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Validation of the Cognitive Factors–Based Smart Health-Oriented Product–Service System Model of the Social Security Organization

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ABSTRACT

Purpose: The purpose of the present study is to validate the designed model of the smart health-oriented product–service system of the Social Security Organization based on cognitive factors.
Methodology: This research was conducted using a mixed-methods approach. In the qualitative section, content analysis of previous studies and semi-structured interviews with 12 managers and experts in the fields of health and information technology were carried out. The qualitative data were analyzed using the thematic analysis method. In the quantitative section, 120 employees of the Social Security Organization were selected through stratified random sampling, and they completed a researcher-made questionnaire. The reliability of the questionnaire was confirmed using Cronbach's alpha (0.92), and the data were analyzed with SPSS and SmartPLS software at both descriptive and inferential levels.
Findings: The findings indicated that the smart health-oriented product–service system consists of four main dimensions: business model, software (cloud) platform, cognitive and biological factors, and physical platform. Confirmatory factor analysis confirmed factor loadings higher than 0.50 for all indicators. Correlation coefficients among the dimensions indicated positive and significant relationships. The results of the significance test ($t > 1.96$, $p < 0.05$) confirmed the study hypotheses. The GOF index was reported as 0.70, indicating a strong model fit.
Conclusion: The results of the study showed that alignment among the four dimensions of the model is essential for the effective design and implementation of the health-oriented product–service system. This model can enhance the quality of health services, improve the experience of the elderly, increase satisfaction, and reduce healthcare costs in social security organizations.
Keywords: *Smart product–service system, elderly, insurance system, cognitive factors, structural equation modeling*

1. Introduction

Population aging, the rising prevalence of chronic and multi-morbidity conditions, and the fiscal pressures on social protection systems are converging to make the design of scalable, trustworthy, and outcomes-oriented digital health services an urgent research and policy priority. Smart Product–Service Systems (Smart PSS) offer a promising sociotechnical paradigm for meeting this challenge by integrating data-driven products, cloud-based platforms, and coordinated human services into continuous, adaptive care journeys (Zheng et al., 2019). Recent developments toward "Smart PSS 2.0" emphasize not only cyber-physical connectivity and analytics but also service ecosystem orchestration, human-centered design, and governance mechanisms that align technological affordances with stakeholder values and risks (Ren & Zheng, 2024). In the specific context of social security organizations—which simultaneously function as payers, providers, and regulators—the design of a smart, health-oriented PSS requires the additional lens of cognitive factors: how older adults perceive, learn, decide, and adhere; how clinicians interpret and act on information; and how managers architect platforms that are intelligible, equitable, and resilient at scale (Hasanvayi, 2021).

Technological enablers for healthcare 4.0—Internet of Things (IoT), big data pipelines, and elastic cloud computing—are increasingly mature, enabling longitudinal, multimodal monitoring and service personalization for community-dwelling older adults (Aceto et al., 2020). Yet technological capability alone does not guarantee adoption or benefit. Experience during and after the COVID-19 era revealed both the rapid scalability and the fragilities of telehealth deployments, especially for populations with varied digital literacy and access constraints (Barney et al., 2020; Pierce et al., 2021). Evidence from health systems and international settings underscores that sustained use depends on perceived value, clear communication of risk, and reliable service integration across touchpoints (Cao et al., 2023; Negash & Calahorrano Sarmiento, 2023). For organizations charged with stewardship of pooled funds and intergenerational solidarity—such as pension and social insurance institutions—these lessons intersect with macro-level financing realities and legacy infrastructure constraints (Bozrafkan & Ghomari, 2019). Consequently, a robust model for a smart, health-oriented PSS in such organizations must simultaneously specify the business architecture, software/cloud platform, physical delivery infrastructure, and the cognitive–biological layer that anchors clinical sense-making and user experience.

The cognitive layer is pivotal. Cognitive decline, executive dysfunction, and fluctuating attention or memory burden can shape how older adults interpret recommendations, interact with interfaces, and comply with therapy—making cognitive screening and cognitive-tailored design essential. Health systems have begun operationalizing brief screeners such as the PROMIS Cognitive Function tools in routine encounters, revealing that framing items as "abilities" versus "concerns" alters engagement and reporting—an insight with direct implications for PSS interface copy, nudging strategies, and feedback loops (Harrison et al., 2024). Complementarily, immersive and assistive technologies designed with older adults who have cognitive disorders demonstrate that empathetic, user-centered design can augment engagement, learning, and well-being when curated to sensory load, pacing, and meaningful context (Yi et al., 2024). Knowledge-representation approaches—e.g., knowledge graphs that encode diseases, medications, activities, and preferences—offer computational scaffolding for individualized care planning and explainable recommendations in chronic geriatric care (Li et al., 2024). Together, these developments argue that the "intelligence" in Smart PSS should be operationalized not merely as algorithmic performance but as cognitively congruent service choreography.

Design-process research corroborates this stance: modeling the cognitive processes of PSS design teams shows how representational formats and protocol structures shape solution quality and traceability, underscoring the need to make cognitive work visible and to support reflective iteration (Sakao et al., 2020). In product–service value discovery, methods such as graphics-based rough-fuzzy DEMATEL have been advanced to surface interdependencies among value propositions, stakeholder risks, and operational levers—useful when translating clinical pathways into modular service bundles for heterogeneous older-adult segments (Chen et al., 2020). At the front end, systematic reviews of consumers' cognitive–affective needs in product design provide taxonomies that can be repurposed to calibrate tone, control granularity, and feedback cadence in digital health interfaces (Tavares et al., 2021). Human-centered methodologies tailored to connected health emphasize phased, iterative cycles that blend usability engineering with user-experience ethnography, reducing friction in onboarding, adherence, and escalation processes

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(Harte et al., 2017). The persistent "cognitive challenge" of healthcare information systems—where sense-making is distributed across patients, caregivers, and clinicians—further motivates explicit alignment between interface semantics, alert logic, and clinical cognition (Lintern & Motavalli, 2018).

