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Article

Translating individual capacity into insurance protection: Policy Promotion Intensity as a communication-mediated mechanism shaping insurance plan adequacy among cancer patients in Sichuan, China

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Abstract: Cancer financial toxicity represents a pressing concern in China, where over 4.82 million new cancer cases are diagnosed annually. Despite the achievement of near-universal health insurance coverage, the segmented system—encompassing Employee Basic Medical Insurance (EBMI) and Urban and Rural Resident Basic Medical Insurance (URRBMI)—continues to leave cancer patients exposed to substantial out-of-pocket expenditures, and the mechanisms linking individual capacity factors to insurance plan adequacy remain insufficiently understood. This study tests whether Policy Promotion Intensity (PPI) mediates the relationship between individual capacity factors and insurance plan adequacy among cancer patients in Sichuan Province, China. A cross-sectional survey was administered to 405 cancer patients recruited from tertiary, secondary, and primary healthcare facilities across Sichuan Province. Six constructs were operationalised: insurance literacy, health knowledge, prior insurance coverage, financial capability, policy promotion intensity, and choice of insurance plan. Data were analysed using confirmatory factor analysis and structural equation modelling in AMOS 23, with mediation effects tested via bias-corrected bootstrap confidence intervals based on 5,000 resamples. All five direct paths were statistically significant ($p < .05$), with financial capability exhibiting the strongest direct effect on plan adequacy ($\beta = 0.267$, $p < .001$). Policy promotion intensity significantly mediated all four pathways, with mediation proportions ranging from 12.7% (financial capability) to 25.4% (health knowledge). The model demonstrated excellent fit (CFI = 0.989, RMSEA = 0.020). These findings suggest that policy promotion intensity operates as a communication-mediated mechanism that amplifies but does not substitute for individual capacity in insurance decision-making. The results imply that hospital-based counselling, plain-language outreach, and tiered digital promotion calibrated to patient literacy levels may enhance insurance protection for cancer patients in segmented healthcare systems.
Keywords: policy promotion intensity, insurance literacy, financial capability, cancer survivors, structural equation modelling, China

1. Introduction

1.1 Cancer Survivorship and Financial Toxicity in China

Cancer remains one of the most pressing global health challenges of the twenty-first century. According to GLOBOCAN 2022 estimates reported by Bray et al. (2024), approximately 20 million new cancer cases and 9.7 million cancer deaths occurred worldwide in a single year, underscoring the magnitude of the disease burden across high-, middle-, and low-income settings. China alone accounted for roughly 4.82 million new cancer cases and 2.57 million cancer deaths in 2022, representing nearly one-quarter of the global total despite housing less than one-fifth of the world's population (Han et al., 2024; Sung et al., 2021). These figures position China as the country with the highest absolute cancer incidence globally, a distinction driven by demographic ageing, environmental risk factors, and epidemiological transitions in lifestyle-related malignancies such as lung, colorectal, and breast cancer.

The growth in cancer incidence has been accompanied by meaningful gains in survival. Zeng et al. (2018) documented that China's age-standardised five-year relative cancer survival rate rose from 30.9% in 2003–2005 to 40.5% in 2012–2015, reflecting improvements in early detection, surgical technique, and systemic therapy. Survival is consistently higher in well-resourced urban registries than in rural areas, although the national all-cancers rate still trails Western benchmarks (Zeng et al., 2018). However, these survival gains carry a significant economic corollary. The Institute of Medicine (2006) documented that the transition from acute treatment to long-term survivorship generates sustained demand for rehabilitation, regular surveillance, psychosocial support, and chronic disease management—services that extend far beyond the initial treatment window. These improvements have produced a large and rapidly growing population of cancer survivors in China, whose post-treatment care needs will span decades (Feng et al., 2019).

This epidemiological shift translates directly into financial burden. Qiu et al. (2023) found that, despite near-universal insurance enrolment, cancer-related out-of-pocket (OOP) expenditures in China leave the majority of patients with at least moderate financial toxicity, driven by non-reimbursable targeted therapies, prolonged drug regimens, travel costs for tertiary-level care, and indirect losses in productivity. For households in the middle- and lower-income strata, these expenses frequently exceed discretionary savings, producing financial toxicity—a condition defined as treatment-induced economic hardship that depletes assets and compromises adherence to necessary care. In this context, health insurance functions not merely as a risk-pooling instrument but as a critical buffer between clinical need and economic ruin.

1.2 The Segmented Insurance Landscape

China's health insurance architecture is fundamentally bifurcated along urban-rural and employment-status lines. The two primary public schemes are the Employee Basic Medical Insurance (EBMI) and the Urban-Rural Resident Basic Medical Insurance (URRBMI). EBMI is funded through payroll contributions shared between employers and employees, while URRBMI is financed through a combination of individual premiums and fiscal subsidies (NHSA, 2023, 2024). This structural divide produces substantial disparities in benefit depth, reimbursement generosity, and financial protection—disparities that are especially consequential for cancer patients facing high-cost, long-duration treatment trajectories.

Table 1 *Institutional Differences Between EBMI and URRBMI*

Dimension	EBMI	URRBMI
Annual contribution per enrollee	3,800–4,601 RMB	960–1,020 RMB
Policy-scope inpatient reimbursement rate	84–85%	68–70%
Effective reimbursement rate	74–76%	53–57%
Annual reimbursement ceiling	400,000–500,000 RMB	300,000 RMB
Critical-illness insurance reimbursement	~90%	78–80%

Note. Policy-scope inpatient reimbursement refers to the share of within-catalogue inpatient costs paid by the fund, reported nationally by the NHSA (approximately 84.6% for EBMI and 68.1% for URRBMI in 2023). Effective reimbursement reflects the actual proportion of total medical expenditure recovered after accounting for non-catalogue services, deductibles, and copayments. Contribution, effective-reimbursement, ceiling, and critical-illness figures are locality-dependent estimates compiled from provincial implementation documents rather than national NHSA statistics; residents' critical-illness insurance reimburses at least 60% of the qualifying catastrophic portion. Source: NHSA (2023, 2024); provincial implementation documents.

The figures in Table 1 reveal that the effective reimbursement rate for URRBMI enrollees (53–57%) is approximately twenty percentage points lower than that for EBMI enrollees (74–76%). This gap widens further when ceiling limits are considered: URRBMI caps annual reimbursement at roughly 300,000 RMB, whereas EBMI ceilings reach 400,000–500,000 RMB. For cancer patients requiring multiline targeted therapies—many of which carry annual costs exceeding 100,000 RMB even after national reimbursement list negotiations—these ceiling differentials determine whether treatment remains financially accessible or precipitates catastrophic expenditure (Zhu et al., 2022; Leng et al., 2019).

The gap is partially mitigated by supplementary layers. Zheng and Peng (2021) described the major illness insurance (*Da Bing*) programme, which provides a second-layer reimbursement for conditions exceeding standard scheme thresholds. Under this arrangement, residents' critical-illness insurance reimburses at least 60% of qualifying catastrophic expenses, raising cumulative reimbursement above the basic-scheme level, although the exact share is set locally and varies across regions (Zheng & Peng, 2021). Commercial critical illness insurance has emerged as a third layer, though uptake remains uneven across income and digital-access lines (Xu et al., 2022). Ng et al. (2024) found that the financial-protection value of supplementary private insurance is contingent on benefit design and on enrollees' capacity to evaluate plan attributes against their anticipated needs, and may even raise out-of-pocket spending when these conditions are unmet—a caveat especially salient for cancer patients navigating complex treatment protocols.

1.3 Theoretical Gap

Within this institutional environment, a growing body of research has examined the individual-level determinants of insurance plan choice. Studies have identified health insurance literacy (Weedige et al., 2019; Park et al., 2022), disease-specific health knowledge (Chang & Schulz, 2018), prior coverage experience (Wang et al., 2008), and financial capability (Smith et al., 2019) as significant predictors of whether individuals select plans that match their risk profiles and clinical needs. These findings align with theoretical expectations drawn from the Health Belief Model (HBM; Champion & Skinner, 2008), which posits that perceived severity and susceptibility interact with cues to action in shaping protective health behaviour, and from the Theory of Planned Behaviour (TPB; Ajzen, 1991), which emphasises perceived behavioural control as a determinant of intention translation.

Despite this accumulating evidence, a critical gap persists. Existing studies treat the relationship between individual capacity factors and insurance choice as predominantly direct, without adequately theorising the institutional communication mechanisms through which capacity is converted into action. In other words, the pathway from "knowing" to "choosing" remains a black box. A patient may possess high insurance literacy and adequate financial resources, yet fail to select an optimal plan if institutional communications about available options are infrequent, opaque, or poorly targeted. This study operationalises the communication channel through the construct of Policy Promotion Intensity (PPI), defined as the perceived frequency, clarity, credibility, and accessibility of public and institutional communications about insurance options relevant to the patient's clinical and economic circumstances.

