After the Shock
Reform, Resilience, and Economic Transformation in MENA
ERF 32nd Annual Conference
June 14-16 | Cairo, Egypt

2026

Unpacking PHC's Financial Protection Effects:

From the Lived Experience of Patients to the Promise of Systemic Equity in Tunisia

Chokri Arfa

ECONOMIC RESEARCH FORUM
منتدى البحوث الاقتصادية

Unpacking PHC's Financial Protection Effects: From the Lived Experience of Patients to the Promise of Systemic Equity in Tunisia

Chokri Arfa
Professor at National Institute of Labor and Social Studies, University of Carthage
ORCID Number: 0000-0002-0966-2911

Abstract

Background: Primary Health Care first entry is widely recognized for improving population health outcomes, although its potential contribution to financial risk protection remains insufficiently explored. This study investigates the extent to which PHC-first entry strengthens financial protection within the Tunisian health system.

Methods: A dual-level approach was applied. At the patient level, a quasi-experimental analysis estimated the causal impact of PHC-first entry on out-of-pocket expenditure using representative survey data for diabetes (n = 1624) and hypertension patients (n = 1749). At the population level, Structural Equation Modelling assessed the direct and indirect effects of PHC-first entry, referral adherence, and service utilization on financial protection using the 2021 household expenditure survey (n = 59,042).

Results: The quasi-experimental analysis showed that PHC-first entry reduced OOPE by 14–19%, although not all patients followed the PHC pathway, limiting its full protective effect. Referral adherence yielded stronger reductions (17–26%) and significantly lowered catastrophic spending. SEM confirmed that PHC enhances financial protection through both direct (54%) and indirect (46%) pathways, with protection maximized when referral protocols are followed rather than bypassed.

Conclusion: In Tunisia, PHC serves as a financial protection lever when it functions as the first point of entry and is not bypassed. Its protective potential is significantly enhanced when referral protocols are enforced, insurance coverage is aligned with mandatory PHC-first pathways, and PHC capacity is strengthened through digital platforms and coordinated care. Under these conditions, household-level reductions in OOPE can be scaled into broader gains in equity, financial protection, and overall health system resilience.

Keywords: Primary Health Care, Financial Protection, Quasi-experimental analysis, SEM, Tunisia.

Background

Primary Health Care (PHC), a principle established by the 1978 Alma-Ata Declaration (1) and reaffirmed in Astana 2018 (2) remains the core of any well-functioning health system that strives to achieve the goals of better health outcomes, equitable access to health services and financial protection (FP). As the entry point to the health system, PHC is central to advancing Universal Health Coverage (UHC), which aims to ensure access to essential services while protecting from financial burden due to out-of-pocket expenditures (OOPE). This burden is a major concern in LMICs, where OOPE represented, on average, 40% of total health expenditures in 2018 (3, 4). Under SDG 3.8, financial risk protection is assessed using two threshold-based indicators: CHE, when OOPE exceeds 10% or 25% of household income, and impoverishment, when health spending pushes households below the poverty line (5).

International evidence shows that PHC fosters rational care-seeking behavior, reduces health expenditures, and leads to better population health outcome (6-8). PHC ensures simultaneously rational use of financial resources (9-13). In Thailand (14), Brazil (15), the United Kingdom (16), and Canada, PHC services delivery have improved equity, access and health outcomes. In Thailand, UHC reforms built on a district-level PHC referral system have significantly reduced CHE and impoverishment, while Brazil's Family Health Strategy has markedly decreased infant mortality and inpatients care.

In Tunisia, the public health system is formally structured around a mandatory PHC pathway, whereby Basic Health Centers (BHCs) and District Hospitals (DHs) serve as first contact and gatekeeping providers. However, a considerable proportion of patients bypass PHC facilities and directly self-refer to specialists, hospital outpatient departments, emergency wards, or private providers, without formal referral. This widespread bypassing fragments care pathways, escalates OOPE) and compromises PHC's role in enhanced patient's FP. The public network follows a three-tier structure: the first level includes 2,102 BHCs and 110 DHs forming the core of PHC; the second level comprises 35 regional hospitals; and the third level includes 31 university hospitals. PHC facilities are widely distributed, with nearly two-thirds located in rural areas, ensuring broad geographic accessibility. They provide preventive services, family medicine, maternal and child health care, health education, and outpatient care. DHs serve as referral points and offer basic inpatient services such as internal medicine, maternity, emergency care, and limited diagnostics. Despite representing 14% of total hospital beds, around 6% of DH beds are non-functional, and efficiency is low, with bed occupancy rates persistently below 40% (17, 18).