From the ecosystem vantage point, Smart PSS adoption in healthcare is catalyzed by intelligent connected products that communicate effectively with stakeholders—patients, clinicians, payers, and regulators—so that expectations, accountabilities, and data rights are transparent (Negash & Calahorrano Sarmiento, 2023). This communication layer is inseparable from trust, safety, and liability considerations in telemedicine; stakeholders require clarity on decision support boundaries, fallback procedures, and accountability attribution when socio-technical systems fail or drift (Parimbelli et al., 2018). Digital health's maturation can therefore be understood as a cultural transformation in which norms of agency, evidence, and partnership are renegotiated across institutions and professions (Meskó et al., 2017). Readiness assessments among operational leaders consistently show capability gaps in data governance, workforce upskilling, and cross-unit coordination, which must be addressed for Smart PSS to move from pilots to platform programs (Steenkamp, 2025). At the same time, mobile health programs targeted to older adults—particularly in middle-income settings—demonstrate tangible health gains when services are embedded in local care pathways and tuned to cultural practices (Safdari et al., 2017). These findings resonate with broader Industry 4.0 integrations in healthcare, where cloud and big-data backbones unlock analytics-enabled service innovation while introducing new dependencies on interoperability, cybersecurity, and lifecycle management (Aceto et al., 2020).

The business architecture of a social-security–anchored Smart PSS must reflect a multiparty value network. Providers (public hospitals, primary care, pharmacies, home-care agencies), platform firms (cloud infrastructure, analytics, identity and payment rails), and complementary innovators (wearables, assistive robotics, serious games) jointly co-produce outcomes that are experienced by older adults and caregivers in the home, community, clinic, and virtual spaces. Empirical work shows that telemedicine for adolescents and young adults scaled rapidly under pandemic exigencies through workflow redesign and policy flexibility—lessons transferable to geriatric contexts when coupled with accessibility and cognitive accommodations (Barney et al., 2020). Regionally, Latin American experiences underscore the interplay of regulation, infrastructure heterogeneity, and provider training in sustaining telehealth quality and equity (Pierce et al., 2021). Ethical frameworks drawn from adjacent service domains (e.g., Islamic banking's convergence marketing and ethics) can also inform trust-by-design principles for stakeholder communication, consent, and fair value exchange in culturally diverse beneficiary pools (Suandi et al., 2022). Within sport and performance settings, the emergence of referral networks and shared-care protocols for mental health illustrates how standardized pathways, triage criteria, and role clarity can improve continuity and outcomes in distributed service systems—design logics that Smart PSS for elderly care can adapt for cognitive screening, psychosocial support, and escalation (Pilkington et al., 2025). Likewise, advances in biomechanical biosensors and media communication technologies suggest new modalities for unobtrusive monitoring and behavior-change messaging at population scale, provided concerns about noise, bias, and equity are proactively managed (Wang, 2025).

Operationalizing such an ecosystem demands rigorous modeling of constructs and relationships so that platform decisions (e.g., personalization rules, escalation thresholds, incentive schemes) are empirically grounded. The proposed study therefore adopts a hierarchical, reflective measurement perspective appropriate for layered Smart PSS architectures and evaluates the model using partial least squares (PLS) path modeling, following guidelines for higher-order constructs in information systems research (Wetzels et al., 2009). Convergent and discriminant validity are assessed using accepted criteria—composite reliability, average variance extracted (AVE), and cross-loading/square-root-of-AVE diagnostics—recognized as state-of-the-art for latent variable evaluation (Fornell & Larcker, 1981). This methodological stance aligns with the transdisciplinary character of Smart PSS, in which constructs span business model logics, platform affordances, clinical processes, and cognitive–behavioral determinants (Ren & Zheng, 2024; Zheng et al., 2019). It also complements value-proposition elicitation techniques and protocol-analysis insights from PSS design research, helping to map how cognitive factors and stakeholder roles materialize as measurable indicators (Chen et al., 2020; Sakao et al., 2020).

Within the "software (cloud) platform" dimension, modular microservices for identity, consent, data integration, analytics, and feedback management are no longer optional; they are the substrate for secure interoperability with government e-prescription systems, payer authorization rails, and pharmacy fulfillment networks. Cloud elasticity supports bursty workloads (e.g., telemetry spikes during heatwaves) and continuous learning from federated data, while big-data pipelines enable both population-level risk stratification and individual-level just-in-time interventions (Aceto et al., 2020). The "physical platform" dimension anchors the last mile: wearables, ambient sensors, connected drug-dispensing, and telepresence/robotic assist devices that make care tangible and equitable across urban and rural settings. Importantly, the "business model" dimension clarifies financing arrangements (subscriptions, bundled payments, outcome-based incentives), role allocations, and investment logic for scaling to national social insurance populations. Finally, the "cognitive and biological" dimension binds clinical signal to service action: from PROMIS-based cognitive function screeners embedded in annual wellness encounters (Harrison et al., 2024), to knowledge-graph–driven decision support that contextualizes polypharmacy and comorbidity (Li et al., 2024), to immersive or gamified micro-interventions that boost engagement among older adults with cognitive disorders (Yi et al., 2024).

