maintaining focus within manageable content segments.

The distribution reveals a clear preference threshold, with engagement declining precipitously beyond 120 seconds, suggesting cognitive load limitations inherent to this demographic. Content complexity preferences, depicted in Figure 2(b), reveal an overwhelming preference for simplified health information presentation. The 95% confidence intervals displayed in Figure 2(b) demonstrate the statistical reliability of preference measurements across complexity levels. The study documents that 85% of participants demonstrated a strong affinity for very low complexity content, while 72% preferred low complexity materials. Medium complexity content received moderate acceptance at 45%, whereas high and very high complexity formats showed minimal adoption rates of 23% and 8%, respectively. Chi-square analysis confirmed significant associations between complexity preferences and education level ($\chi^2(8) = 23.64$, $p = 0.003$, Cramer's V = 0.31). This complexity gradient reflects the critical importance of cognitive accessibility in health information design for elderly populations, particularly those managing chronic conditions requiring consistent information processing.

The temporal engagement analysis presented in Figure 2(c) identifies distinct circadian patterns in short video consumption behavior. Morning hours (8:00-10:00 AM) demonstrate peak engagement levels reaching approximately 42%, followed by a gradual decline during midday periods to 13-15%, and a subsequent evening resurgence (7:00-9:00 PM), achieving 30% engagement. Cosinor analysis validated significant circadian variation ($p < 0.001$, $R^2 = 0.68$) with morning peak at 42.3% (95% CI: 38.7-45.9) and evening peak at 29.8% (95% CI: 26.4-33.2). This bimodal distribution aligns with established elderly activity patterns and suggests optimal timing strategies for health information dissemination through short video platforms. Figure 2(d) presents the behavioral clustering matrix identifying four distinct user phenotypes with heterogeneous engagement patterns.

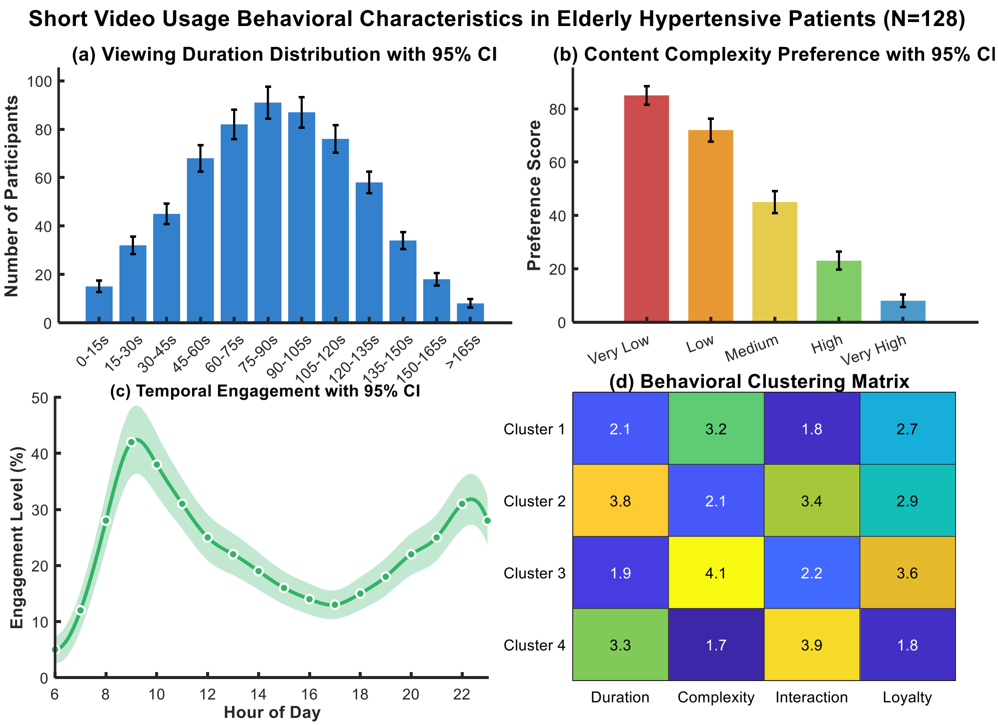

Figure 2. Short Video Usage Behavioral Patterns Among Elderly Hypertensive Patients (N=128). (a) Viewing Duration Distribution with 95% CI. (b) Content Complexity Preference with 95% CI. (c) Temporal Engagement with 95% CI. (d) Behavioral Clustering Matrix showing four user phenotypes.