While Tunisia's PHC network is geographically accessible and designed to serve as the first point of entry, its capacity to function as a FP lever is constrained not only by bypassing behaviors and weak referral enforcement, but also by structural financing limitations. Health financing in Tunisia operates through a mixed public–private framework, with public accounting for 58% of total health expenditure, private "OOPE" represents 36%, followed by social health insurance (33.4%) and private insurance (3.3%). According to World Health Organization (19), Tunisia's health financing system suffers from limited fiscal space, fragmented pooling, and persistently high OOPE, all of which compromise financial protection. These financial protection gaps persist despite social health protection schemes managed and operated through the Caisse Nationale d'Assurance Maladie (CNAM) and the "Assistance Médicale Gratuite" (AMG/AMEN programme) and formally covering 82% of the population. Although CNAM is formally designed to support a PHC-first pathway through the family physician scheme, effective referral enforcement remains weak. Nearly 90% of beneficiaries are enrolled in the public and private-reimbursed schemes, which allow direct access to specialists and to secondary and tertiary hospital levels, thereby reinforcing the widespread bypassing of PHC facilities (20). CNAM financing model reimburses secondary and tertiary public care through fee-for-service billing mechanisms (21, 22). PHC facilities, by contrast, are not covered under such financing arrangements and are therefore chronically underfunded, which results in lower quality of care (23), ineffective service delivery, and weak integration into the formal insurance pathway. AMG provides free access to public health services for around 21% of Tunisians poor and pro-poor households. Meanwhile, 17% of the population uninsured relies on OOPE and face high risk of financial hardship (24).

Although PHC has significantly contributed to Tunisia's health gains over the past four decades such as improving life expectancy, reducing maternal and child mortality, expanding vaccination coverage, and increasing access to essential services, its structural constrains have been intensified which leads to growing bypassing. Bypassing is driven by individual factors such as disease severity, income, insurance coverage, perceived quality, and care-seeking preferences (25-27); facility-level constraints including equipment shortages, stockouts of medicines, waiting times, and limited care coordination (28, 29); and system-level issues such as weak referral enforcement, poor integration with higher-level providers, and chronic resource shortages (30). These conditions reduce responsiveness and increasingly push patients toward specialist and hospital-based care (31-33). In addition, PHC network suffers received only findings only 25% of public health expenditures which is insufficient financing to sustain a resilient first line of care, people-centered PHC and mitigate the burden of OOPE. Nationally, around 18% of households incur CHE, and 1–3% are pushed into poverty (34-36). Tunisia's health system has failed to operationalize and prioritize people-centred PHC, leading to persistent patient bypassing and greater reliance on higher-cost, hospital-based services (37-39).

The extent to which PHC-first entry and referral adherence contribute to financial risk protection in Tunisia is insufficiently studied and deserves to be unpacked. To fill this gap, the study employs a referral pathway conceptual framework where PHC-first entry (D) lowers bypassing, enhances referral adherence (R), and leads to higher PHC utilization intensity (U) (40). Through the sequential mechanisms of D, R, and U, PHC-first entry is expected to strengthen financial protection by shifting care toward prevention, reducing costly hospital services, and improving population health outcomes. The findings will demonstrate how reinforcing PHC-first entry can convert individual care-seeking behaviors into better financial protection at the system level.

A dual-method approach was applied at both the patient and population levels. At the patient level, quasi-experimental methods (41-44) were used to capture the lived experience of PHC-first entry, referral adherence, and their causal effects on OOPE and financial hardship, using the nationally representative 2019 patient survey. At the population level, Structural Equation Modelling (SEM) (40, 45) was applied using the national household survey to test the sequential mediation pathway linking PHC-first entry to financial protection through referral adherence and utilization intensity. This combined approach captures how patient care-seeking behaviors can be translated into system-level impacts on financial risk exposure. The paper is organized as follows. Section 2 outlines the PHC context in Tunisia and Section 3 presents the conceptual pathway and dual-method approach (quasi-experimental and SEM). Our empirical results are introduced in Section 4 and discussed in Section 5. Section 6 concludes the paper.

2. Methods

The study investigates the role of PHC as a referral gateway and its potential mechanisms for financial protection. When respected as the first point of entry, PHC is expected to reduce OOPE, CHE, and impoverishment. Two main hypotheses are tested: (i) entry through PHC improves financial protection compared to bypassing, and (ii) PHC strengthens financial protection through its referral and utilization functions. A mixed-method approach was applied in two complementary stages: a quasi-experimental design to estimate the causal effect of PHC-first entry at the patient level, completed by econometric modelling SEM to examine the mechanisms linking PHC-first entry, referral adherence, utilization patterns, and financial protection at the population level.

2.1. Patient-based quasi-experimental analysis

This study used a quasi-experimental design with retrospective 2018 data from a nationally representative sample of diabetic and hypertensive patients. A four-stage sampling strategy (governorates, districts, BHCs, and patients) ensured nationwide representativeness. Socioeconomic, health status, service utilization, and OOPE data were extracted from medical records and patient surveys, while disease-related episode costs were estimated using a bottom-up micro-costing approach. Patients were ex-post classified into two groups based on their initial point of entry: PHC-first contact and non-PHC-first (direct entry into secondary/tertiary hospitals or private facilities)

To estimate the causal effect of PHC-first entry on financial protection, propensity score-based methods, specifically matching and inverse probability of treatment weighting (IPTW) are used. These methods help reduce selection bias by balancing observable patients' characteristics between PHC-first and non-PHC-first and simulating a randomized comparison. First, propensity scores were estimated using a logistic regression model predicting the probability of entering the system through PHC based on observed covariates (age, sex, income quintile, education, insurance type, comorbidities, disease severity, and geographic location).