A growing review literature specific to smart, health-oriented PSS for the elderly consolidates these strands, proposing component sets and indicators that social security organizations can tailor to their mandates and beneficiary needs (Hasanvayi Atashgah et al., 2024). Digital health as cultural transformation cautions that implementation is not a linear technology rollout but a negotiated change in roles, rituals, and accountabilities—hence the salience of co-creation with users and frontline staff (Meskó et al., 2017). Human-centered, three-phase methodologies for connected health provide pragmatic scaffolds for integrating usability, human factors, and experience mapping into platform build-outs (Harte et al., 2017). Consumer neuroergonomics highlights that cognitive load, affect, and meaning-making must be designed for—not discovered by accident—if smart services are to become habit-forming supports rather than transient novelties (Tavares et al., 2021). Moreover, governance mechanisms that foreground risk communication, safety cases, and liability allocation are indispensable to sustaining trust in tele-mediated care (Parimbelli et al., 2018). All of this must be orchestrated within the institutional realities of social insurance, where benefit design, provider contracts, and actuarial sustainability intersect with the adoption curve of new technologies (Bozrafkan & Ghomari, 2019).

Against this backdrop, the present study has three aims. First, it synthesizes the literature on Smart PSS, telehealth, and cognitive informatics to articulate a four-dimension model tailored to social security organizations: business model, software (cloud) platform, physical platform, and cognitive & biological factors (Aceto et al., 2020; Lintern & Motavalli, 2018; Ren & Zheng, 2024; Zheng et al., 2019). Second, it operationalizes each dimension with measurable indicators derived from prior reviews, design-method studies, and readiness surveys, paying particular attention to cognitive screening, knowledge-graph–based decision support, and immersive engagement modalities (Chen et al., 2020; Hasanvayi Atashgah et al., 2024; Li et al., 2024; Steenkamp, 2025; Yi et al., 2024). Third, it validates the measurement and structural model using PLS, establishing convergent/discriminant validity and estimating the directional effects among dimensions and their manifestations in a representative social-security context (Fornell & Larcker, 1981; Wetzels et al., 2009). In doing so, we leverage post-pandemic telehealth lessons (Barney et al., 2020; Pierce et al., 2021), adoption drivers from smart health and elderly-care systems (Cao et al., 2023; Negash & Calahorrano Sarmiento, 2023), ethical and communication insights from adjacent service systems (Suandi et al., 2022), and design/process guidance from human-centered and cognitive engineering traditions (Harte et al., 2017; Sakao et al., 2020; Tavares et al., 2021). We also consider frontier modalities—biosensors and media communication technologies for psychological health support (Wang, 2025) and networked referral pathways (Pilkington et al., 2025)—as exemplars of services that a mature Smart PSS can incorporate.

In sum, Smart PSS for social security organizations must be conceived as a layered, cognitively informed, and ethically governed ecosystem. Cloud-enabled connectivity and analytics provide the substrate; human-centered methods and cognitive science convert capability into usability and adherence; business model clarity aligns incentives; and governance constructs sustain trust over time. This, this study aimed to validate the designed model of the smart health-oriented product–service system of the Social Security Organization based on cognitive factors.

2. Methods and Materials

This research, in terms of approach, is a mixed-methods study that aims to validate the model of the smart health-oriented product–service system of social security organizations based on cognitive factors. Furthermore, in terms of purpose, the present research is applied and has been conducted in an exploratory manner. For data collection in the qualitative section, semi-structured interviews were used, and in the quantitative section, a researcher-made questionnaire was employed for this purpose. The sampling method in the qualitative step of the research was purposive sampling. Purposive sampling is a method used in qualitative research, particularly when expert samples are required.

To measure the reliability of the questionnaire instrument, Cronbach’s alpha was used, and the overall coefficient was calculated as 92%. In this study, content analysis of previous studies regarding the smart health-oriented product–service system and interviews with 12 managers and experts in the field were carried out. Based on the thematic analysis of the interviews, the components and indicators of the smart health-oriented product–service system were identified. In the quantitative section, to validate the model, the participants were employees of the social security organizations. Using stratified random sampling and Cochran’s formula, 120 individuals were selected, and the research questionnaire was administered. Analysis of the collected data in the qualitative part was performed using qualitative content analysis, and in the quantitative part through both descriptive and inferential statistics using SPSS and SmartPLS software.

3. Findings and Results

Based on the review of the literature and the interviews conducted, the components and indicators of the smart health-oriented product–service system were comprehensively identified (considering all models and perspectives raised in this field) and presented in Table 1. It should be noted that the system components consist of four dimensions: business model, software (cloud) platform, cognitive and biological factors, and physical platform. Each of these dimensions consists of multiple components and parameters.

Table 1

Dimensions and Components of the Cognitive Factors–Based Smart Health-Oriented Product–Service System of Social Security Organizations