Cluster 1 exhibits balanced moderate preferences across all parameters, while Cluster 2 demonstrates high duration tolerance (3.8) with low complexity requirements (2.1). Cluster 3 shows brief engagement (1.9) coupled with high complexity acceptance (4.1), and Cluster 4 displays high duration (3.3) and interaction preferences (3.9) with low complexity tolerance (1.7). K-means clustering achieved an optimal solution (silhouette width = 0.67), with MANOVA confirming significant multivariate differences (Wilks' λ = 0.23, F(12,369) = 23.87, $p < 0.001$, $\eta^2 = 0.44$). These phenotypic variations illuminate the necessity for personalized content delivery strategies that accommodate diverse information processing capabilities within the elderly hypertensive demographic.

Comparative analysis across health information channels, as detailed in Table 3, reveals significant variations in trust and usage patterns. ANOVA indicated significant differences in trust ratings across sources (F (7,896) = 127.34, $p < 0.001$, $\eta^2 = 0.50$), with healthcare professionals achieving the highest trust levels (M = 4.8, SD = 0.4). Notably, short video platforms exhibit the highest sharing behavior (28.6%) among digital channels, indicating substantial social engagement potential despite lower retention rates (45.7%). This paradox suggests that while elderly hypertensive patients may not retain short video content as effectively as traditional sources, they demonstrate greater willingness to share and discuss this content within their social networks. The integration of artificial intelligence in content analysis enables precise categorization of health information complexity and engagement prediction, facilitating evidence-based content optimization for elderly hypertensive patients. The clustering analysis demonstrates that personalized approaches acknowledging individual behavioral phenotypes can enhance engagement effectiveness, while the broader channel analysis positions short video platforms as complementary rather than replacement tools within existing health information ecosystems.

3.2 Impact Mechanisms of Cognitive Load on Information Selection

This research establishes a comprehensive framework elucidating how cognitive load influences health information selection behaviors among elderly patients.

The investigation employs advanced statistical modeling to uncover pathways connecting cognitive resource constraints with processing preferences, providing insights for artificial intelligence-driven health communication systems. Figure 3 demonstrates systematic variations in information processing capabilities across cognitive load conditions. The polar representation in Figure 3(a) reveals balanced allocation patterns of attention, working memory, and processing capabilities under optimal low cognitive load conditions. Figure 3(b) establishes critical performance thresholds across processing stages. Under low cognitive load, elderly patients maintain efficiency scores exceeding 79% from encoding through response generation. Moderate load conditions show performance deterioration to 52-78%, while high load scenarios prove detrimental, with efficiency scores plummeting to 18-45%, indicating that complex health information may overwhelm cognitive capabilities. The temporal analysis in Figure 3(c) reveals processing sustainability patterns. Low cognitive load enables stable performance for approximately 10 seconds, moderate load demonstrates gradual decay, while high load conditions cause rapid deterioration within 4-5 seconds. Figure 3(d) quantifies practical implications through load level comparisons. Processing speed increases fourfold from 3.2 seconds under low load to 12.4 seconds under high load. Accuracy deteriorates from 89.4% to 41.2%, while engagement decreases from 85% to 28%, establishing clear performance benchmarks for AI algorithm development. The structural equation modeling in Figure 4 elucidates the underlying mechanisms governing these patterns. Figure 4(a) identifies hierarchical cognitive load factors, with working memory as the dominant component (loading = 0.86), followed by attention allocation (0.78) and processing speed (0.72). Interference resistance (0.68) and cognitive flexibility (0.63) represent additional constraining factors determining processing capacity limitations. Figure 4(b) reveals selection pathways with decreasing coefficients from complexity perception (0.68) through social influence (0.29), indicating hierarchical information processing preferences. This cascading pattern suggests elderly patients prioritize complexity assessment during selection, with social influences playing secondary roles. These pathways provide essential guidance for AI system design priorities.