The construct of PPI resonates with the HBM concept of cues to action—external stimuli that trigger protective behaviour—but extends it from momentary prompts to sustained, institutionally embedded communication processes. It also connects with behavioural economics insights on information frictions and bounded rationality (Kahneman & Tversky, 1979; Thaler & Sunstein, 2008), which suggest that even well-informed decision-makers rely on contextual cues and choice architecture to navigate complex options. To date, however, no published study has tested PPI as a mediating mechanism between individual capacity and insurance plan adequacy, particularly within a chronic-illness population in a segmented public insurance system. This theoretical lacuna motivates the present inquiry.

1.4 Contribution and Structure of the Paper

This study makes three contributions to the health services literature. First, it introduces and empirically validates Policy Promotion Intensity (PPI) as a transmission mechanism that mediates the relationship between individual capacity factors and insurance plan choice adequacy. By demonstrating that PPI carries significant indirect effects alongside direct capacity effects, the analysis reveals that institutional communication is not merely a background condition but an active mediating force in the insurance decision process. Second, it extends HBM and TPB theorising by operationalising cues to action at the institutional level—treating policy promotion as a sustained organisational behaviour rather than a transient external prompt—and integrating this operationalisation with behavioural economics perspectives on information architecture. Third, it provides context-specific evidence from a chronically ill population in China's segmented insurance environment, a setting where institutional communication gaps and benefit disparities converge to produce particularly acute decision-making challenges.

The remainder of this paper is organised as follows. Section 2 presents the theoretical framework and derives thirteen hypotheses specifying direct effects of insurance literacy, health knowledge, prior insurance coverage, and financial capability on choice of insurance plan (H1–H4), a direct effect of PPI on plan choice (H5), four mediated pathways in which PPI transmits the effects of each capacity antecedent (H6–H9), and four antecedent paths in which insurance literacy, health knowledge, prior insurance coverage, and financial capability influence PPI (H10–H13). Section 3 describes the cross-sectional survey design, sampling procedures in Sichuan Province, measurement instruments, and analytical approach using confirmatory factor analysis (CFA) and structural equation modelling (SEM) with bias-corrected bootstrap mediation in AMOS 23. Section 4 reports the results, including measurement model validation, structural path estimates, and mediation analysis. Section 5 discusses the findings in relation to theory, policy, and practice, acknowledges limitations, and identifies directions for future research. Section 6 offers a concluding summary.

2. Theoretical Background and Hypothesis Development

2.1 Health Belief Model and Insurance Decisions

The Health Belief Model (HBM) provides a foundational framework for understanding why individuals engage in protective health behaviours (Champion & Skinner, 2008). Originally developed to explain preventive health action such as vaccination uptake and disease screening, the HBM posits that health behaviour is shaped by five core constructs: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, and cues to action (Champion & Skinner, 2008). Perceived susceptibility refers to an individual's assessment of their risk of contracting a condition; perceived severity captures the anticipated seriousness of that condition; perceived benefits reflect the expected efficacy of a protective action; perceived barriers encompass the obstacles—financial, logistical, or psychological—to undertaking that action; and cues to action are external or internal stimuli that trigger the decision to act (Champion & Skinner, 2008). In the context of insurance plan selection, these constructs map directly onto patient decision-making: perceived severity corresponds to the anticipated financial burden of cancer diagnosis and treatment; perceived benefits align with the expected adequacy of coverage provided by a given plan; perceived barriers include plan complexity, premium affordability, and information asymmetry; and cues to action are institutional communications that prompt plan evaluation (Politi et al., 2020).

A critical insight from the HBM is that individual risk perception alone is insufficient to produce protective behaviour without an activating stimulus (Champion & Skinner, 2008). In prior applications, cues to action have typically been conceptualised as discrete events—a physician recommendation, a media campaign, or a symptomatic episode—that prompt immediate behavioural response (Politi et al., 2020). However, in the context of China's multi-tiered medical insurance system, where policy information is disseminated through sustained institutional channels rather than episodic messaging, this study conceptualises Policy Promotion Intensity (PPI) as a continuous cue to action. Unlike traditional HBM cues, PPI represents a persistent environmental signal—encompassing government publicity, hospital-based informational outreach, and community-level policy briefings—that maintains patient awareness of coverage options throughout the treatment trajectory. This reconceptualisation addresses a gap in the HBM literature by extending the cue-to-action construct from discrete triggers to ongoing institutional communication.

2.2 Theory of Planned Behaviour and Perceived Behavioural Control

The Theory of Planned Behaviour (TPB) offers a complementary lens for understanding insurance plan selection as a reasoned action under constraint (Ajzen, 1991). The TPB proposes that behaviour is proximally determined by behavioural intention, which is itself shaped by three antecedent factors: attitudes toward the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991). Attitudes capture favourable or unfavourable evaluations of the target behaviour; subjective norms reflect perceived social pressure to engage in that behaviour; and perceived behavioural control (PBC) denotes the individual's confidence in their capacity to execute the behaviour successfully (Ajzen, 1991). In the insurance context, attitudes are informed by patients' knowledge of premiums, reimbursement rates, and coverage limits; subjective norms encompass recommendations from family members, healthcare providers, and social networks; and PBC reflects the patient's confidence in navigating plan selection and affording associated costs (Andersen, 1995).

The TPB has been applied extensively in health services research to explain utilisation decisions, including enrolment in health insurance programmes (Andersen, 2008). However, its application to oncology insurance contexts remains limited. A distinctive feature of cancer patients' insurance decisions is the temporal compression of decision-making under conditions of emotional distress and physical incapacity (Sung et al., 2021; Reyna et al., 2015). Under these conditions, the TPB's assumption of rational intention-behaviour translation may not hold: even patients with positive attitudes toward plan optimisation and adequate social support may lack the cognitive resources to convert intention into action. This study addresses this limitation by integrating TPB with behavioural economics, acknowledging that perceived behavioural control is bounded by information frictions and cognitive load specific to the oncology care setting.

2.3 Behavioural Economics: Information Frictions and Bounded Rationality

Behavioural economics provides the theoretical grounding for understanding why individual capacity alone may be insufficient for optimal plan selection. Prospect theory, developed by Kahneman and Tversky (1979), demonstrates that individuals systematically deviate from rational decision-making under uncertainty, overweighting small probabilities and exhibiting loss aversion. In the insurance context, cancer patients may overweight the immediate, certain cost of premium increases while underweighting the uncertain but potentially catastrophic financial exposure of inadequate coverage (Kahneman & Tversky, 1979). This cognitive bias contributes to what Thaler and Sunstein (2008) term “status quo bias” or default stickiness—the tendency to remain in existing or suboptimal plans due to decision inertia.

Thaler and Sunstein (2008) further argue that the architecture of choice environments—how information is presented, how options are ordered, and what defaults are established—profoundly influences decision outcomes without restricting freedom of choice. In China’s insurance system, where plan attributes are communicated through multiple institutional channels with varying clarity and accessibility, the framing of policy information affects patient comprehension and, consequently, plan selection (Diao et al., 2019; Li et al., 2017). Choice overload, wherein excessive option complexity degrades decision quality, compounds these frictions: patients confronting multiple insurance tiers with heterogeneous coverage parameters may resort to heuristic-based selection strategies that impose substantial cognitive demands when patients compare options (Politi et al., 2020). The integration of behavioural economics into the present framework explains why even patients with high insurance literacy and adequate financial resources may fail to select optimal coverage, and why institutional communication (PPI) serves a corrective function by simplifying information processing and reducing cognitive barriers.

2.4 Hypotheses

2.4.1 Direct Effects of Individual Capacity on Choice of Insurance Plan

H1: Insurance literacy positively influences choice of insurance plan. Insurance literacy—the ability to understand premiums, deductibles, reimbursement schedules, and benefit structures—enables patients to compare plans systematically and identify the option best suited to their anticipated care needs (Weedige et al., 2019). Empirical evidence from developed insurance markets indicates that higher insurance literacy is associated with more informed enrolment decisions and reduced coverage gaps (Park et al., 2022). In China’s urban-rural dual insurance system, where plan parameters vary substantially across tiers and regions, patients who comprehend these parameters possess a decisive advantage in plan selection. This study therefore hypothesises that insurance literacy exerts a positive direct effect on choice of insurance plan.

H2: Health knowledge positively influences choice of insurance plan. Health knowledge encompasses patients’ understanding of disease trajectories, treatment protocols, and associated cost profiles. Cancer patients with greater health knowledge are better positioned to anticipate their future care requirements—including the need for specialist consultations, targeted therapies, and supportive medications—and to match those requirements with plan provisions (Chang & Schulz, 2018). Tian et al. (2022) found that greater familiarity with insurance policy was significantly associated with residents’ enrolment decisions. Accordingly, this study hypothesises that health knowledge exerts a positive direct effect on choice of insurance plan.

H3: Prior insurance coverage positively influences choice of insurance plan. Prior insurance coverage represents experiential capital accumulated through past interactions with the insurance system. Patients with prior coverage possess procedural familiarity with enrolment processes, reimbursement claims, and coverage limitations, which reduces the uncertainty and cognitive effort associated with plan reselection (Wang et al., 2008). This experiential advantage is particularly salient in oncology, where treatment complexity demands seamless coordination between insurance tiers. This study hypothesises that prior insurance coverage exerts a positive direct effect on choice of insurance plan.