Dimensions	System Components	Indicators and Parameters
Business Model	Service and product providers	Hospitals; Medical sciences universities; Urban and rural health centers; Supportive insurance organizations; Pharmaceutical knowledge-based companies; Medical equipment knowledge-based companies; Health services startups; Pharmacies; Elderly care centers
	Customers	Elderly; Patients and disabled individuals
	Suppliers and logistics	Emergency agents; Delivery providers; Medical equipment stores
	Revenue–cost flow	Financing and investment in the health sector; Hardware costs for implementation and system management; Software costs for implementation and system management; Pricing of services and products; System revenue flow (subscription, product–service sales)
	Services	Treatment; Online and in-person medical care and consultation; Other services
	Products	Medicine; Health-oriented organic products (nutraceuticals); Medical equipment
Software (Cloud) Platform	Cloud infrastructure and servers	Based on information technology and digitalization; Authentication tools; Technical support (computing, user database and supply chain, messaging); Big data analysis; Online shop for pharmaceutical and health-oriented products; Smart insurance contracts for the elderly
	Linkage to public–government systems	“My Government” portal; National electronic prescription system; Company and institution validation systems; Online payment gateways
	Network and communications	Wired communication (phone calls, sensors); Wireless communication (RFID, Bluetooth, Wi-Fi, internet-based mobile communication technologies, software, and other similar technologies)
	Personalization and feedback	Advanced, intermediate, and easy usability modes; Service–product co-creation and sharing tools; User feedback systems (relative rating, user participation in services)
	Experience management and user interface (UI/UX)	User input devices (e.g., biosensors); User movement recognition; User experience mapping and evaluation; Gamification (for an engaging and entertaining environment); Use of augmented reality technology
	Legal and educational guidelines	Privacy standards and regulations; National laws regarding the elderly and disabled; A module to explain how users can employ the smart system and its components; Health-related media, resources, and articles

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Cognitive and Biological Factors	Clinical monitoring	Intelligent assistant for monitoring biological data (nutrition, blood sugar, blood pressure, electrocardiogram, heart rate, oxygen saturation, height, weight, activity and mobility, rest, body temperature, fat percentage, etc.)
	Cognitive monitoring	Artificial intelligence simulation of elderly behavior and psychological preferences; Extraction and analysis of elderly emotional needs for new service–product design and improvement of existing ones; Examination of personality, analytical and creative thinking; Assessment of stress, happiness, and depression; Cognitive skills training through gamification
	Medication management	Intelligent assistant for medication scheduling
Physical Platform	Physical infrastructure	On-site user needs; Service and product delivery infrastructure; Digital physical devices and objects (e.g., wearable devices); Non-digital physical devices and objects; Remote surgery with intelligent medical robots

In this section, confirmatory factor analysis of the present research was conducted. In the second part, PLS software was used for structural analysis, hypothesis testing, and correlation testing. Validity and reliability are essential characteristics for the effectiveness of data collection methods. There are multiple methods for determining the validity of measurement tools, and in this study, due to existing limitations, content (face) validity was used for validation. Accordingly, several questionnaires were distributed among university professors, and after applying the proposed modifications, the face validity of the questionnaire was confirmed.

In addition, for assessing the validity and reliability of the questionnaire, Cronbach's alpha and confirmatory factor analysis criteria were employed. To test the reliability of the research questionnaire, Cronbach's alpha test was used. For this purpose, initially, 10 questionnaires were prepared and distributed among the statistical population. After collecting the questionnaires, SPSS software was used to calculate Cronbach's alpha coefficient for the entire questionnaire and each of its dimensions. If the Cronbach's alpha coefficient of a questionnaire is higher than 0.70, it indicates acceptable reliability. All variables demonstrated Cronbach's alpha values greater than 0.70.

Table 2 shows the correlation of latent variables in the PLS algorithm calculations. According to these coefficients, all five main criteria had high correlations with the main variable and with each other. In other words, an increase in one variable would lead to an increase in another, and a decrease in one would result in a decrease in another.

Table 2

Correlation of Latent Variables in the PLS Algorithm

Variable	SPSS	A	B	C	D
Smart Health-Oriented Product–Service System	1.000	0.832	0.874	0.458	0.622
A_Business Model	0.832	1.000	0.791	0.796	0.530
B_Physical Platform	0.874	0.791	1.000	0.445	0.612
C_Software Platform	0.458	0.796	0.445	1.000	0.583
D_Cognitive and Biological Factors	0.622	0.530	0.612	0.583	1.000

Confirmatory factor analysis, in this context, illustrates the relationships between items (questionnaire questions) and factors (latent variables). In addition to factor loadings, validity criteria (AVE, Cronbach's alpha, composite reliability, rho_A), and coefficients of determination (R^2) were calculated in this analysis. A factor loading is a numerical value that determines the strength of the relationship between a latent variable and its corresponding observed variable in the path analysis process. The higher the factor loading of an indicator in relation to a specific construct, the greater the share of that indicator in explaining the construct. If the factor loading of an indicator is negative, it indicates its negative contribution in explaining the related construct; in other words, the question corresponding to that indicator is designed in reverse. The strength of the relationship between a factor (latent variable) and the observable variable is demonstrated by the factor loading. Factor loadings range between zero and one. If the factor loading is less than 0.40, the relationship is considered weak and is disregarded. A loading between 0.40 and 0.60 is acceptable, and if greater than 0.60, it is highly desirable. The factor loading of all items exceeded the minimum threshold of 0.50. Therefore, the strength of the relationship between each latent variable and its corresponding observed variable was at a desirable level.

Reliability is assessed through factor loadings, Cronbach's alpha, average variance extracted, and composite reliability. To evaluate measurement indicators and model validity, average variance extracted (AVE), composite reliability, and Cronbach's alpha were used. The results of reliability and convergent validity of the model are fully presented in Table 3 and discussed below.