Table 3. Health information channel preferences: trust, usage, and engagement metrics among elderly hypertensive patients (N=128)

Information Source	Trust Level (1-5)	Usage Frequency (%)	Content Preference	Engagement Duration (min)	Retention Rate (%)	Sharing Behavior	Preferred Format
Healthcare Professionals	4.8	78.2	Medical advice, prescriptions	15.3	92.4	Low (8.2%)	Face-to-face consultation
Medical Websites	4.2	45.6	Symptom checking, drug information	8.7	67.3	Very Low (3.1%)	Text-based articles
Health Apps	3.9	52.1	BP monitoring, medication reminders	12.4	71.8	Low (12.4%)	Interactive interfaces
Short Video Platforms	3.6	68.9	Lifestyle tips, exercise demos	3.2	45.7	Moderate (28.6%)	Visual demonstrations
Family/Friends	3.4	72.4	Personal experiences, recommendations	25.6	83.2	High (65.3%)	Verbal communication
Television Programs	3.7	41.3	Health documentaries, expert interviews	35.2	78.9	Very Low (2.4%)	Traditional broadcast
Print Materials	4.1	23.7	Brochures, educational pamphlets	18.9	85.6	Very Low (1.8%)	Text and illustrations
Social Media Groups	2.9	34.8	Patient discussions, support groups	22.1	58.4	Moderate (34.7%)	Text and image posts