- Matching pairs each PHC-first patient with one or more comparable non-PHC-first patients with similar propensity scores.
- IPTW assigns weights to patients based on the inverse of their propensity score, creating a pseudo-population in which both groups are statistically similar.

The formula below is used to assign weights to each patient using IPTW:

$$w_i = \frac{D_i}{\hat{p}(X_i)} + \frac{1 - D_i}{1 - \hat{p}(X_i)}$$

Where: w_i: the weight assigned to patient (i); D_i =1 if PHC-first entry, 0 other facility-first $\hat{p}(X_i)$: Propensity score: probability that patient *i* enters through PHC, based on their covariates Xi. The propensity score is estimated as: $\hat{p}(X_i) = P(D_i = 1|X_i)$; where X_i includes age, sex, education, income quintile, insurance type, health status, comorbidities, and geographic location. The weighting mechanism increases the importance of patients whose treatment choice was unlikely based on their characteristics. Specifically:

- If a PHC-first patient had a low probability of going to PHC, they get a large weight (they are "under-represented" in the data).
- If a non PHC-first patient had a high probability of going PHC (but didn't), they also get a large weight.

These weights re-balance the sample so that PHC-first and non-PHC-first groups become comparable in terms of their observed characteristics. This process creates a pseudo-randomized population, allowing differences in outcomes such as OOPE to more accurately reflect the causal effect of PHC-first entry, rather than differences in patient characteristics. While matching and IPTW help balance observed covariates between PHC-first and non-PHC-first groups, they cannot account for unobserved confounding, such as health-seeking behavior, or unmeasured disease severity, which may influence both referral choice and financial outcomes.

To address unobserved confounding in entry point choice, we applied a two-stage instrumental variable (IV) estimation to isolate the causal effect of PHC-first entry. Two exogenous instruments were used: (i) the relative distance to the nearest BHC, and (ii) the number of physicians per BHC as a proxy of facility capacity. These instruments influence the likelihood of entering through PHC but are not expected to directly affect financial protection outcomes, except through referral behavior. In the first stage, referral adherence (D_i), defined as PHC-first versus non-PHC-first entry is regressed on the selected instruments (Z_i) and observed covariates (X_i): $D_i = \pi_0 + \pi_1 Z_i + \pi_2 X_i + \mu_i$

This stage estimates the predicted probability of PHC-first entry ($\widehat{D_i}$) that capture variation explained by the instruments rather than unobserved preferences or severity. In the second stage, the predicted PHC- first entry ($\widehat{D_i}$) is used in place of the original treatment variable to estimate its effect on financial protection outcomes, including OOPE and cost per patient:

$Y_i = \beta_0 + \beta_1 \widehat{D}_i + \beta_2 X_i + \varepsilon_i$, where: Zi = instrument (e.g., distance to PHC, PHC capacity), Di = referral adherence, Yi = outcome (OOP expenditures), Xi = covariates (demographics, insurance, health status etc.) This two-stage process helps isolate the causa impact of PHC-first entry by removing bias from both observed and unobserved confounders.

2.2. Population-level / econometric analysis

In the second stage, the analysis was extended from the patient level to the population level using data from the national survey (NSBCSL 2021) Survey to assess both the PHC referral system and financial protection. Several econometric frameworks were compared, including two-part models (separating PHC entry from using other facilities- level), latent class analysis (LCA) to capture patient heterogeneity, and structural equation modelling (SEM) to estimate direct and indirect effects on OOP and CHE. Model selection relied on empirical criteria (AIC, BIC, out-of-sample log-likelihood) and conceptual alignment. SEM outperformed the other approaches, yielding the lowest AIC (11,720), lowest BIC (12,050), and highest out-of-sample log-likelihood (–5,830). Unlike the alternatives, SEM provided a unified framework capturing referral dynamics and financial protection, including indirect pathways. Model adequacy was confirmed using conventional fit indices (RMSEA = 0.038, CFI = 0.95, TLI = 0.93, SRMR = 0.041). Consequently, SEM was retained for all subsequent analyses.

Table 1. Econometric Models Selection Tests

Criterion	Two-part	LCA	SEM
Answers the questions related to referral system and financial protection	Partial	Partial	Appropriate
Captures indirect effects	Not appropriate	Not Appropriate	Appropriate
AIC	12,480	12,150	11,720
BIC	12,710	12,520	12,050
Out-of-sample log-likelihood	–6,270	–6,120	–5,830

The SEM can be understood as a four-stage sequence: model specification, estimation, evaluation, and modification. In this study, the SEM model is specified to investigate how PHC-first entry influences financial protection, whatever directly and indirectly through intermediate mechanisms: referral adherence and PHC utilization intensity.