Table 3

Reliability Results

Variable	Cronbach's Alpha	rho_A	Composite Reliability	AVE
Smart Health-Oriented Product–Service System	0.978	0.979	0.979	0.502
A_Business Model	0.947	0.954	0.953	0.525
B_Physical Platform	0.878	0.881	0.911	0.672
C_Software Platform (Cloud)	0.925	0.935	0.935	0.508
D_Cognitive and Biological Factors	0.931	0.934	0.941	0.573
Service and Product Providers	0.822	0.846	0.894	0.738
Clinical Monitoring	0.742	0.747	0.853	0.659
Suppliers and Logistics	0.820	0.826	0.893	0.737
Revenue–Cost Flow	0.860	0.863	0.915	0.782
Services	0.754	0.760	0.845	0.579
Cognitive Monitoring	0.856	0.863	0.898	0.638
Cloud Infrastructure and Servers	0.776	0.788	0.868	0.687
Network and Communications	0.847	0.736	0.803	0.513
Personalization and Feedback	0.822	0.844	0.882	0.654
Legal and Educational Guidelines	1.000	1.000	1.000	1.000
Products	0.722	0.773	0.841	0.641
Experience Management and User Interface (UI/UX)	0.756	0.756	0.860	0.672
Medication Management	0.795	0.805	0.868	0.622
Customers	0.837	0.873	0.905	0.763
Linkage to Public–Government Systems	0.731	0.753	0.834	0.562

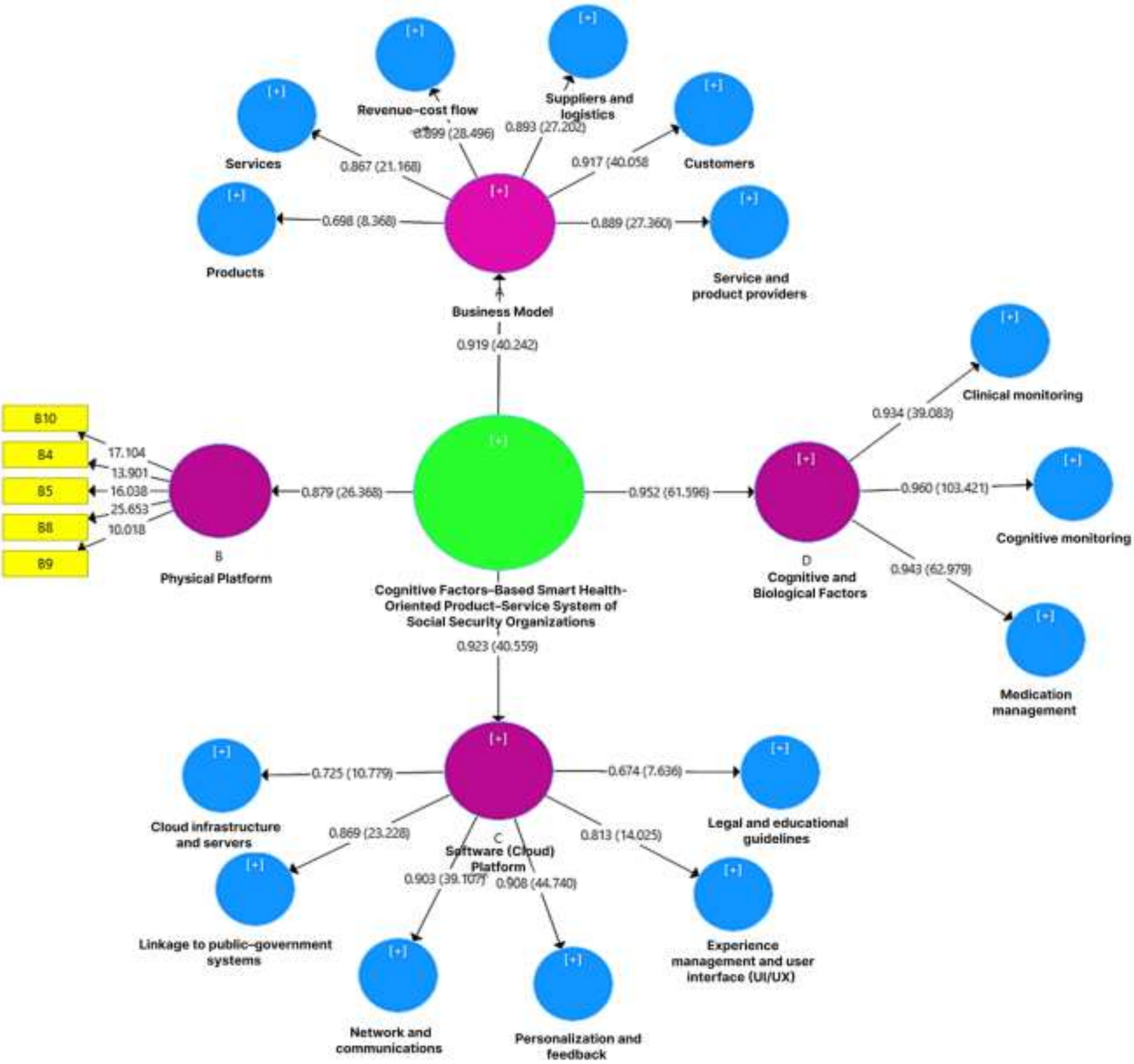
Cronbach's alpha is a criterion for assessing reliability and evaluating internal stability (internal consistency). As shown in Table 3, all Cronbach's alpha values exceeded 0.70, indicating acceptable reliability of the constructs. The rho coefficient is also used to assess internal consistency reliability. Chin and Marcoulides (1998) argued that rho is more reliable than Cronbach's alpha. The rho coefficient is sometimes referred to as the Dillon–Goldstein coefficient. Its value should exceed 0.70. As shown in Table 2, all rho_A values were greater than 0.70, thus the composite reliability of the constructs is acceptable. All composite reliability values exceeded 0.70, confirming the reliability of the constructs.