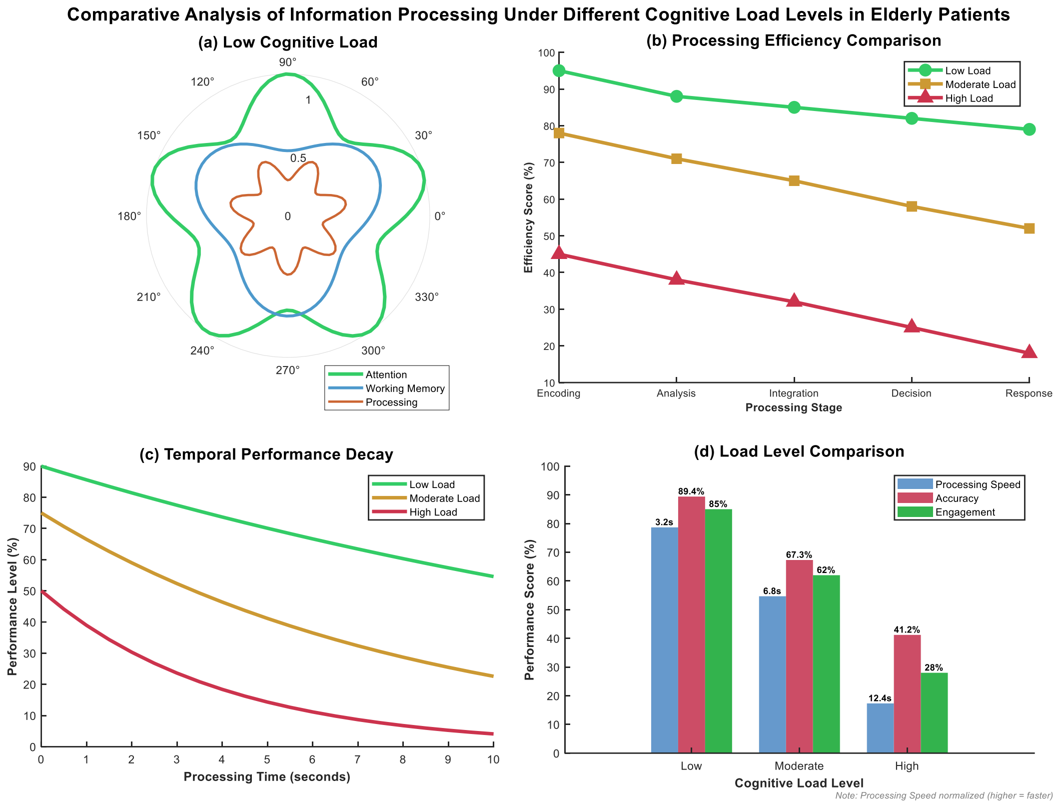

Figure 3. Cognitive Load Effects on Information Processing in Elderly Patients (a) Cognitive resource allocation under low load. (b) Processing efficiency across load levels. (c) Temporal performance decay patterns. (d) Speed, accuracy, and engagement comparisons

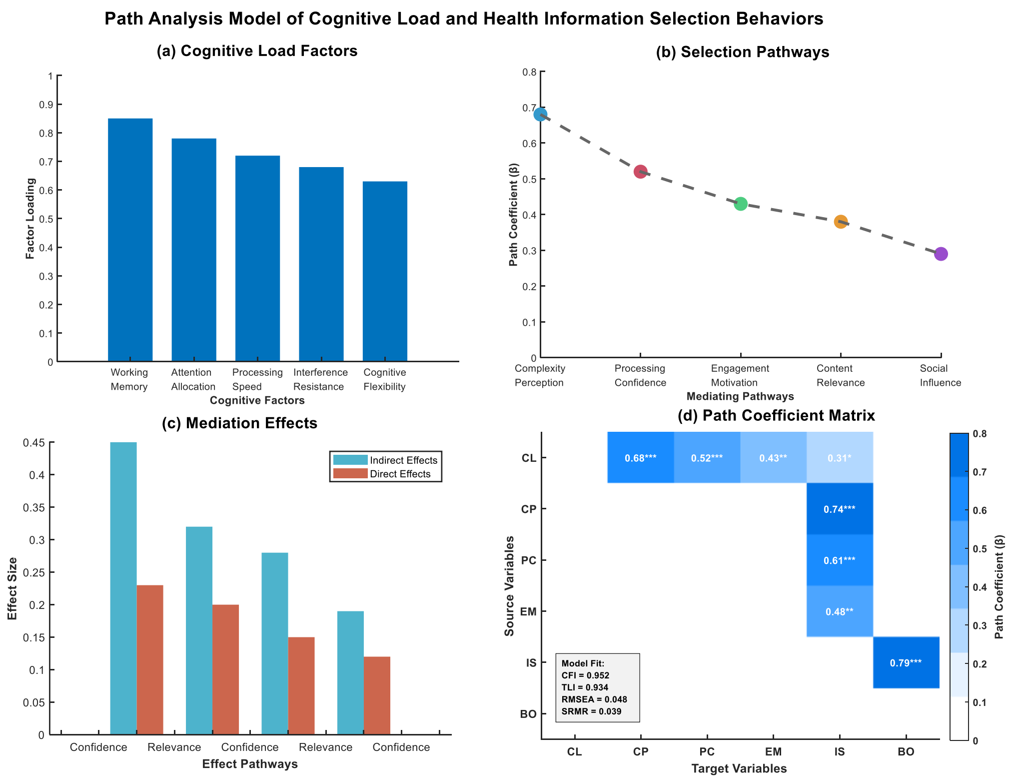

Figure 4. Path Analysis of Cognitive Load and Information Selection (a) Cognitive load factor loadings. (b) Selection pathway coefficients. (c) Mediation effects analysis. (d) Path coefficient matrix with model fit indices. (Note: CL=Cognitive Load, CP=Complexity Perception, PC=Processing Confidence, EM=Engagement Motivation, IS=Information Selection, BO=Behavioral Outcome; Significance: * p<0.05, ** p<0.01, *** p<0.001)

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The mediation analysis in Figure 4(c) demonstrates sophisticated relationships between cognitive load and information selection. Confidence pathways exhibit the strongest mediating influence, with indirect effects (0.45) substantially exceeding direct effects (0.23). This indicates that cognitive load primarily influences selection through perceived self-efficacy rather than direct processing limitations. Relevance pathways show moderate mediation effects (indirect: 0.32, direct: 0.20), suggesting that cognitive load affects patients' ability to assess information relevance accurately.