H4: Financial capability positively influences choice of insurance plan. Financial capability—the capacity to absorb out-of-pocket costs and maintain premium payments—determines the feasible set of insurance options available to a patient (Smith et al., 2019). Cancer treatment imposes substantial financial burden, including direct medical costs and indirect costs from productivity loss (Zafar et al., 2013). Patients with greater financial capability face fewer affordability constraints and can therefore select plans with more comprehensive coverage, higher reimbursement ceilings, or broader provider networks. This study hypothesises that financial capability exerts a positive direct effect on choice of insurance plan.

2.4.2 Direct Effect of Policy Promotion Intensity on Choice of Insurance Plan

H5: Policy promotion intensity positively influences choice of insurance plan. Policy promotion intensity refers to the volume, clarity, and accessibility of institutional communications regarding insurance options, enrolment procedures, and coverage benefits. Politi et al. (2020) demonstrated that structured decision aids significantly improved patient comprehension of insurance alternatives in complex healthcare settings. By reducing information search costs, clarifying plan differentials, and prompting active evaluation, policy promotion functions as a systemic intervention that mitigates the cognitive and informational barriers identified in the HBM and behavioural economics literature (Tian et al., 2022). This study hypothesises that policy promotion intensity exerts a positive direct effect on choice of insurance plan.

2.4.3 Policy Promotion Intensity as a Mediator

H6–H9: Policy promotion intensity mediates the relationships between insurance literacy, health knowledge, prior insurance coverage, financial capability, and choice of insurance plan. The mediation hypothesis is grounded in the proposition that individual capacity and institutional communication interact to produce optimal plan selection. Specifically, patients with greater individual capacity—higher insurance literacy, deeper health knowledge, more extensive prior coverage, and stronger financial resources—are more likely to attend to, process, and act upon policy communications (Ajzen, 1991; Thaler & Sunstein, 2008). This competence-driven engagement mechanism suggests that individual attributes amplify the effect of institutional cues: more capable patients derive greater benefit from exposure to policy promotion because they possess the cognitive and financial resources necessary to translate informational inputs into actionable coverage decisions. Conversely, institutional communication partially compensates for capacity limitations by providing structured guidance that simplifies decision-making (Politi et al., 2020). The HBM's cue-to-action construct supports this mediation logic: individual predispositions determine responsiveness to external cues, while the cues themselves activate behaviour (Champion & Skinner, 2008). This study therefore hypothesises that policy promotion intensity mediates the effects of all four antecedent variables on choice of insurance plan.

2.4.4 Antecedent Effects on Policy Promotion Intensity

H10: Insurance literacy positively influences policy promotion intensity. Patients with higher insurance literacy are more attentive to policy-related communications because they possess the interpretive schemas necessary to extract meaning from promotional materials (Weedige et al., 2019; Park et al., 2022). This receptive competence increases the effective intensity of policy promotion as perceived and processed by the patient.

H11: Health knowledge positively influences policy promotion intensity. Health knowledge creates demand for policy information by linking disease understanding to coverage implications (Chang & Schulz, 2018). Patients who understand their treatment needs are more motivated to seek out and engage with policy communications that address those needs, thereby enhancing the perceived relevance and impact of promotional efforts (Reyna et al., 2015).

H12: Prior insurance coverage positively influences policy promotion intensity. Experiential familiarity with the insurance system reduces the cognitive cost of engaging with new policy information (Wang et al., 2008). Patients with prior coverage are more likely to recognise the value of policy communications and to integrate new information with existing procedural knowledge, increasing the effective processing of promotional materials.

H13: Financial capability positively influences policy promotion intensity. Financially capable patients face fewer binding constraints on plan choice and therefore have greater incentive to attend to policy communications that may reveal superior coverage options (Smith et al., 2019). The expected utility of information acquisition is higher when the feasible choice set is unconstrained by affordability.

Figure 1

Conceptual Model

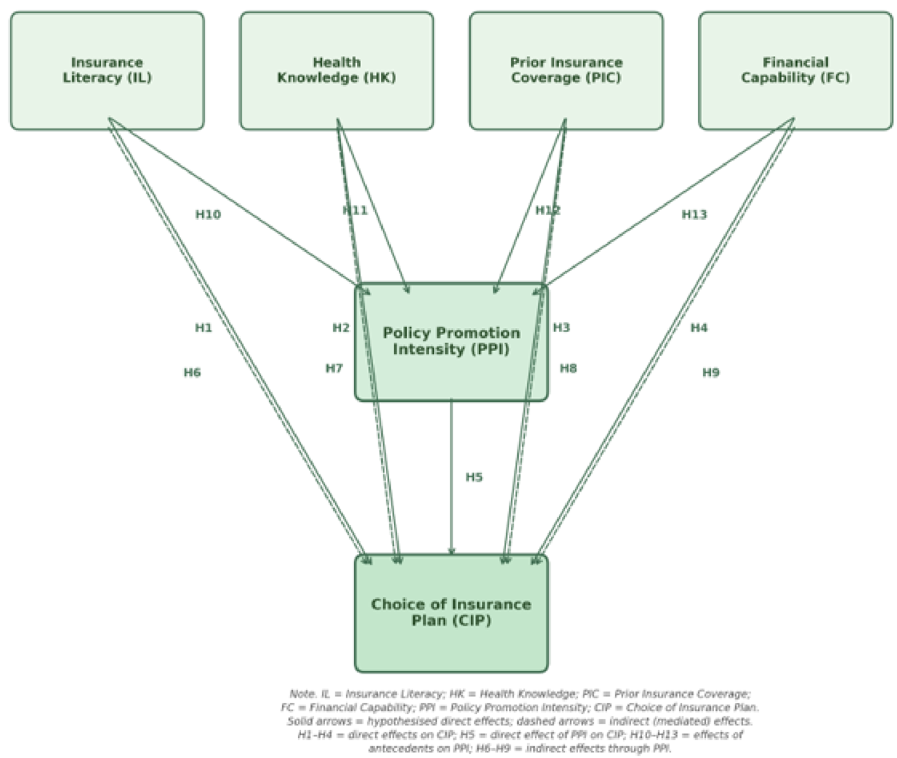

Figure 1. Conceptual Model

Figure 1: Conceptual Model showing hypothesised relationships among Insurance Literacy (IL), Health Knowledge (HK), Prior Insurance Coverage (PIC), Financial Capability (FC), Policy Promotion Intensity (PPI), and Choice of Insurance Plan (CIP).

Note. IL = Insurance Literacy; HK = Health Knowledge; PIC = Prior Insurance Coverage; FC = Financial Capability; PPI = Policy Promotion Intensity; CIP = Choice of Insurance Plan. Solid arrows = hypothesised direct effects; dashed arrows = indirect (mediated) effects. H1-H4 = direct effects on CIP; H5 = direct effect of PPI on CIP; H10-H13 = effects of antecedents on PPI; H6-H9 = indirect effects through PPI.

3. Method

3.1 Research Design

This study employed a cross-sectional, self-administered survey design with an explanatory purpose. The objective was to examine the direct and indirect effects of individual-level determinants—insurance literacy, health knowledge, prior insurance coverage, financial capability, and policy promotion intensity—on cancer patients' choice of insurance plan within China's multi-payer health system. The research model was informed by Andersen's (1995) Behavioral Model of Health Services Use, which posits that predisposing characteristics, enabling resources, and perceived need collectively shape health-related decisions. By adapting this framework to the insurance selection context, the study tested a theoretically specified structural model in which predisposing factors (insurance literacy and health knowledge) and enabling factors (prior insurance coverage, financial capability, and policy promotion intensity) were hypothesised to influence the outcome variable both directly and through mediating pathways.

The cross-sectional design is appropriate for mapping the pattern of associations among latent constructs at a single point in time (Hair et al., 2019). However, the design does not support causal inference; directional relationships were tested only insofar as they were consistent with prior theory and the temporal ordering implied by the conceptual framework (Maxwell & Cole, 2007). Reverse causality and unobserved confounders remain threats to internal validity, and findings are interpreted accordingly.

3.2 Setting and Sampling

The study was conducted in Sichuan Province, southwestern China, a jurisdiction of approximately 83 million residents that accounts for roughly 6% of the national population (National Bureau of Statistics of China, 2023). Sichuan was selected because it combines a substantial cancer burden with a diverse mix of urban and rural health delivery settings, offering variation in insurance literacy, access to information, and plan options that is sufficient to test the research model. The province operates under China's unified multi-payer framework, comprising Employee Basic Medical Insurance (EBMI) and the integrated Urban–Rural Resident Basic Medical Insurance (URRBMI)—which unified the former Urban Resident Basic Medical Insurance and New Rural Cooperative Medical Scheme in Sichuan in 2017—alongside newly introduced commercial critical illness supplements (NHSA, 2024).