The average variance extracted (AVE) values for the constructs were proposed by Fornell and Larcker (1981). Fornell and Larcker stated that discriminant validity is acceptable when the AVE for each variable is greater than the shared variance between that variable and the others. In SmartPLS, this is examined by a matrix in which the cells contain the correlation coefficients between variables and the square root of the AVE for each variable. In Table 3, this matrix related to the variables is shown. The model has acceptable discriminant validity if the numbers on the main diagonal of the matrix are greater than the values beneath them. The acceptable threshold for this criterion, which indicates appropriate validity of the instruments, is at least 0.50.

After determining the correlation of variables and the validity of the model, the significance test (structural model) must be conducted. To assess the significance of relationships between variables, the t-statistic is used. Since significance is tested at the error level of 0.05, if the t-statistic exceeds the critical value of 1.96, the relationship is significant.

Figure 1

Structural Model in the Significance State



The following table reports the path coefficients, standard deviations, t-statistics, and significance levels for each path. The first and most fundamental criterion is the significance coefficients of the t-values. If these values exceed 1.96, it indicates the correctness of the relationship between constructs and consequently confirms the research hypotheses at the 95% confidence level. The results showed that the t-statistic in all main paths exceeded 1.96, with significance levels below 0.05.

Table 4

Summary of Structural Model Criteria

Main Path	Path Coefficient	T-Statistic	Standard Deviation	P-Value
A_Business Model -> Service and Product Providers	0.889	0.032	27.360	0.000
A_Business Model -> Suppliers and Logistics	0.893	0.033	27.202	0.000
A_Business Model -> Revenue–Cost Flow	0.899	0.032	28.496	0.000

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A_Business Model -> Services	0.867	0.041	21.168	0.000
A_Business Model -> Products	0.698	0.083	8.368	0.000
A_Business Model -> Customers	0.917	0.023	40.058	0.000
C_Software Platform (Cloud) -> Cloud Infrastructure and Servers	0.725	0.067	10.779	0.000
C_Software Platform (Cloud) -> Network and Communications	0.903	0.023	39.107	0.000
C_Software Platform (Cloud) -> Personalization and Feedback	0.908	0.020	44.740	0.000
C_Software Platform (Cloud) -> Legal and Educational Guidelines	0.674	0.088	7.636	0.000
C_Software Platform (Cloud) -> Experience Management and User Interface (UI, UX)	0.813	0.058	14.025	0.000
C_Software Platform (Cloud) -> Linkage to Public–Government Systems	0.869	0.037	23.228	0.000
D_Cognitive and Biological Factors -> Clinical Monitoring	0.934	0.024	39.083	0.000
D_Cognitive and Biological Factors -> Cognitive Monitoring	0.960	0.009	103.421	0.000
D_Cognitive and Biological Factors -> Medication Management	0.943	0.015	62.979	0.000
Smart Health-Oriented Product–Service System of Social Security Organizations Based on Cognitive Factors -> A_Business Model	0.919	0.023	40.242	0.000
Smart Health-Oriented Product–Service System of Social Security Organizations Based on Cognitive Factors -> B_Physical Platform	0.879	0.033	26.368	0.000
Smart Health-Oriented Product–Service System of Social Security Organizations Based on Cognitive Factors -> C_Software Platform (Cloud)	0.923	0.023	40.559	0.000
Smart Health-Oriented Product–Service System of Social Security Organizations Based on Cognitive Factors -> D_Cognitive and Biological Factors	0.952	0.015	61.596	0.000

The coefficient of determination (R^2) corresponds to the endogenous (dependent) latent variables of the model and is a criterion that indicates the effect of an exogenous variable on an endogenous variable. R^2 reflects the influence an independent variable exerts on a dependent variable. The coefficient of determination is calculated only for the dependent variable of the model, while for an independent variable, its value is zero. The higher the R^2 for the dependent variable, the better the model fit. Benchmark values of R^2 include 0.19 (weak), 0.33 (moderate), and 0.67 (strong). In this study, the R^2 values were 0.84 for the business model, 0.72 for the physical platform, 0.85 for the software platform, and 0.90 for cognitive and biological factors. According to the classifications of Chin and Marcoulides (1998) and Henseler and Sarstedt (2013), these values demonstrate strong and moderate determination coefficients, confirming the appropriateness of the model fit.

Table 5

Summary of Structural Model Criteria

Main Path	R^2	Adjusted R^2
A_Business Model	0.844	0.841
B_Physical Platform	0.772	0.768
C_Software Platform (Cloud)	0.852	0.850
D_Cognitive and Biological Factors	0.906	0.905
Service and Product Providers	0.791	0.787
Clinical Monitoring	0.872	0.870
Suppliers and Logistics	0.797	0.794
Revenue–Cost Flow	0.808	0.805
Services	0.751	0.747
Cognitive Monitoring	0.922	0.921
Cloud Infrastructure and Servers	0.525	0.518
Network and Communications	0.816	0.813
Personalization and Feedback	0.824	0.821
Legal and Educational Guidelines	0.454	0.445
Products	0.487	0.478
Experience Management and User Interface (UI, UX)	0.662	0.656
Medication Management	0.889	0.887
Customers	0.841	0.839
Linkage to Public–Government Systems	0.756	0.752

As noted, the GOF (Goodness-of-Fit) index relates to the overall fit of structural equation models. This criterion enables the researcher to control the overall fit of the model after separately assessing the fit of the measurement and structural components. The GOF index yields a value between zero and one. Wetzels et al. (2009) proposed three levels for evaluating the GOF index: weak if between 0.10 and 0.25, moderate if between 0.25 and 0.36, and strong if greater than 0.36. The closer the GOF index approaches one, the more suitable the model is considered. The average communalities are derived from the average variance extracted (AVE) for each endogenous variable, and the mean R^2 is the average of the R^2 values of the endogenous variables.