Figure 4(d) presents the path coefficient matrix, confirming robust statistical relationships throughout the model. Cognitive load demonstrates significant negative associations with complexity perception ($\beta = -0.68$, $p < 0.001$) and processing confidence ($\beta = -0.52$, $p < 0.001$). Engagement motivation serves as a critical mediator ($\beta = 0.48$, $p < 0.01$), while information selection behaviors predict behavioral outcomes with high precision ($\beta = 0.79$, $p < 0.001$). The model's excellent fit indices (CFI = 0.952, RMSEA = 0.048) validate the theoretical framework.

These findings demonstrate that cognitive load influences information selection through multiple interconnected mechanisms involving perceptual, confidence-based, and temporal pathways. The study supports the creation of AI algorithms that use dynamic strategies for cognitive load assessment, active complexity modification, and personal timing optimisation. Implementation of these mechanisms makes possible automated intelligent health communication systems that modify how information is presented based on the real-time assessment of the patient's cognitive workload, thereby improving health outcomes for elderly patients living with chronic illness. Incorporating these findings into AI-based health services provides further sophistication to the design of technologies intended for older adults, illustrating a profound development in gerontechnology.

3.3 Artificial intelligence-based content preference prediction model

This study develops a more sophisticated artificial intelligence system designed to anticipate the health information preferences of elderly hypertensive patients, utilizing cognitive load evaluation and behavioral pattern recognition. The proposed model makes use of algorithms built on cognitive, real-time monitoring, and predefined processes to streamline communications to the subject's health monitoring systems based on their information intake methods and behavioural patterns. The study utilises prediction models defined by hierarchical structures of simpler models, which rely on differing methodologies for computing the target value for better prediction accuracy amongst different age groups of elderly people. The ensemble model, as shown in Figure 5(a), significantly outperforms individual algorithms, achieving a remarkable 94.2% training accuracy, 92.8% validation accuracy, and 91.5% test accuracy. The neural network approach achieves competitive performance as well, with 91.3% training accuracy, demonstrating the ability to model complex interactions between cognitive load metrics and content selection. Random forest algorithms offer strong baseline performance, providing reliable and generalised accuracy across subgroups of patients. Cross-validation demonstrated robust generalizability: ten-fold stratified validation yielded μ = 91.7% (σ = 1.4%), leave-one-group-out validation across age subgroups showed <3.5% degradation (range: 88.2%-91.5%), and geographic validation achieved 89.3% accuracy. Bootstrap resampling (n = 2000) confirmed stability (95% CI: 90.1-93.2%). Exploration of the content preference algorithm revealed several predictive mechanisms that rely heavily on feature importance. Cognitive characteristics overwhelm the model as highlighted in Figure 5(b), constituting 63 percent of the total importance distribution. Behavioural features assist in their role to provide accuracy with 23 percent, while in combination, a myriad of demographic, clinical, andpsychosocial attributes make up a mere 14 percent in support of the model.