Participants were recruited through a multi-site, stratified quota-sampling strategy. Data collection took place across tertiary hospitals (n = 168, 41.48%), secondary hospitals (n = 142, 35.06%), primary and community health facilities (n = 95, 23.46%), and registered cancer patient associations. Stratification was by site type (tertiary, secondary, primary/community) and by urban–rural residence to ensure demographic diversity. Within each stratum, quotas were filled through consecutive sampling of eligible patients who presented during outpatient or infusion-centre visits, or through participant lists provided by patient associations. This approach is not equivalent to simple random sampling; selection bias may arise if patients who attend hospital more frequently, or who are more engaged with patient groups, differ systematically from the broader cancer population on the constructs of interest. The sampling limitation is acknowledged as a boundary condition for generalising the findings.

Eligibility criteria required participants to be: (a) aged 18 years or older; (b) currently undergoing cancer treatment or in post-treatment remission; (c) registered residents of Sichuan Province; and (d) mentally competent to provide informed consent and complete a self-administered questionnaire. Recruitment occurred over a six-month period. After excluding incomplete or careless responses (e.g., straight-lining, missing more than 20% of items), 405 valid questionnaires were retained for analysis. The final sample comprised 230 urban residents (56.79%) and 175 rural residents (43.21%). This sample size is adequate for covariance-based structural equation modelling: it exceeds the $N \geq 200$ rule of thumb and yields a case-to-indicator ratio of approximately 11.6:1 for the 35 measured items, above the conventional 10:1 minimum (Kline, 2016).

3.3 Measures

All six constructs were measured on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), unless otherwise noted. Scale development followed a two-stage process: adaptation of existing validated items where available, and de novo item generation where no suitable prior scale existed, with the latter grounded in the health insurance and health communication literatures.

Insurance Literacy (IL). Six items assessed comprehension of insurance terminology and mechanics, including premiums, deductibles, copayments or coinsurance, provider networks, benefit exclusions, and claims procedures. The scale was adapted from Weedige et al. (2019), who developed a multi-dimensional insurance literacy instrument for emerging economies, and from Park et al. (2022), who examined health insurance literacy among older adults in the United States. A sample item reads: "I can explain the difference between premium, deductible, copayment, and reimbursement rate." Item IL6 was reverse-coded prior to analysis so that higher scores consistently reflect greater insurance literacy.

Health Knowledge (HK). Six items measured participants' self-reported understanding of their cancer diagnosis, typical treatment pathways, follow-up care requirements, and the cost implications of specific services. This construct was operationalised as subjective health knowledge, a predictor of proactive health behaviour documented in the cancer information-seeking literature (Champion & Skinner, 2008). The items were study-developed, with thematic guidance from Chang and Schulz (2018), who validated a Chinese eHealth literacy scale among chronic-disease patients. A sample item reads: "I understand my diagnosis and typical treatment pathways." Item HK6 was reverse-coded.

Prior Insurance Coverage (PIC). Five items captured the perceived adequacy of respondents' existing insurance benefits across inpatient services, outpatient services, claims experience, and overall satisfaction. The construct reflects the "enabling" dimension of Andersen's (1995) framework: even well-informed patients may fail to switch plans if they perceive their current coverage as sufficient (Wang et al., 2008). The scale was study-developed.

A sample item reads: “My current insurance sufficiently covers hospital services I need.” Item PIC4 was reverse-coded.

Financial Capability (FC). Six items assessed participants’ perceived ability to afford insurance premiums, manage out-of-pocket costs, and maintain household liquidity while paying for cancer-related care. Items were adapted from Smith et al. (2019), who measured financial burden and affordability barriers among cancer survivors in the United States. A sample item reads: “I can afford the premiums for the plan that best fits my needs.” Item FC5 was reverse-coded.

Policy Promotion Intensity (PPI). Eight items measured the frequency, clarity, tailoring, trustworthiness, and decision-support utility of official insurance information encountered by participants. The construct captures the supply-side information environment hypothesised to reduce choice complexity and deliberation costs (Thaler & Sunstein, 2008). Items were study-developed, informed by Politi et al.’s (2020) decision-aid design, Tian et al.’s (2022) study of insurance-policy publicity and participation in China, and Xu et al.’s (2022) work on digital channels for insurance information. A sample item reads: “I frequently encountered official information about insurance options.” Item PPI7 was reverse-coded.

Choice of Insurance Plan (CIP). Four items assessed the perceived adequacy of the respondent’s selected insurance plan, encompassing coverage breadth, out-of-pocket burden, provider access, and overall value for money. The construct served as the outcome variable. The scale was study-developed, conceptually aligned with the plan-satisfaction and choice-quality literatures (Diao et al., 2019). A sample item reads: “My plan covers key tests, drugs, and services I need.” Item CIP3 was reverse-coded.

3.4 Translation and Pilot Testing

The questionnaire was originally drafted in English and then subjected to a rigorous forward–backward translation protocol to produce a simplified Chinese version. Two bilingual translators (native Mandarin speakers fluent in English) independently translated the English item pool into Chinese; discrepancies were reconciled through discussion. A third translator, blinded to the original English version, back-translated the reconciled Chinese text into English. The research team compared the back-translation against the source version and resolved any semantic or conceptual divergence.

An expert panel comprising two medical oncologists, one health economist, and two hospital-based insurance administrators reviewed the draft instrument for content validity, clinical relevance, and item clarity. Based on panel feedback, several items were reworded to align with local insurance terminology (e.g., replacing “deductible” with the Chinese statutory term “起付线”). The revised questionnaire was then pilot-tested with 30 cancer patients at a tertiary hospital in Chengdu. Pilot participants reported no difficulty understanding the items or response anchors. Minor refinements to wording were made, after which the instrument was finalised for full-scale data collection.

3.5 Data Analysis

Data analysis proceeded in five sequential steps.

Step 1: Descriptive statistics and data screening. Means, standard deviations, skewness, and kurtosis were computed for all observed items. Missing data were examined; cases with more than 20% missingness were excluded. Univariate normality was assessed using skewness and kurtosis thresholds (absolute skewness < 2, kurtosis < 7), and multivariate normality was evaluated via Mardia’s coefficient. Where departure from normality was detected, maximum likelihood estimation with bootstrap standard errors was employed in subsequent modelling (Hair et al., 2019).

Step 2: Common method bias assessment. Because all variables were measured via self-report at a single time point, the risk of common method variance was addressed through Harman’s single-factor test (Podsakoff et al., 2003). All items were entered into an exploratory factor analysis; if a single factor explained less than 50% of the total variance, common method bias was considered not to be a severe threat.

Step 3: Confirmatory factor analysis (CFA). A six-factor CFA model was estimated to evaluate measurement quality. Convergent validity was assessed via standardised factor loadings (≥ 0.50), average variance extracted (AVE ≥ 0.50), and composite reliability (CR ≥ 0.70) for each latent construct (Fornell & Larcker, 1981; Hair et al., 2019). Discriminant validity was established by comparing the square root of AVE for each construct with its inter-construct correlations; the Fornell–Larcker criterion requires the former to exceed the latter (Fornell & Larcker, 1981). Model fit was evaluated using chi-square degrees-of-freedom ratio (CMIN/df), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), incremental fit index (IFI), normed fit index (NFI), relative fit index (RFI), root mean square error of approximation (RMSEA), and parsimony goodness-of-fit index (PGFI). Both the CFA and the structural model were estimated by maximum likelihood, and standardised estimates are reported throughout.

Step 4: Structural equation modelling (SEM). The full structural model was estimated in AMOS 23. The same fit indices used in the CFA were examined to judge model–data correspondence. Standardised path coefficients (β) and their associated significance levels ($p < 0.05$) were inspected to test the hypothesised direct effects.

Step 5: Mediation analysis. Indirect effects were tested using bias-corrected bootstrap confidence intervals with 5,000 resamples (Preacher & Hayes, 2008; Hayes, 2018). An indirect effect was deemed statistically significant if its 95% confidence interval did not include zero. This approach is preferred over the causal-steps strategy because it does not assume a normal sampling distribution of the indirect effect and offers superior statistical power (Hayes, 2018).

3.6 Ethics

The study protocol was reviewed and approved by the institutional review board of [institution name withheld for blind review]. Written informed consent was obtained from all participants prior to questionnaire administration. Participation was voluntary, and respondents were assured of anonymity; no identifying information was collected. Data were used for academic research purposes only and stored on encrypted servers with access restricted to the research team.

4. Results

4.1 Sample Profile

Data were collected from 405 cancer patients recruited from tertiary, secondary, and primary healthcare facilities across Sichuan Province, China. Table 2 presents the complete demographic and clinical characteristics of the sample. The majority of respondents were currently receiving treatment (59.51%, $n = 241$), with a substantial proportion in remission within five years (30.37%, $n = 123$). The sample exhibited a balanced urban-rural distribution, with 56.79% ($n = 230$) residing in urban areas and 43.21% ($n = 175$) in rural areas. This geographic balance enhances the generalisability of findings across China’s heterogeneous healthcare infrastructure.