PHC-first entry (D) is assumed to influence referral adherence (R) and PHC utilization intensity (U), with referral adherence further affecting utilization. Financial protection (FP), measured as lower OOPE, is modelled as a direct outcome of D and indirectly through R and U. OOPE is log-transformed (ln (OOPE + 1)) to address zeros and reduce skewness. Socio-demographic and health-related covariates (X) are included as exogenous controls influencing R, U, and FP. Referral adherence (R) is defined as a binary indicator, coded as 1 when the patient had more than one visit (i.e., at least one follow-up visit beyond the initial entry), reflecting continued engagement with the PHC referral pathway, and 0 otherwise. These relationships are estimated through a system of structural equations. Observable constructs (D, R, FP) are directly coded as binary or continuous indicators, while the latent construct of utilization intensity (U) is defined using its observed indicators (frequency of PHC visits). The measurement of each construction is defined as follows:

$$\mathrm{D_i} = \text{PHC\_first entre } (1 = \text{PHC visit}, 0 = \text{bypass})$$

$$\mathrm{R_i} = \text{Referral adherence } (1 = \text{referal pathway respected}, 0 = \text{bypassed})$$

$$\mathrm{FP_i} = \log(\mathrm{OOPE_i} + 1)$$

The relationships were estimated using a SEM framework that combines structural and measurement components. PHC-first entry (D_i), referral adherence (R_i), and financial protection ($FP_i = \log(OOPE_i + 1)$) were modeled as observed variables, while utilization intensity (U_i) was treated as a latent construct measured by frequency of PHC visits. A probit specification was preferred, as it aligns with the normality assumption underlying SEM. Estimation was performed using ML with numerical integration for continuous outcomes and probit functions for categorical outcomes, with Weighted Least Squares Mean and Variance Adjusted (WLSMV) employed as a sensitivity approach. Socio-demographic and health-related covariates (X_i) were included as exogenous predictors influencing R_i, U_i, and FP_i. The latent variable PHC utilization intensity (U_i) is modeled using a reflective measurement specification. Identification of the latent variable requires fixing one factor loading to unity. Accordingly, the first loading (λ_1) is set to 1, and the latent variable is expressed as:

$U_i = \lambda_1\mu_{1i} + \lambda_2\mu_{2i} + \lambda_3\mu_{3i} + \epsilon_i, \lambda_1 = 1$ where i indexes individuals, μ_{1i}, μ_{2i}, μ_{3i} are observed indicators of PHC use and ϵ_i is the measurement of error term: μ_{1i}: Number of CSB visits, μ_{2i}: proportion of all visits occurring at PHC facilities, μ_{3i} : Number of chronic follow-up visits at PHC facilities. The pathways linking PHC-first entry to financial protection are estimated through the following structural equations:

$$R_i = \alpha_R + \beta_{RD}D_i + \gamma_R X_i + \varepsilon_{Ri}$$

$$U_i = \alpha_U + \beta_{UD}D_i + \beta_{UR}R_i + \gamma_U X_i + \varepsilon_{Ui}$$

$$FP_i = \alpha_{FP} + \beta_{FPD}D_i + \beta_{FPR}R_i + \beta_{FPR}U_i + \gamma_{FP}X_i + \varepsilon_{FPi}$$

Where X_i is the individual's covariates and $\varepsilon_{Ri}, \varepsilon_{Ui}, \varepsilon_{FPi}$ are disturbance terms.

This specification shows that PHC-first entry (D) affects financial protection (FP) through a sequential mediation pathway, in which its effects are transmitted via referral adherence (R) and PHC utilization (U). It captures both the direct effects of PHC-first entry on referral adherence (R), utilization (U), and financial protection (FP), as well as the indirect effects that operate through referral adherence (R) and utilization (U).

SEM Estimation and Evaluation

The SEM is estimated, using Maximum Likelihood (ML). For each observation i, let $y_i$denote the vector of observed variables, which includes the binary indicators D_i, R_i, the continuous outcome FP_i, and the latent construct U_i. The log-likelihood function is given by:

$$L(\theta) = \sum_{i=1}^{N} w_i * \ln \mathrm{f}(y_i|\theta)$$

Where θ is the vector of parameters, $\mathrm{f}(y_i|\theta)$ is the multivariable density implied by the model, and w_i are the survey weights to account for unequal probability of distribution. To address the complex survey design and non-independence of observations, we apply the Huber–White sandwich covariance estimator, which adjusts standard errors for heteroskedasticity and clustering:

$$\widehat{Var}(\hat{\theta}) = \frac{1}{N}(A^{-1}BA^{-1})$$

$$A = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial^2 L_i(\theta)}{\partial\theta\partial\theta^T}, \quad B = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\partial L_i(\theta)}{\partial\theta}\right)\left(\frac{\partial L_i(\theta)}{\partial\theta}\right)^T$$

Where $\hat{\theta}$ is the vector of estimated parameters (factor it), N is the sample size, A is the expected information matrix (curvature of the likelihood), and B is the empirical variance of the score vectors.