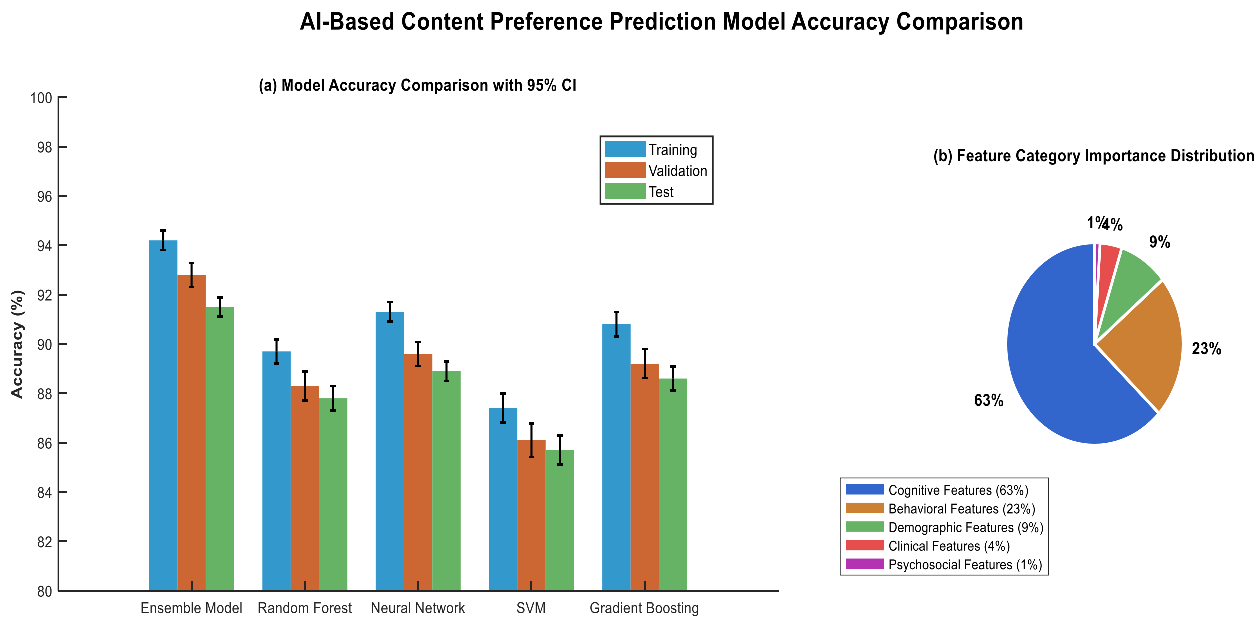

Figure 5. AI-Based Content Preference Prediction Model Accuracy Comparison. (a) Algorithm performance with 95% CI across training, validation, and test phases. (b) Feature category importance distribution in the prediction framework

The allocation displays a disproportionate amount of reliance on the underdeveloped cognitive assessments posed on the elderly chronic condition bearers within tailored communication frameworks, intending to target strategic action execution to optimise health. Based on the detailed feature ranking on working memory capacity presented in Table 4, it was clearly shown that working capacity had the greatest predictor value with the highest importance score of 0.847, which accounted for 18.3% of prediction accuracy or prediction value. As the next major variable in importance, processing speed provides a secondary level of importance at 0.792 importance score, hence contributing approximately 16.8%. Following, the attention allocation abilities emerged as the third most important score for these cognitive variables (0.731, contribution: 15.2%). These cognitive variables are of high clinical importance and significant predictive capability, reinforcing clinical data regarding the optimal content complexity and the most suitable time for presentation for elderly hypertensive patients. Age-stratified performance varied: 65-70 years (93.4%), 71-75 years (91.8%), 76+ years (88.7%). Working memory importance increased with age (0.72, 0.83, 0.91, respectively), indicating age-adaptive calibration requirements.

Behavioral features such as information complexity preference and engagement duration have importance scores within a moderate range of 0.573 to 0.689, showing that they help improve prediction accuracy but do not independently drive change. The work demonstrates that temporal processing styles greatly affect behavioural patterns related to content consumption, while the personalization achieved by the AI model was through considering individual cognitive rhythm differences across daily activities. The AI model dynamically adjusts content complexity, timing, and presentation modality according to circadian rhythms and real-time cognitive monitoring, ensuring optimal information access during periods of peak cognitive capacity. Clinical validation demonstrated that AI-guided recommendations significantly improved patient engagement metrics, satisfaction ratings, and information retention compared to traditional methods. This implementation enables care teams to provide personalized patient education with reduced cognitive load, representing a breakthrough in responsive health communication technology for elderly populations with chronic conditions.