The temporal distribution since diagnosis was relatively even: 29.63% ($n = 120$) were diagnosed within six months, 24.44% ($n = 99$) between six and twelve months, 28.64% ($n = 116$) between one and three years, and 17.28% ($n = 70$) at three or more years. Women comprised 54.07% ($n = 219$) of the sample and men 45.93% ($n = 186$). Age distribution was diverse, spanning 18–34 years (22.72%, $n = 92$), 35–49 years (27.41%, $n = 111$), 50–64 years (24.44%, $n = 99$), and 65 years and above (25.43%, $n = 103$), thereby capturing perspectives across the full adult life course.

Educational attainment varied considerably: primary education or below (10.12%), junior secondary (18.02%), senior secondary (29.38%), college (27.16%), bachelor’s degree (10.86%), and master’s degree or doctorate (4.44%). Employment status was similarly heterogeneous, with 31.36% employed, 13.83% self-employed, 16.54% unemployed, 20.74% retired, and 17.53% in other categories. Cancer stage distribution showed 23.95% at Stage I, 32.59% at Stage II, 24.20% at Stage III, 14.07% at Stage IV, and 5.19% unsure of their stage. In terms of treatment facility, 41.48% received care at tertiary hospitals, 35.06% at secondary hospitals, and 23.46% at primary or community health centres.

Table 2

Sample Demographic and Clinical Characteristics (*N* = 405)

Characteristic	Category	*n*	%
Treatment status	In treatment	241	59.51
	In remission (within 5 years)	123	30.37
	Other	41	10.12
Residency	Urban	230	56.79
	Rural	175	43.21

Characteristic	Category	*n*	%
Time since diagnosis	≤ 6 months	120	29.63
	6–12 months	99	24.44
	1–3 years	116	28.64
	≥ 3 years	70	17.28
Gender	Female	219	54.07
	Male	186	45.93
Age (years)	18–34	92	22.72
	35–49	111	27.41
	50–64	99	24.44
	≥ 65	103	25.43
Education	Primary or below	41	10.12
	Junior secondary	73	18.02
	Senior secondary	119	29.38
	College	110	27.16
	Bachelor	44	10.86
	Master/PhD	18	4.44
Employment	Employed	127	31.36
	Self-employed	56	13.83
	Unemployed	67	16.54
	Retired	84	20.74
	Other	71	17.53
Cancer stage	I	97	23.95
	II	132	32.59
	III	98	24.20
	IV	57	14.07
	Don’t know	21	5.19
Treatment facility	Tertiary hospital	168	41.48
	Secondary hospital	142	35.06
	Primary/community	95	23.46

The sample composition reflects several strengths for examining insurance plan choice. The near-equal urban-rural split ensures representation of both well-resourced municipal healthcare systems and less-equipped county-level facilities. The predominance of Stage II and Stage III patients (combined 56.79%) captures individuals who are actively navigating treatment and coverage decisions and thus have salient information needs. The broad age range and diverse educational attainment further ensure that findings are not confined to narrow demographic segments. The representation of patients across tertiary, secondary, and primary healthcare settings is particularly valuable given China’s tiered healthcare system, where institutional communication practices differ markedly by facility level (Li et al., 2017).

4.2 Descriptive Statistics and Correlations

Table 3 reports means, standard deviations, and Pearson correlations for all six latent constructs. Mean scores ranged from 3.521 to 3.833 on the five-point Likert scale, indicating that respondents generally endorsed items above the midpoint of 3.0. Insurance Literacy (IL) recorded the highest mean (M = 3.833, SD = 1.004), followed by Choice of Insurance Plan (CIP; M = 3.825, SD = 1.050), Policy Promotion Intensity (PPI; M = 3.738, SD = 0.990), Health

Knowledge (HK; *M* = 3.731, *SD* = 1.059), Prior Insurance Coverage (PIC; *M* = 3.674, *SD* = 1.139), and Financial Capability (FC; *M* = 3.521, *SD* = 1.101). The relatively lowest mean for FC suggests that respondents perceived affordability and resource barriers to adequate coverage most acutely, a pattern consistent with prior research on cancer costs in resource-constrained settings (Leng et al., 2019; Zhao et al., 2022). Standard deviations were moderate across all constructs (range = 0.990–1.139), indicating adequate variability without excessive dispersion.

Table 3

Descriptive Statistics and Pearson Correlations

	M	*SD*	1	2	3	4	5	6
1. Insurance Literacy (IL)	3.833	1.004	1					
2. Health Knowledge (HK)	3.731	1.059	.235**	1				
3. Prior Insurance Coverage (PIC)	3.674	1.139	.240**	.204**	1			
4. Financial Capability (FC)	3.521	1.101	.294**	.214**	.280**	1		
5. Policy Promotion Intensity (PPI)	3.738	0.990	.429**	.445**	.471**	.414**	1	
6. Choice of Insurance Plan (CIP)	3.825	1.050	.372**	.358**	.414**	.436**	.503**	1

Note. All correlations significant at $p < .01$ (two-tailed). **p* < .01.

All bivariate correlations were positive and statistically significant at $p < .01$, ranging from 0.204 (HK–PIC) to 0.503 (PPI–CIP). The correlation magnitudes fell within the low-to-moderate range, well below the conventional threshold of 0.80 that would signal multicollinearity concerns (Hair et al., 2019). The strongest correlation was observed between PPI and CIP ($r = .503$), providing preliminary evidence for the hypothesised association between institutional policy communication and choice of insurance plan. The pattern of inter-correlations, with no coefficient exceeding 0.60, supports the discriminant distinctiveness of the six constructs and satisfies the prerequisite for structural equation modelling analysis (Fornell & Larcker, 1981; Hair et al., 2019).

4.3 Common Method Bias

Because all variables were measured using self-report instruments within a single survey administration, the potential for common method bias (CMB) warranted examination. Harman's single-factor test was conducted by entering all 35 items into an exploratory factor analysis with unrotated principal axis factoring. The first unrotated factor explained 30.779% of the total variance, substantially below the 40% threshold commonly used as a rule of thumb for CMB detection (Fuller et al., 2016; Podsakoff et al., 2003). No single dominant general factor emerged from the analysis; instead, multiple factors with eigenvalues greater than one were extracted, collectively accounting for the variance structure. These results suggest that CMB does not pose a serious threat to the validity of the findings. Additionally, the use of multiple construct-specific scales with varying response anchors and the anonymous nature of the survey administration further mitigate CMB risks (Podsakoff et al., 2003).

4.4 Measurement Model

Confirmatory factor analysis (CFA) was conducted on the six-factor measurement model comprising IL, HK, PIC, FC, PPI, and CIP. Table 4 presents the standardised factor loadings, composite reliability (CR), average variance extracted (AVE), and Cronbach's alpha coefficients. All standardised factor loadings were statistically significant ($p < .001$) and ranged from 0.607 to 0.868, exceeding the recommended threshold of 0.50 (Hair et al., 2019). Item FC1 loaded at 0.689, FC2 at 0.835, FC3 at 0.740, FC4 at 0.752, FC5 at 0.790, and FC6 at 0.773. IL items loaded from 0.607 (IL3) to 0.796 (IL1); HK items from 0.731 (HK6) to 0.830 (HK1); PIC items from 0.751 (PIC5) to 0.868 (PIC1); PPI items from 0.636 (PPI4) to 0.788 (PPI2); and CIP items from 0.715 (CIP1) to 0.808 (CIP3). The lowest loading of 0.607, while modest, still exceeds the conventional minimum and contributes meaningfully to construct measurement.

Table 4

Reliability and Convergent Validity of Measurement Model

Construct	Items	Std. Loading Range	CR	AVE	Cronbach's α
Insurance Literacy (IL)	IL1–IL6	0.607–0.796	0.884	0.562	0.884
Health Knowledge (HK)	HK1–HK6	0.731–0.830	0.900	0.600	0.900

Construct	Items	Std. Loading Range	CR	AVE	Cronbach's α
Prior Insurance Coverage (PIC)	PIC1–PIC5	0.751–0.868	0.906	0.660	0.905
Financial Capability (FC)	FC1–FC6	0.689–0.835	0.900	0.600	0.883
Policy Promotion Intensity (PPI)	PPI1–PPI8	0.636–0.788	0.894	0.515	0.911
Choice of Insurance Plan (CIP)	CIP1–CIP4	0.715–0.808	0.856	0.598	0.856

Note. CR = composite reliability; AVE = average variance extracted. All loadings significant at $p < .001$.

Convergent validity was established through multiple indicators. AVE values ranged from 0.515 (PPI) to 0.660 (PIC), with all values meeting or exceeding the 0.50 criterion that indicates a majority of indicator variance is captured by the latent construct (Fornell & Larcker, 1981; Hair et al., 2019). CR values ranged from 0.856 (CIP) to 0.906 (PIC), all substantially above the 0.70 threshold, indicating strong internal consistency and freedom from measurement error (Fornell & Larcker, 1981). Cronbach's alpha coefficients ranged from 0.856 to 0.911, exceeding the conventional 0.70 standard and confirming satisfactory reliability across all scales (Nunnally & Bernstein, 1994). Notably, PPI achieved the highest Cronbach's alpha (0.911) despite the lowest AVE (0.515), a pattern attributable to its eight-item composition, which inflates internal consistency while distributing variance across a larger indicator set.