Model Fit Evaluation

Model fit was assessed using several complementary indices to evaluate how well the proposed SEM structure linking PHC-first entry (D), referral adherence (R), PHC utilization (U), and financial protection (FP), aligns with the observed data. The chi-square test of exact fit provides a baseline measure of overall discrepancy: $X^2 = (N-1)^{-1}F_{ML}$ where F_{ML} is the minimized discrepancy function under ML estimate. Because the chi-square statistic is sensitive to sample size and deviations from exact fit, additional indices were used to evaluate approximate fit. The Root Mean Square Error of Approximation (RMSEA) assesses the degree of misfit per degree of freedom, adjusting for model complexity: RMSEA $= \sqrt{\frac{Max(X^2 - df, 0)}{df(N-1)}}$. It favors parsimonious models that fit the data without overfitting. Incremental fit indices, including the Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI), compare the proposed model against a baseline independence model. The CFI is specified as:

CFI $= 1 - \frac{Max(X^2_{model} - df_{model}, 0)}{Max(X^2_{baseline} - df_{baseline}, 0)}$, where: X^2_{model} and df_{model} are the chi-square statistic and degrees of freedom for the hypothesized model, $X^2_{baseline}$ and $df_{baseline}$ are the corresponding values for the baseline (independence) model. The Standardized Root Mean Square Residual (SRMR) captures the average discrepancy between observed and model-implied covariances among the four primary constructs (D, R, U, FP) and their related indicators:

$$\text{SRMR} = \sqrt{\frac{2}{p(p+1)}\sum_{j\leq k}\left(s_{jk} - S_{jk}\right)^2}$$

where s_{jk} are sample covariances and S_{jk} are model-implied covariances. SRMR is valued for its intuitive interpretation as an average residual and particularly useful for assessing whether the model adequately reproduces correlations among D, R, U, and FP. Even when global fit indices indicate acceptable fit, local areas of misfit may remain. Model modification procedures help identify where the specification D, R, U, or FP deviates from the observed data structure. The most common diagnostic is the Modification Index (MI), which quantifies the expected decrease in the fitting function if a fixed parameter (q) were freely estimated:

$$MI_q = \left(\frac{\partial F}{\partial\theta_q}\right)^2 \Big/ Var\left(\frac{\partial F}{\partial\theta_q}\right)$$

Large MI values suggest that relaxing certain constraints (e.g., freeing a path between R and FP, or allowing correlated errors between utilization indicators) may improve fit. However, modifications are only considered when statistically justified and aligned with theoretical constructions to avoid data-driven adjustments that could compromise model interpretability or introduce overfitting.

3. Data Overview and Variables

3.1. Patient-Level

This study used retrospective observational survey data from diabetes and hypertension patients selected from 24 PHC facilities (BHCs and DHs) in disadvantaged regions of Tunisia. A four-stage random sampling strategy was applied to select governorates, health districts, PHC facilities, and patients, resulting in survey data from 1,624 diabetes and 1,749 hypertension patients in 2018. The survey includes four modules: (1) patient demographics and insurance status; (2) direct and indirect disease-related expenditures; (3) perceived health, complications, care use, and risk behaviours; and (4) care needs and exposure to CHE.

The treatment variable is PHC-first entry ($D_i = 1$), defined as initially seeking care at PHC facility. Referral adherence is coded as adherent when patients entered through PHC, followed an official referral, or were managed at PHC without referral. OOPE for the most recent care episode (consultation, medicines, diagnostics, transport, and other direct payments) is used as the financial outcome**.**

A set of covariates age, sex, education, insurance status, and comorbidities was retained for matching, IPTW, and IV estimation. To address endogeneity in referral choice, two instruments were used. To address endogeneity in referral choice, two instrumental variables were used: distance to the nearest BHC, serving as a proxy for geographic accessibility and the likelihood of choosing and adhering to a PHC-first contact; and the number of physicians per BHC, used as a proxy for PHC service capacity. Table 2 summarizes key variables. The sample includes 3,433 diabetes and 3,244 hypertension patients. PHC-first entry (60% vs. 55%) and referral adherence (65% vs. 58%) are higher among diabetes patients. Hypertension patients incur higher OOPE (171.2±34.7 TND) compared to diabetes (147.6±51.1 TND). Diabetes patients are older (61.2 vs. 54.5 years), less educated (37% vs. 30% illiterate), and have more comorbidities (30% vs. 25%). Hypertension patients have slightly higher CNAM coverage (53% vs. 48%), while diabetes patients are more likely uninsured (24%). Geographic and capacity differences support instrument validity: diabetes patients live closer to BHCs (1.8 vs. 4.6 km) and have access to more physicians per BHC (3.2 vs. 1.7).

3.1. Population-level

Tunisian Household Survey 2021(24) covering 59,092 individuals is used (table 2). The survey provides detailed information on health status and utilization, OOPE, health insurance, and socio-demographic characteristics. The OOPE was disaggregated into medicines, consultations, hospitalization, transport etc (Module 6, UN COICOP classification). CHE was measured using conventional thresholds: 10% of total expenditure (CHE10) and 25% of non-food expenditure (CHE25). The main explanatory variable is PHC-first entry (1 = first contact; 0 = hospital, emergency, or private facility). Control variables include demographics (age, sex, education, household size), socioeconomic status (expenditure quintiles), insurance coverage (CNAM, AMG, uninsured), and health status (chronic disease, disability).