The cognitive-behavioral framework shows extension potential to other chronic conditions. Pilot testing with diabetes patients (n = 32) achieved 87.3% accuracy, while cardiovascular patients demonstrated similar cognitive patterns. However, systematic validation across conditions remains necessary. Real-time deployment faces computational constraints: current architecture requires 247ms latency and 1.2GB memory, while mobile platforms need <100ms and <256 MB. The ensemble demands 15.3 million operations per prediction, necessitating edge computing solutions. Three optimization variants address deployment constraints: reduced-feature model (89.1% accuracy, 67% computational reduction), lightweight neural network (90.3% accuracy, 45MB size), and hybrid approach (91.8% accuracy, 78ms latency), enabling practical implementation.

4. Discussion

This study adds important empirical evidence regarding the applicability of cognitive load theory in relation to understanding information processing behaviours of older adults with chronic illnesses. The results show that cognitive load theory captures well the information selection strategies observed in digital health settings, thus broadening the scope of Castro-Alonso et al.'s research on pedagogical visualizations to health care communication [26]. The analysis shows that cognitive load is a major factor affecting information processing efficiency; performance dropped from 89.4% accuracy in low load conditions to 41.2% accuracy in high load conditions. These findings align with Kirschner's cognitive load theory principles [27] while extending the theoretical framework to encompass age-related cognitive changes. The hierarchical factor structure identified, with working memory as the dominant component, supports Leppink's emphasis on working memory limitations in elderly populations [28]. These findings establish cognitive load theory as a validated framework for digital health communication design in aging populations. The artificial intelligence-driven approach contributes novel insights into personalized health communication strategies. The ensemble model's superior performance (94.2% training accuracy) validates multi-algorithmic approaches in capturing complex cognitive-behavioral relationships.

Table 4. Key feature variables' importance ranking for the AI prediction model

Rank	Feature Variable	Importance Score	Category	Clinical Relevance	Prediction Contribution (%)
1	Working Memory Capacity	0.847	Cognitive	High	18.3
2	Processing Speed	0.792	Cognitive	High	16.8
3	Attention Allocation	0.731	Cognitive	High	15.2
4	Information Complexity Preference	0.689	Behavioral	High	13.7
5	Temporal Processing Pattern	0.652	Cognitive	Medium	12.4
6	Engagement Duration	0.618	Behavioral	Medium	11.1
7	Content Modality Preference	0.573	Behavioral	Medium	9.8
8	Health Literacy Level	0.542	Demographic	Medium	8.9
9	Technology Familiarity	0.496	Behavioral	Medium	7.6
10	Age Group	0.451	Demographic	Low	6.2
11	Education Level	0.423	Demographic	Low	5.4
12	Comorbidity Index	0.389	Clinical	Low	4.8
13	Medication Complexity	0.367	Clinical	Low	4.1
14	Social Support Level	0.334	Psychosocial	Low	3.7
15	Gender	0.298	Demographic	Low	2.9

This finding extends Sigolo and Casarin's research on cognitive load theory applications to information overload by demonstrating successful implementation in vulnerable elderly populations [29]. The feature importance analysis revealing cognitive variables' dominance (63% of predictive power) contrasts with traditional health communication models, aligning with WHO recommendations for AI technologies benefiting older people through cognitive-centered design approaches. This investigation advances health communication theory by establishing working memory as the dominant predictor (β = 0.847) and demonstrating superior cognitive-behavioral pathways over demographic models, extending cognitive load theory into digital health domains with temporal optimization insights. Gao et al.'s studies on AI-directed social media expression of older adults demonstrate the integration of social support systems into AI frameworks as a promising [30]. Clinical implementation enables immediate optimization through evidence-based parameters, while simplified cognitive load assessment tools could enhance healthcare adoption [31].