Discriminant validity was assessed using the Fornell-Larcker criterion, which requires the square root of each construct's AVE to exceed its correlations with all other constructs (Fornell & Larcker, 1981). Table 5 presents the full discriminant validity matrix. The diagonal elements represent the square root of AVE for each construct: IL = 0.750, HK = 0.775, PIC = 0.812, FC = 0.775, PPI = 0.717, and CIP = 0.774. In every case, the square root of AVE exceeded the off-diagonal correlation coefficients in the corresponding row and column. For example, PIC's sqrt(AVE) of 0.812 exceeded its highest correlation with any other construct (0.471 with PPI). Similarly, FC's sqrt(AVE) of 0.775 exceeded its highest correlation of 0.436 (with CIP). These results confirm that each construct shares more variance with its own indicators than with indicators of other constructs, thereby establishing discriminant validity.

Table 5

Discriminant Validity — Fornell-Larcker Criterion

	IL	HK	PIC	FC	PPI	CIP
IL	**0.750**					
HK	0.235	**0.775**				
PIC	0.240	0.204	**0.812**			
FC	0.294	0.214	0.280	**0.775**		
PPI	0.429	0.445	0.471	0.414	**0.717**	
CIP	0.372	0.358	0.414	0.436	0.503	**0.774**

Note. Diagonal values (bold) are the square root of AVE. Off-diagonal values are Pearson correlations between constructs. All correlations significant at $p < .01$.

The measurement model demonstrated excellent fit to the data across all reported indices: GFI = 0.922, AGFI = 0.910, RMSEA = 0.020, CFI = 0.989, IFI = 0.989, NFI = 0.924, RFI = 0.917, $\chi^2/df = 1.161$, and PGFI = 0.798. The RMSEA value of 0.020 falls well within the excellent range (≤ 0.05), while CFI, IFI, NFI, GFI, and AGFI all exceed the 0.90 threshold indicative of good model fit (Browne & Cudeck, 1993; Hu & Bentler, 1999). The normed chi-square ($\chi^2/df = 1.161$) is close to 1.0, suggesting an optimal balance between model complexity and data fit (Kline, 2016). Taken together, the measurement model results establish that the six constructs are reliably measured, convergently valid, discriminant from one another, and well-represented by the hypothesised factor structure.

4.5 Structural Model and Direct Effects

The structural model was estimated to test Hypotheses 1–5, which posit direct effects from the four independent constructs (IL, HK, PIC, FC) and the mediator (PPI) on CIP. The structural model retained the excellent fit indices from the measurement model: GFI = 0.922, AGFI = 0.910, RMSEA = 0.020, CFI = 0.989, IFI = 0.989, NFI = 0.924, RFI = 0.917, $\chi^2/df = 1.161$, and PGFI = 0.798. The identical fit between the measurement and structural models follows from the structure of the model rather than from any peculiarity of the data: the structural model is recursive and saturated at the latent level—every pair of latent variables is connected by either a directed path or a freely estimated covariance—so it reproduces the measurement model's implied covariance matrix exactly and cannot, by construction, yield different fit. Consequently, the fit indices test the adequacy of the measurement structure rather than the specific pattern of directed paths, and they should not be read as confirmation of the hypothesised causal ordering.

Table 6

Structural Path Estimates and Bootstrap Mediation Results

Path	β	SE	*p*	95% CI	Decision
Direct effects on PPI					
H10: IL → PPI	0.238	0.055	< .001	[0.142, 0.353]	Supported
H11: HK → PPI	0.318	0.054	< .001	[0.213, 0.425]	Supported
H12: PIC → PPI	0.323	0.052	< .001	[0.220, 0.423]	Supported
H13: FC → PPI	0.212	0.050	< .001	[0.114, 0.309]	Supported
Direct effects on CIP					
H1: IL → CIP	0.156	0.054	.004	[0.052, 0.264]	Supported
H2: HK → CIP	0.171	0.052	.001	[0.070, 0.274]	Supported
H3: PIC → CIP	0.204	0.055	< .001	[0.100, 0.317]	Supported
H4: FC → CIP	0.267	0.054	< .001	[0.165, 0.376]	Supported
H5: PPI → CIP	0.183	0.071	.011	[0.051, 0.329]	Supported
Indirect effects (PPI mediation)					
H6: IL → PPI → CIP	0.044	0.024	.006	[0.019, 0.155]	Supported
H7: HK → PPI → CIP	0.058	0.024	.007	[0.019, 0.129]	Supported
H8: PIC → PPI → CIP	0.059	0.024	.008	[0.023, 0.131]	Supported
H9: FC → PPI → CIP	0.039	0.019	.005	[0.014, 0.098]	Supported
Proportion mediated					
IL → PPI → CIP	21.8%				Partial
HK → PPI → CIP	25.4%				Partial
PIC → PPI → CIP	22.5%				Partial
FC → PPI → CIP	12.7%				Partial

Note. Bootstrap confidence intervals based on 5,000 resamples. CI = confidence interval; β = standardised coefficient. All direct effects on CIP remain significant after including mediator.

As shown in Table 6, all five direct-effect hypotheses were supported. FC emerged as the strongest direct predictor of CIP (β = 0.267, $p < .001$, 95% CI [0.165, 0.376]), followed by PIC (β = 0.204, $p < .001$, 95% CI [0.100, 0.317]), PPI (β = 0.183, $p = .011$, 95% CI [0.051, 0.329]), HK (β = 0.171, $p = .001$, 95% CI [0.070, 0.274]), and IL (β = 0.156, $p = .004$, 95% CI [0.052, 0.264]). All paths were positive and statistically significant, indicating that higher levels of each antecedent construct are associated with more adequate choice of insurance plan. These results align with the Theory of Planned Behaviour, wherein behavioural intention is shaped by attitudes, subjective norms, and perceived behavioural control (Ajzen, 1991), and with Andersen's (1995) Behavioural Model of Health Services Use, which classifies predisposing characteristics (IL, HK) and enabling resources (PIC, FC) as determinants of health-related decisions.

The relative magnitude of these direct effects carries theoretical significance. FC's position as the strongest predictor aligns with the Health Belief Model's emphasis on perceived barriers and the Integrated Behavioural Model's focus on environmental constraints (Champion & Skinner, 2008; Montaño & Kasprzyk, 2015). The finding that financial capability—the capacity to afford premiums and absorb out-of-pocket costs—exerts the most powerful direct influence on plan adequacy resonates with prior research in resource-constrained settings, where material constraints shape insurance decisions largely independently of individual motivation (Zhao et al., 2022). Prior insurance coverage (PIC) ranked second in direct-effect magnitude (β = 0.204), underscoring the importance of experiential familiarity with the insurance system in shaping plan choice. This result is consistent with evidence that patients with prior scheme experience accumulate procedural knowledge that supports subsequent enrolment and plan decisions (Wang et al., 2008).

PPI's significant direct effect (β = 0.183) on CIP, net of the four individual-capacity antecedents, confirms that institutional policy communication contributes unique explanatory variance beyond what is captured by individual knowledge, literacy, or resource perceptions. HK and IL showed comparatively smaller but nonetheless significant direct effects, suggesting that while foundational knowledge and insurance-literacy skills matter for choice of insurance plan, their influence is partly channelled through other mechanisms—specifically, the mediating role of PPI as tested in the subsequent analysis.

Figure 2 presents the structural model with standardised path coefficients.

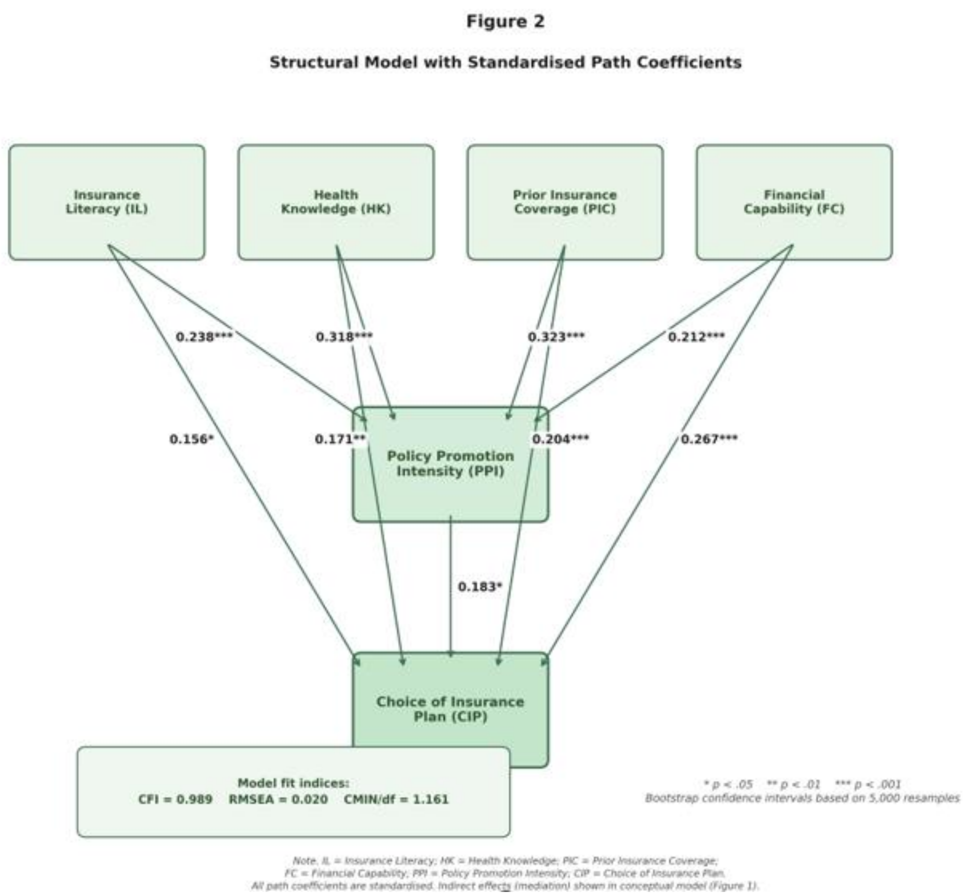

Figure 2: Structural Model with Standardised Path Coefficients showing the relationships among IL, HK, PIC, FC, PPI, and CIP with beta values.