Table 2 presents descriptive statistics used. OOPE is estimated to 512 TND, with medicines representing the largest share and 25% of households exceed the CHE10 threshold. Most patients (58%) initiated care at a PHC level, highlighting the continuing role of PHC as the entry point. The sample is 52% female, with a mean age of 56, and nearly half reside in rural areas. Insurance coverage is uneven: 44% are covered by CNAM, 21% by AMG, and over one quarter remain uninsured.

- PHC-first entry (D) indicates whether the respondent entered the health system through a PHC facility as the initial point of care based on the survey question "Did you visit a PHC facility?" Coded as 1 if the answer is *Yes*, and 0 if *No*.
- Referral adherence (R) indicates whether the respondent followed the intended referral pathway and maintained continuity of care within PHC. Based on survey data, it is coded as follows: 1 if the respondent had at least two PHC visits within a month (initial plus follow-up) or respected a referral to higher-level care; and 0 if they bypassed PHC or had no follow-up after the initial visit.
- PHC utilization intensity (U) is a composite index combining normalized annual PHC visits (0–1 Min–Max scale) and a binary indicator of chronic follow-up, ranging from 0 (no use) to 1 (high use and regular follow-up).

Table 2. Descriptive Statistics for Patients vs. Population Levels

Patient-Level	**Diabetes**	**Hypertension**
Number of patients	1624	3244
PHC-first entry (%)	60	55
Referral adherence (%)	65	58
Mean OOPE per episode (TND)	147.6 ± 51.1	171.2 ± 34.7
Age (years)	61.2	54.5
Female (%)	58	66
Education level (%)		
No formal schooling	37	30
Primary education	44	48
Secondary or higher	19	22
Insurance status (%)		
CNAM	48	53
AMG	19	22
AG/Mutual	2.3	3.6
Uninsured	24	21
Comorbidities (%)	30	25
Distance to nearest PHC facility (km)	1.8	4.6
Number of physicians per PHC facility	3.2	1.7
Population-Level	Mean / %	SD
Total Household expenditure (TND)	15,480	6,230
OOPE (TND)	512.4	385.2

OOPE Medicines (TND)	298.7	224.5
OOPE Consultations (TND)	112.5	96.8
OOPE Hospitalization (TND)	79.3	142.4
OOPE Transport (TND)	21.9	38.2
CHE10 (1 = OOPE ≥10% of total exp)	0.24	0.43
CHE25 (1 = OOPE ≥25% of total exp.)	0.17	0.38
PHC-first entry (D) - 1 = PHC-first	0.58	0.49
Referral adherence - 1 = referral pathway followed	0.61	0.48
PHC utilization (U)- Composite index (0–1)	0.44	0.32
$\mu 1$: Total PHC visits	3.74	2.61
$\mu 2$: Share of total PHC visits	0.47	0.29
$\mu 3$: PHC Chronic follow-up visits	2.41	1.83
Chronic disease - 1 = ≥1 chronic condition	0.41	0.49
Disability - 1 = disability condition	0.09	0.28
Age (years)	55.6	13.2
gender (1=female)	0.52	0.5
Education (years of schooling)	7.1	4.8
Household size	4.8	2.1
CNAM	0.47	0.5
AMG	0.18	0.41
AG/Mutual	0.14	0.27
Uninsured	0.21	0.45
Rural residence (1=rural area)	0.47	0.5

4. Results

4.1. Patient-Level Effects of PHC-first Entry (Adjusted Estimates)

Table 3 presents the adjusted estimates using inverse probability of treatment weighting (IPTW) and propensity score matching, controlling for age, sex, education, insurance status, and comorbidities. PHC-first entry is significantly associated with lower OOPE in both diabetes and hypertension groups. The estimated Average Treatment Effect (ATE) indicates a reduction of −29.4 TND (−18.6%) for diabetes and −24.7 TND (−14.3%) for hypertension, compared to non-PHC-first patients. PHC-first entry also increased referral adherence by 24.3 and 18.9 percentage points (pp), respectively. The financial protection effect of PHC-first entry is significant but moderate, indicating that while it reduces OOPE, its impact is not fully effective, and bypassing may persist.

Table 3. Adjusted Effects of PHC-first Entry on OOPE and Referral Adherence

Variable	Diabetes	Hypertension
Adjusted OOPE among PHC-first (TND)	135.2	156.4
Adjusted OOPE among non-PHC-first (TND)	164.6	182.5
Average Treatment Effect (ATE, TND)	−29.4	−24.7
Relative reduction (%)	−18.6%	−14.3%
95% CI for ATE (TND)	[−35.5, −22.2]	[−28.7, −18.2]
Increase in referral adherence (%)	+24.3	+18.9

To address possible endogeneity of referral behavior, an IV approach was implemented using distance to nearest CSB and number of physicians per CSB as instruments. In Table 4, these instruments demonstrated strong relevance (F-statistic = 14.8). The IV results show a stronger causal effect compared to the adjusted ATE estimates, confirming that when referral pathways are properly followed, the reduction in OOPE is significantly larger. Referral adherence causally reduces OOPE by −37.6 TND (−25.5%) in diabetes and −29.8 TND (−17.4%) in hypertension, lowers specialist visits, and reduces the probability of catastrophic expenditure (CHE10).