Table 6

Overall Model Fit Values (GOF)

Latent Variable	Communality Values	R^2	Mean Communality	Mean R^2	GOF
Smart Health-Oriented Product–Service System	0.502	–	0.651	0.767	0.701
A_Business Model	0.525	0.844			
B_Physical Platform	0.672	0.772			
C_Software Platform (Cloud)	0.508	0.852			
D_Cognitive and Biological Factors	0.573	0.906			
Service and Product Providers	0.738	0.791			
Clinical Monitoring	0.659	0.872			
Suppliers and Logistics	0.737	0.797			
Revenue–Cost Flow	0.782	0.808			
Services	0.579	0.751			
Cognitive Monitoring	0.638	0.922			
Cloud Infrastructure and Servers	0.687	0.525			
Network and Communications	0.513	0.816			
Personalization and Feedback	0.654	0.824			
Legal and Educational Guidelines	1.000	0.454			
Products	0.641	0.487			
Experience Management and User Interface (UI, UX)	0.672	0.662			
Medication Management	0.622	0.889			
Customers	0.763	0.841			
Linkage to Public–Government Systems	0.562	0.756			

Based on Table 6, the GOF index obtained was 0.67, which is considered strong. This indicates that the overall fit of the structural equation model in the present study is strong.

4. Discussion and Conclusion

The findings of this study provide empirical validation for the proposed model of a smart health-oriented product–service system (Smart PSS) within the context of social security organizations. The confirmatory factor analysis demonstrated that the model encompasses four critical dimensions: the business model, software (cloud) platform, cognitive and biological factors, and the physical platform. Each dimension was supported by statistically significant loadings, with path coefficients and t-statistics exceeding recommended thresholds, while reliability and validity tests confirmed robustness through Cronbach's alpha, rho_A, composite reliability, and AVE scores. Furthermore, the structural model results revealed strong correlations across dimensions, with R^2 values ranging from moderate to strong, thereby indicating substantial explanatory power of the model. Collectively, these results highlight the adequacy of the four-dimension framework in addressing both technological and cognitive demands for elderly-centered health services in social security systems.

The integration of business model considerations with software and physical platforms reflects a comprehensive ecosystem approach. This study found strong positive relationships between the business model and its associated components such as service providers, suppliers, customers, and revenue–cost flows. These relationships emphasize that sustainable Smart PSS solutions cannot emerge from isolated technological deployments but must be aligned with viable financial and operational strategies. This result aligns with prior conceptualizations of Smart PSS as socio-technical systems that simultaneously integrate economic and technological logics (Zheng et al., 2019). The retrospective and prospective analysis of Smart PSS 2.0 further supports this interpretation, emphasizing that the transition from isolated product–service offerings toward ecosystemic configurations requires attention to value-network design and service orchestration (Ren & Zheng, 2024).

Another critical outcome of the analysis was the strong role of the software (cloud) platform dimension, which displayed significant correlations with its underlying elements, including cloud infrastructure, networking, personalization, and experience management. These results confirm that digital backbones such as cloud and big data pipelines are indispensable for delivering scalable and adaptive elderly care. This is consistent with evidence that Industry 4.0 enablers—IoT, cloud computing, and big data—constitute the infrastructure of Healthcare 4.0, enabling intelligent monitoring and personalization of care delivery (Aceto et al., 2020). Similarly, research on innovative value propositions for Smart PSS highlighted the need for digital integration methods that allow stakeholders to evaluate interdependencies between risks, costs, and values (Chen et al., 2020). The significance of these findings lies in showing that digital infrastructures are not only technical enablers but are deeply entwined with value-creation processes and trust among multiple actors.

The cognitive and biological dimension emerged as particularly robust, with very high factor loadings for subcomponents such as clinical monitoring, cognitive monitoring, and medication management. These results demonstrate that embedding cognitive and biological data streams into Smart PSS is essential for addressing the unique needs of elderly populations. Evidence from the implementation of PROMIS cognitive function screeners suggests that systematically integrating cognitive data into wellness visits improves both clinical insight and patient engagement, though outcomes vary depending on how items are framed (Harrison et al., 2024). Similarly, user-centered immersive designs for older adults with cognitive disorders have shown that tailoring interfaces to sensory and emotional contexts significantly enhances engagement (Yi et al., 2024). Knowledge graph–based systems for chronic elderly care further support these findings by illustrating how structured representation of patient knowledge enables more accurate and explainable decision support (Li et al., 2024). Taken together, these studies confirm that Smart PSS effectiveness depends critically on how cognitive and biological complexity is captured, represented, and acted upon.

The results also validate the importance of human-centered design and usability considerations. Our model demonstrated that user experience management and personalization were significant subcomponents of the cloud platform. This resonates with findings that human-centered methodologies for connected health reduce friction in adoption by aligning interfaces with user expectations and cognitive patterns (Harte et al., 2017). Moreover, the cognitive challenge in healthcare information systems has been well-documented, underscoring the need to align technical semantics with the interpretive capacities of both patients and providers (Lintern & Motavalli, 2018). By confirming these relationships empirically, this study provides quantitative support for design traditions that advocate iterative, participatory, and cognitively attuned development processes.

The inclusion of business model variables such as financing, revenue–cost streams, and service-provider configurations underscores that Smart PSS viability extends beyond technology adoption. Our findings that business model elements had strong explanatory power mirror earlier analyses of pension funds and social insurance structures, which argue that financial sustainability and institutional arrangements directly shape the feasibility of adopting innovative health solutions (Bozrafkan & Ghomari, 2019). These findings also echo arguments from telehealth adoption studies that rapid scaling, such as during the COVID-19 pandemic, required not just technological readiness but also reimbursement policies and organizational capacity (Barney et al., 2020; Pierce et al., 2021). Thus, the present study contributes empirical weight to the claim that socio-technical and financial architectures must be jointly addressed.