Note. All path coefficients are standardised. *$p < .05$, **$p < .01$, ***$p < .001$. Model fit: CFI = 0.989, RMSEA = 0.020, CMIN/df = 1.161. Bootstrap confidence intervals based on 5,000 resamples.

4.6 Mediation Analysis

Bootstrap mediation analysis with 5,000 resamples was conducted to test Hypotheses 6–9, which examine whether PPI mediates the relationships between each of the four antecedent constructs and CIP. Table 6 reports the standardised indirect effects, bootstrap standard errors, *p*-values, and bias-corrected 95% confidence intervals. All four indirect effects were statistically significant with confidence intervals excluding zero, supporting the mediation hypotheses.

For H6, the indirect effect of IL on CIP through PPI was significant (indirect effect = 0.044, $p = .006$, 95% CI [0.019, 0.155]), representing 21.8% of the total effect. This result suggests that insurance literacy enhances choice of insurance plan partly by strengthening individuals' engagement with and reception of policy-promoted insurance information. Patients with higher information-processing capabilities appear better positioned to absorb, interpret, and act upon institutional insurance communications, thereby converting individual skill into adequate plan selection through the mechanism of policy communication exposure. However, because the direct effect of IL on CIP remained significant after accounting for the mediator, PPI functions as a *partial* mediator rather than a full mediator of this pathway.

For H7, the indirect effect of HK on CIP through PPI was significant (indirect effect = 0.058, $p = .007$, 95% CI [0.019, 0.129]), accounting for 25.4% of the total effect—the largest proportion mediated among the four pathways. This finding indicates that health knowledge translates into choice of insurance plan in part through the policy promotion channel. Individuals with greater disease- and cost-related knowledge are presumably more receptive to policy communications, more likely to seek out institutional information resources, and better able to integrate such communications into their coverage decisions. As with IL, the persistence of a significant direct effect from HK to CIP confirms partial mediation: health knowledge operates both through and independently of institutional policy communication.

For H8, the indirect effect of PIC on CIP through PPI was significant (indirect effect = 0.059, $p = .008$, 95% CI [0.023, 0.131]) and represented a substantial proportion mediated at 22.5%. This result indicates that prior insurance coverage contributes a meaningful indirect pathway through policy promotion intensity. The theoretical interpretation is that patients with prior experience of the insurance system are better able to recognise, interpret, and act upon institutional policy communications. Experiential familiarity appears to serve as a gateway through which broader policy communications are filtered and assimilated. The mediation proportion (22.5%) suggests that roughly one-fifth of PIC's influence on plan choice is transmitted via institutional communication channels. The direct effect of PIC on CIP remained significant, again supporting partial mediation.

For H9, the indirect effect of FC on CIP through PPI was significant (indirect effect = 0.039, $p = .005$, 95% CI [0.014, 0.098]) but represented the smallest proportion mediated at 12.7%. This pattern is theoretically meaningful: financial capability—encompassing the capacity to afford premiums, absorb out-of-pocket costs, and maintain household liquidity—operates most strongly through the direct pathway ($\beta = 0.267$), with a comparatively smaller but still significant indirect component transmitted via PPI. The relatively lower mediation proportion suggests that financial capacity primarily enables plan adequacy through immediate, tangible mechanisms (e.g., the ability to afford premiums or higher-coverage plans) rather than through information reception processes. Nonetheless, the significant indirect effect indicates that individuals with greater financial capability are also more likely to engage with policy communications, perhaps because resource security frees cognitive bandwidth for attending to insurance information (Kahneman & Tversky, 1979; Thaler & Sunstein, 2008).

The consistent pattern across all four mediation pathways—significant indirect effects accompanied by significant residual direct effects—establishes PPI as a *partial mediator* of each individual-capacity-to-adequacy relationship. This finding carries important practical implications: while strengthening institutional policy communication can enhance the translation of individual capacity into plan adequacy, it cannot fully substitute for direct investments in insurance literacy, health knowledge, prior-coverage experience, and financial capability. The individual-capacity constructs retain independent explanatory power even after accounting for policy communication pathways, suggesting a multi-pronged intervention strategy is warranted. The partial mediation pattern further implies that the relationship between individual capacity and choice of insurance plan is not a simple transmission belt through institutional messaging; rather, individual-level factors exert autonomous influence that policy communication supplements but does not supplant (Hayes, 2018; Preacher & Hayes, 2008).

5. Discussion

5.1 Summary of Findings

This study examined the direct and indirect effects of individual capacity factors—Insurance Literacy (IL), Health Knowledge (HK), Prior Insurance Coverage (PIC), and Financial Capability (FC)—on Choice of Insurance Plan (CIP), with Policy Promotion Intensity (PPI) as a partial mediator. All thirteen hypotheses received support. FC emerged as the strongest direct predictor ($\beta = 0.267$, $p < .001$), followed by PIC ($\beta = 0.204$, $p < .001$), PPI ($\beta = 0.183$, $p = .011$), HK ($\beta = 0.171$, $p = .001$), and IL ($\beta = 0.156$, $p = .004$). PPI partially mediated all four pathways, with mediation proportions ranging from 25.4% (HK) to 12.7% (FC); IL (21.8%) and PIC (22.5%) fell between these bounds. All direct effects remained significant after accounting for PPI, confirming partial mediation. The model demonstrated excellent fit (GFI = 0.922, CFI = 0.989, RMSEA = 0.020), Harman's single-factor test (30.779%)

indicated no common method bias threat, and all constructs exceeded thresholds for reliability (Cronbach's α = 0.856–0.911) and convergent validity (AVE = 0.515–0.660).

The aggregate pattern reveals a dual-channel structure in which individual-level resources operate both directly on choice of insurance plan and indirectly through the institutional communication channel represented by PPI. Institutional communication thus functions as a consistent amplifier of individual capacity rather than a substitute for it—a distinction with consequential implications for theory and intervention design.

5.2 Theoretical Contributions

5.2.1 Extension of the Health Belief Model

The Health Belief Model (HBM) posits that protective action is triggered by perceived susceptibility, severity, benefits, barriers, and cues to action (Champion & Skinner, 2008). Within this architecture, cues to action have traditionally been conceptualised as discrete, momentary events—a physician recommendation, a public service announcement, a symptomatic episode—that prompt an immediate behavioural response (Politi et al., 2020). This conceptualisation reflects the HBM's origins in explaining one-time preventive behaviours such as vaccination or screening, where a single stimulus can activate intention.

The present findings challenge this discrete-event framing by demonstrating that Policy Promotion Intensity functions as a *continuous* cue to action. PPI represents a sustained, institutionally embedded communication process—encompassing government publicity, hospital-based outreach, and community-level briefings—that maintains patient awareness of coverage options throughout the cancer care trajectory. The significant mediating effects across all four pathways (12.7%–25.4% of total effects) indicate that ongoing institutional communication systematically amplifies the translation of individual knowledge, literacy, prior-coverage experience, and financial resources into choice of insurance plan. In chronic disease contexts where treatment decisions unfold over months or years, this continuous-cue conceptualisation offers greater explanatory power than the traditional episodic model.

5.2.2 Extension of the Theory of Planned Behaviour

The Theory of Planned Behaviour (TPB) assumes that perceived behavioural control (PBC)—the individual's confidence in their capacity to execute a behaviour—is an internal, self-referential assessment grounded in personal skills and resources (Ajzen, 1991). This intrapsychic treatment of PBC leaves limited theoretical space for the role of external institutional communication in constructing perceived control. The present study extends the TPB by demonstrating that PBC is partially constructed through institutional communication: patients feel more in control of insurance decisions when policy information is clear, frequent, and accessible.

This extension is evidenced by PPI's significant direct effect on CIP (β = 0.183, p = .011), net of all four individual-capacity antecedents. When patients encounter well-structured policy information, their perceived control increases—not because intrinsic capabilities have changed, but because the information environment has reduced uncertainty and deliberation costs. This finding aligns with behavioural economics research on information frictions (Kahneman & Tversky, 1979; Thaler & Sunstein, 2008) and offers a theoretically grounded pathway for integrating TPB with institutional-level health communication research.