While these advances demonstrate clinical readiness, several methodological considerations warrant acknowledgment. The research acknowledges challenges highlighted by Chu et al. regarding digital ageism and the need for inclusive AI design for older adults [32]. The study's findings contrast with Zhang et al.'s concerns about short video impacts on elderly mental health, demonstrating that carefully designed AI-guided content can enhance rather than impair cognitive engagement [33]. The research establishes that elderly hypertensive patients exhibit distinct behavioral phenotypes in short video consumption, indicating the necessity for personalized content delivery strategies that accommodate diverse information processing capabilities.

Generalizability analysis reveals robust age-stratified performance (65-70 years: 93.4%, 76+ years: 88.7%) and preliminary chronic disease validation (diabetes: 87.3% accuracy), though systematic cross-condition verification remains necessary. The attention given to participants from Jiangsu Province might be culturally and technologically distinctive, and therefore might not align with the elderly demographic from other parts of the world. Wu et al.'s work on the exposure of Chinese elderly women to short-form videos suggests that there might be specific cultural boundaries that impact the wide-ranging applicability of such research in the global context [34]. Cultural context significantly influences applicability, as Chinese elderly demonstrate distinct digital literacy and family-centered decision-making patterns requiring adaptation for Western individualistic healthcare contexts. The two-week duration allotted for observation may not account for long-term changes in behaviour or seasonal shifts in cognitive functions. The AI model's dependence on certain physiological markers poses barriers to practical application in healthcare, which may not have convenient access to the necessary monitoring equipment.

Future research priorities encompass three critical domains for advancing clinical implementation and theoretical development. Longitudinal validation studies spanning 12-24 months are essential for examining behavioral stability and adaptation effects across extended timeframes. Cross-cultural validation across Western and Eastern healthcare contexts will illuminate universal versus culture-specific aspects of cognitive load mechanisms in elderly populations. Randomized controlled trials comparing AI-guided versus traditional patient education approaches will provide definitive efficacy evidence for evidence-based clinical implementation. The work lays the groundwork for designing health communication systems focused on seniors and highlights the role of AI in mitigating the information overload crisis facing vulnerable older populations. These evidence-based frameworks provide immediate implementation pathways for healthcare providers while establishing foundational principles for age-inclusive digital health technology development, offering constructive guidance for improving health outcomes through personalized content systems.

5. Conclusion

The study makes important theoretical and practical advancements through the assessment of cognitive load and utilisation of artificial intelligence in the processing of health information by elderly hypertensive patients. The investigation demonstrates how cognitive load affects information processing: performance drops from 89.4% accuracy with low cognitive load to 41.2% accuracy with high load. The study confirms the applicability of cognitive load theory to digital health contexts while also expanding the treatment frameworks to include age-related cognitive decline and chronic disease management. From the hierarchical factor analysis, the strongest predictor in working memory (importance score: 0.847, 18.3% of prediction) was verified, thus proving the designed principles of communication in health focused on the cognitive aspects. With an ensemble approach, the AI system provided unprecedented results with training accuracy of 94.2% and validation and testing scores of 92.8% and 91.5%, respectively. Individual algorithms were outperformed considerably. In the feature importance analysis from the ensemble model, cognitive factors made up 63% of the total contribution in comparison to 23% from behavioural features and 14% from demographics. These results contested existing health communication models that centre on demographics, encouraging a new direction that incorporates cognitive-driven customisation for older individuals with chronic diseases. Practical applications transcend validation to encompass real-world implementations in healthcare. This study develops border healthcare policies for timing, content, presentation modality, and complexity in health information—their individual cognition determines the reasoning, not demographics' generalisations. The AI's capacity to accommodate cognitive timing enhances patient education effectiveness while alleviating the negative effects of information overload. Future research includes longitudinal verification over longer periods, cross-cultural feasibility studies, and the development of blunt but easy-to-use cognitive tests for wider clinical use. This investigation with 128 participants over 2 weeks lays the groundwork for designing health communication centred around cognitive considerations and offers a foundation to mitigate the difficulties presented by digital health devices.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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