The robustness of the R^2 values across all latent variables in this study indicates that the model captures significant variance in Smart PSS performance indicators. The GOF index of 0.70 further confirms strong model fit, surpassing the threshold for a robust structural equation model (Wetzels et al., 2009). The statistical rigor of this model builds on established practices for evaluating latent constructs in structural equation modeling, particularly the use of composite reliability and AVE for convergent and discriminant validity (Fornell & Larcker, 1981). By employing these benchmarks, this study provides methodologically sound evidence for the multidimensional structure of Smart PSS.

These results align with the broader narrative of digital health as a cultural transformation rather than a mere technological shift. Evidence suggests that digital health adoption requires reshaping norms, professional roles, and inter-institutional relationships (Meskó et al., 2017). This cultural transformation is echoed in our findings that cognitive monitoring, personalization, and user-experience factors are integral to Smart PSS, suggesting that trust,

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usability, and co-creation are as critical as technical reliability. Research on stakeholder communication in smart healthcare similarly highlights that effective adoption depends on transparent and intelligent communication mechanisms among all stakeholders (Negash & Calahorrano Sarmiento, 2023). Trust, legal clarity, and liability considerations remain key, as evidenced by analyses of telemedicine risks and stakeholder responsibilities (Parimbelli et al., 2018).

At the same time, the global telehealth experience illustrates both opportunities and limitations. The rapid deployment of telehealth in adolescent and young adult populations showed that digital modalities could be scaled quickly, but sustaining quality required attention to training, workflows, and ethical challenges (Barney et al., 2020). In Latin America, telehealth progress has been uneven, shaped by regulatory heterogeneity and infrastructure limitations (Pierce et al., 2021). These lessons suggest that while Smart PSS frameworks offer significant potential, their success will depend on continuous adaptation to local institutional and cultural contexts.

The practical implications of our findings extend to operational readiness and strategic planning. Studies of healthcare leaders indicate persistent capability gaps in digital health readiness, particularly around governance and cross-unit integration (Steenkamp, 2025). Addressing these gaps will be essential for translating Smart PSS models into practice. Similarly, evidence that mobile health interventions can enhance elderly well-being in resource-constrained settings illustrates the potential for Smart PSS to reduce disparities if designed with cultural and infrastructural sensitivities (Safdari et al., 2017). Lessons from adjacent domains, such as Islamic marketing ethics and convergence marketing, highlight that aligning services with ethical principles can reinforce trust and legitimacy in diverse communities (Suandi et al., 2022). Furthermore, the use of gamified, immersive, and biosensor-driven tools for psychological and behavioral support demonstrates the frontier opportunities available for Smart PSS integration (Pilkington et al., 2025; Wang, 2025).

Overall, this study provides empirical evidence that Smart PSS, when modeled with attention to business, technological, physical, and cognitive–biological dimensions, can offer a comprehensive framework for improving health services in social security organizations. By aligning our findings with prior literature, we confirm that the integration of cognitive factors is not only innovative but necessary for designing systems that are equitable, usable, and sustainable.

Despite the robustness of findings, this study is not without limitations. First, the sample was limited to employees of a single social security organization, which constrains the generalizability of the results across diverse institutional and cultural contexts. Different organizational structures, policy frameworks, and funding models may influence Smart PSS adoption differently. Second, although cognitive and biological factors were operationalized quantitatively, the complexity of human cognition and behavior may not be fully captured through structured questionnaires alone. Qualitative explorations could provide richer insight into user experiences and barriers. Third, the cross-sectional design limits causal inference. While the statistical models demonstrate strong associations, longitudinal research would be required to evaluate causal pathways and the evolution of Smart PSS adoption over time. Finally, while this study validated the measurement and structural model, real-world implementation data were not available, meaning that practical performance outcomes such as improved health or reduced costs remain inferred rather than directly observed.

Future research should expand on these findings in several directions. Comparative studies across multiple social security organizations and cultural contexts would be valuable to test the model’s transferability and identify context-specific adaptations. Longitudinal designs should be employed to examine how Smart PSS adoption and outcomes evolve over time, particularly in relation to elderly health trajectories and institutional policy shifts. Future studies could also incorporate experimental or quasi-experimental designs to assess the causal impact of specific Smart PSS interventions on health outcomes, satisfaction, and costs. Furthermore, qualitative studies with elderly participants, caregivers, and providers could deepen understanding of cognitive, emotional, and cultural factors shaping adoption. Finally, interdisciplinary research integrating cognitive science, management, informatics, and policy analysis would enrich the theoretical and practical dimensions of Smart PSS design.

Practitioners seeking to implement Smart PSS in social security organizations should prioritize alignment between technological infrastructure and institutional strategy. Cloud-based platforms should be designed with scalability, interoperability, and user-centered interfaces. Cognitive screening and personalization features should be embedded

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to ensure inclusivity for elderly users with varying cognitive and physical capacities. Financial and operational models must be developed to ensure sustainability, including clear revenue–cost structures and value-sharing mechanisms. Policymakers and managers should also invest in capacity building and digital readiness to bridge workforce and governance gaps. Finally, pilot projects should be co-created with end-users and frontline providers to foster trust, usability, and adoption, laying the groundwork for sustainable scaling.

Authors' Contributions

Authors equally contributed to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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Ethical Considerations

All procedures performed in studies involving human participants were under the ethical standards of the institutional and, or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

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