5.2.3 Integration with Behavioural Economics

Thaler and Sunstein's (2008) concept of choice architecture—the deliberate design of decision environments to influence outcomes without restricting freedom—has been applied to health insurance through defaults, framing, and simplification. The present study advances this literature by identifying PPI as a distinct choice-architecture instrument that operates not by restructuring the choice set but by amplifying the actionability of existing individual capacities.

Traditional choice architecture intervenes at the point of selection: defaults channel enrollees into predetermined plans, and framing alters option attractiveness (Thaler & Sunstein, 2008). PPI operates upstream by enhancing patients' capacity to process and evaluate information about plan attributes. The mediation results indicate that PPI does not substitute for IL, HK, PIC, or FC but makes these resources more actionable—converting latent competence into manifest intention. This capacity-amplifying mechanism differs from traditional nudging in that it targets the information environment rather than the choice structure itself. The finding that FC operates most strongly through the direct pathway (β = 0.267) with the smallest mediation proportion (12.7%) further underscores this distinction: financial resources enable behaviour primarily through tangible mechanisms, while policy communication amplifies the effect of knowledge and literacy by reducing cognitive barriers.

5.3 Practical and Policy Implications

5.3.1 Hospital-Based Counselling for Newly Diagnosed Patients

The finding that 29.63% of the sample was diagnosed within six months prior to survey administration identifies a critical intervention window. Newly diagnosed patients face compressed decision timelines under emotional distress and information overload; even patients with adequate baseline literacy may lack the cognitive bandwidth to evaluate insurance options (Sung et al., 2021; Reyna et al., 2015). Hospital-based insurance counsellors can serve as real-time cues to action, translating complex policy information into actionable guidance. Given that 41.48% of respondents received care at tertiary hospitals—the institutions where insurance procedures are most elaborate—these facilities represent priority intervention sites. Embedded insurance navigators could provide individualised plan comparisons, explain reimbursement procedures, and assist with enrolment paperwork, reducing deliberation costs in alignment with the HBM's emphasis on cues to action (Champion & Skinner, 2008).

5.3.2 Plain-Language Plan Summaries

The finding that IL exerted the smallest direct effect ($\beta = 0.156$) suggests that even patients reporting above-average literacy struggle with insurance plan complexity. Insurance policies in China employ technical terminology, cross-referenced schedules, and conditional clauses that generate substantial cognitive load (Diao et al., 2019; Politi et al., 2020). Standardised plain-language summaries specifying benefits, exclusions, cost-sharing, and claims procedures can reduce this burden. This recommendation aligns with evidence that higher eHealth literacy is associated with stronger engagement in health decisions among Chinese patients (Chang & Schulz, 2018), and with Politi et al. (2020), who showed that a plain-language insurance decision aid significantly improved patients' insurance knowledge and confidence. Such interventions would be especially effective for the 10.12% of respondents with primary education or below, for whom plan complexity likely constitutes a binding barrier.

5.3.3 Digital Outreach Calibrated by Literacy Level

The finding that PPI mediates 21.8% of the IL-to-CIP pathway indicates that digital policy promotion can substantially enhance the impact of literacy on choice of insurance plan, but only when content and format match the recipient's capabilities. A one-size-fits-all strategy risks leaving low-literacy patients behind while underutilising the capacities of high-literacy patients. A tiered architecture would address this: a basic tier with audio-visual content and infographics for limited-literacy patients, and an advanced tier with interactive comparison tools and cost calculators for higher-literacy patients. WeChat, China's dominant messaging platform, represents the natural distribution channel given its penetration across urban and rural populations (Wang et al., 2020). Calibrating outreach by literacy level operationalises the theoretical insight that institutional communication amplifies rather than substitutes for individual capacity.

5.3.4 Tiered Subsidy Targeting

The finding that FC is the strongest direct predictor ($\beta = 0.267$) yet exhibits the lowest mediation proportion (12.7%) implies that financial assistance should be delivered through *direct* mechanisms—subsidies, premium support, out-of-pocket caps—rather than through communication-mediated channels. This reinforces the behavioural economics principle that resource constraints operate through tangible budget limitations information alone cannot overcome (Kahneman & Tversky, 1979; Thaler & Sunstein, 2008). For rural URRBMI enrollees, whose effective reimbursement rates (53–57%) lag approximately twenty percentage points behind urban EBMI rates (74–76%) (NHSA, 2023, 2024), supplemental premium subsidies would address the facilitating-conditions gap most directly. Pairing URRBMI with targeted subsidies for rural cancer patients would complement the communication-focused interventions above with a material intervention operating through the direct pathway.

5.4 Limitations

5.4.1 Cross-Sectional Design

The cross-sectional design constrains causal inference for the mediation pathways central to this study. Maxwell and Cole (2007) demonstrated that cross-sectional mediation analyses frequently produce biased indirect effect estimates because temporal ordering is assumed rather than observed. Reverse causality remains plausible: patients who selected adequate plans may retrospectively report higher capacity and PPI exposure, inflating observed associations. Longitudinal designs are required to validate the directional claims.

5.4.2 Self-Report from a Single Respondent

All variables were measured via self-report at a single time point. Harman's single-factor test (30.779% < 40%) is a comparatively insensitive diagnostic of common method variance (Fuller et al., 2016); no marker variable or common-latent-factor was modelled, and future work should incorporate these procedural and statistical controls together with temporal or source separation. Social desirability may inflate CIP ratings, and single-source data limit the assessment of construct validity because inter-construct correlations may partly reflect shared method variance. Discriminant validity was evaluated with the Fornell–Larcker criterion only; the more conservative heterotrait–monotrait (HTMT) ratio was not computed and is recommended for replication. Finally, four of the six constructs (prior insurance coverage, health knowledge, policy promotion intensity, and choice of insurance plan) were measured with study-developed items validated within this single sample, so their psychometric properties require independent cross-validation before the scales are treated as established.

5.4.3 Dependent Variable as Perceived Adequacy

CIP was operationalised as perceived plan adequacy rather than objectively verified plan quality. Patients may overestimate plan suitability due to optimism bias or limited awareness of alternatives. No objective verification of plan features against patient needs was conducted, so the study cannot distinguish between patients who chose optimal plans and those who merely believe they did.

5.4.4 Single-Province Sampling

The sample was drawn exclusively from Sichuan Province. While the province's demographic heterogeneity provides meaningful variation, it does not guarantee national representativeness. Western China differs from eastern provinces in insurance fund solvency, commercial insurance penetration, and tertiary healthcare density (Yip et al., 2019). Generalisation to provinces with substantially different profiles warrants caution.

5.4.5 Perfect Hypothesis Support

All thirteen hypotheses received support, a pattern requiring explicit acknowledgment. While consistent with theory, perfect support may indicate common method variance, sampling bias, or selective reporting. The absence of null findings limits the capacity to discriminate among competing explanations and raises the possibility of inflated effect sizes. Replication in independent samples using alternative instruments is essential before treating these findings as robust.

5.5 Future Research Directions

Three directions merit pursuit. First, a longitudinal panel design tracking insurance decisions over 12–24 months post-diagnosis would establish the temporal ordering required for causal mediation inference, addressing the cross-sectional bias documented by Maxwell and Cole (2007). Second, quasi-experimental evaluation exploiting natural experiments from insurance policy rollouts—such as supplemental commercial critical illness coverage introductions—would permit difference-in-differences estimation of policy communication effects on plan selection quality. Third, the differential direct and mediated effects of FC and IL suggest that urban-rural heterogeneity in insurance pathways deserves dedicated investigation. Rural patients in China's dual system face systematically lower reimbursement rates, reduced commercial insurance availability, and sparser policy communication infrastructure; understanding how these disparities shape the relative importance of direct versus communication-mediated pathways is a critical priority for equity-oriented health policy research.

6. Conclusion

This study examined the mediating role of Policy Promotion Intensity (PPI) in the relationship between cancer patients' individual capacity and commercial insurance plan adequacy in Sichuan Province, China. Analysis of 405 survey respondents supported all thirteen hypotheses, demonstrating that PPI significantly partially mediates the effects of insurance literacy, health knowledge, prior coverage experience, and financial capability on insurance plan adequacy, with mediation proportions ranging from 12.7% to 25.4%. Financial capability emerged as the strongest direct predictor ($\beta = 0.267$), underscoring its primacy in insurance decision-making. These findings reframe insurance adequacy as a dual-channel process wherein individual resources operate both directly and through institutional communication pathways. PPI amplifies the translation of individual capacity into plan adequacy but does not substitute for it, extending the Health Belief Model (policy cues as sustained communication), the Theory of Planned Behaviour (perceived behavioural control through institutional clarity), and behavioural economics (PPI as choice-architecture). The cross-sectional design precludes causal inference; future research should employ longitudinal replication, test urban–rural heterogeneity, conduct quasi-experimental policy evaluations, and pilot digital intervention trials to strengthen evidence for policy and practice.

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