Table 4. Instrumental Variable Estimates of Referral Adherence on Financial Protection

	Diabetes	Hypertension
OOPE reduction (TND)	−37.6*	−29.8*
Relative OOPE reduction (%)	−25.5%	−17.4%
Reduction in specialist visits (pp)	−9.1***	−7.5***
Reduction in CHE10 risk (pp)	−4.3**	−3.1*
Share of PHC effect mediated by referral adherence (%)	54%	49%

*p<0.05; **p<0.01; ***p<0.001

Subgroup analysis shows clear variation in financial protection by insurance status (Table 5). The largest OOPE reductions occur among uninsured (−25.9%) and AMG (−17.4%) patients, indicating stronger equity-enhancing benefits for financially vulnerable groups, while CNAM patients experience a more modest reduction (−12.1%), likely due to bypassing and weaker referral compliance. AG/Mutual beneficiaries were merged with CNAM due to small sample size. Referral adherence further amplifies financial protection, particularly among uninsured (+28.4%) and AMG (+21.2%), confirming that PHC-first entry is most effective when coupled with coordinated referral pathways. However, moderate adherence rates (58–65%) among insured patients limit the full protective potential. Overall, these results highlight the equity-promoting role of PHC-first strategies, especially when reinforced through referral enforcement and insurance alignment.

Table 5. Reduced OOPE by PHC-first entry and referral adherence, by insurance category

Insurance Category	OOPE Reduction (TND)	Relative Reduction (%)	Referral Adherence Effect
CNAM	−22.3	−12.1%	+17.5
AMG	−31.6	−17.4%	+21.2
Uninsured	−45.7	−25.9%	+28.4

4.2. Population-Level Analysis: SEM Core Pathways and Directional Effects

Model fit was assessed using multiple indices to evaluate how well the proposed SEM structure linking PHC-first entry (D), referral adherence (R), PHC utilization (U), and financial protection (FP) reflects the observed data. The model demonstrated a good overall fit, with RMSEA (0.038), SRMR (0.041), CFI (0.95), and TLI (0.93) meeting conventional thresholds (RMSEA <0.05, CFI/TLI >0.90, SRMR <0.08) and indicating adequate structural validity and acceptable approximation of the covariance structure. Although the chi-square statistic was significant: χ^2/df ratio (1.94) remained below the recommended cutoff of 2.0, further confirming good model fit. Modification indices were examined to assess potential specification improvements. No theoretically justified modifications were required, and all retained paths aligned with the hypothesized D → R → U → FP sequence, supporting the conceptual model without data-driven adjustments

In table 6, SEM results confirmed the hypothesized sequential pathway through which PHC-first entry (D) influences financial protection (FP). Individuals who initiated care at PHC facilities were significantly more likely to comply with referral protocols and to exhibit higher PHC utilization intensity, compared to those who bypassed PHC and directly accessed hospitals or private providers. Referral adherence also showed a positive association with utilization intensity, indicating that patients who follow referral pathways tend to complete multiple PHC visits and maintain continuity of care.

A significant direct effect of PHC-first entry on financial protection (measured as reduced log-transformed OOPE) was observed, confirming that PHC entry plays a protective financial role independent of other mediators. However, referral adherence did not exert a significant direct effect on financial protection ($p = 0.078$), suggesting that merely following referral pathways does not reduce financial burden unless it results in sustained PHC utilization. In contrast, PHC utilization intensity was significantly associated with lower OOPE, indicating that households with frequent PHC use experience financial protection compared to those with low or no PHC use. Four directional effects were detected (i) PHC-first entry significantly increases referral adherence and PHC utilization; (ii) Referral adherence increases utilization but does not independently reduce OOPE, (iii) Higher PHC utilization is associated with significantly lower OOPE and (iv) PHC-first entry protects financially both directly and indirectly.

All models were adjusted for socio-demographic, economic, health status, and geographic covariates: age, sex, education, household size, household expenditure, chronic disease, disability, and rural residence. Covariates were specified as exogenous predictors of referral adherence (R), PHC utilization (U), and financial protection (FP); coefficients are not displayed because they are not part of the conceptual pathway (D → R → U → FP).

Table 6. Structural Path Estimates from SEM

Path	**Coefficient (β)**	**Std. Error**
PHC-first entry → Referral adherence	0.42*	0.16
PHC-first entry → PHC utilization	0.27*	0.11
Referral adherence → PHC utilization	0.33*	0.13
PHC-first entry → Financial protection	−0.18*	0.08
Referral adherence → Financial protection	−0.06 (ns)	0.03
PHC utilization → Financial protection	−0.15*	0.04

Significant at $p<0.05$; ns = not significant

Table **7** give the decomposition of direct, indirect, and total effects. PHC-first entry improves financial protection through both direct and mediated pathways. While the direct effect accounted for 54% of the total impact, 46% of the effect was transmitted indirectly through referral adherence and PHC utilization. The indirect pathway was the sequential chain PHC-first → referral adherence → utilization → financial protection (20% of the total effect) which confirm the mediating role of PHC utilization. PHC-first entry reduces OOPE by 27-31% annually compared to bypassing PHC. Nearly half of this impact occurs through mediated effects, particularly via referral adherence leading to sustained PHC use.

Table 7. Direct, Indirect, and Total Effects of PHC-first Entry on Financial Protection

Effect Type	coefficient	Std. Error	% of Total Effect
Direct effect (PHC-first vs. bypass)	−0.18*	0.04	54%
Indirect via referral adherence	−0.046**	0.02	14%
Indirect via PHC utilization	−0.040 (ns)	0.02	12%
Sequential indirect (D → R → U → FP)	−0.063*	0.02	20%
Total Effect	−0.329 **	0.05	100%

*Significant at $p<0.05$; **$p<0.01$; ns = not significant

As shown in Table 8, the FP effects of PHC-first entry varied substantially by insurance status. The strongest benefits were observed among uninsured and AMG-covered households, with total effects of −0.43 and −0.32 and relative OOPE reductions of 35.7 and 26.9%, respectively. For these groups, PHC-first entry acted as a strong substitute for more expensive specialist or hospital-based care, enhancing financial protection when higher-level care was less affordable or less accessible. Among CNAM beneficiaries, the total effect was moderate (−0.25; −18.3%), reflecting partial but incomplete FP. This pattern is consistent with CNAM's financing model based on an extensive contracting with specialists and private providers, which dilute PHC gatekeeping and weaken its protective role. The Private insurance (AG/Mutual) showed the weakest effects (total effect −0.18; OOPE reduction −12.4%), consistent with a tendency to bypass PHC and directly seek specialist or hospital care, where insurance coverage mainly facilitates access rather than discouraging high-cost use. Consequently, PHC-first entry offers minimal financial protection gains for this group.

Table 8. SEM Estimates of PHC-first Entry Effect on Financial Protection, by Insurance Status

Insurance Category	Direct Effect	Indirect Effect	Total Effect	Relative OOPE Reduction
CNAM	−0.14***	−0.11**	−0.25***	−18.3%
AMG	−0.19***	−0.13***	−0.32***	−26.9%
Private / Mutual	−0.10*	−0.08*	−0.18**	−12.4%
Uninsured	−0.24**	−0.19**	−0.43**	−35.7%

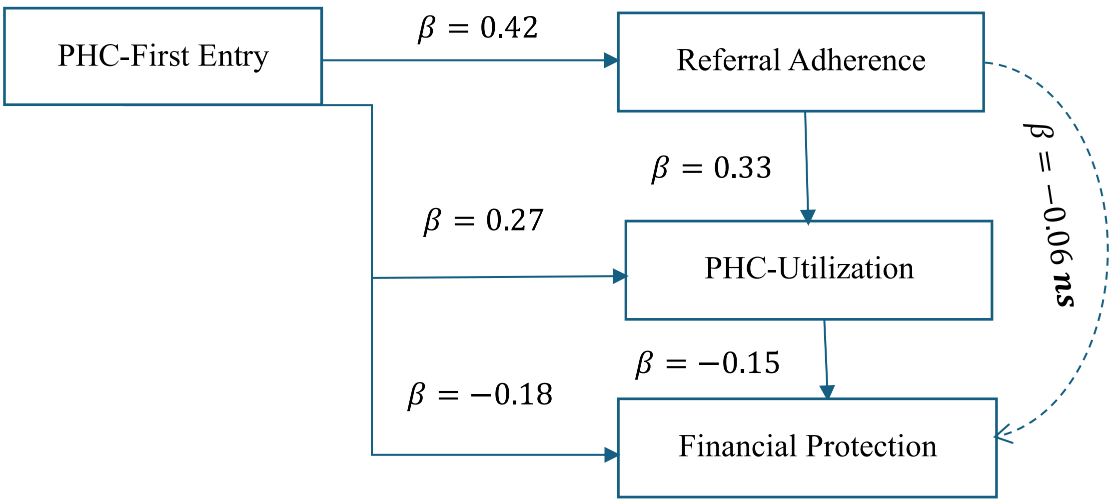
*$p<0.05$; **$p<0.01$; ***$p<0.001$

The SEM diagram (Figure 1) visually represents the structural relationships specified in the model. It shows how PHC-first entry influences financial protection both directly and indirectly through referral adherence and PHC utilization.

- PHC-first entry demonstrates a significant positive effect on both referral adherence and utilization, indicating that individuals who enter the system through PHC are more likely to respect the referral pathway and make greater use of PHC services compared to those who bypass it.

- Referral adherence exerts a significant positive effect on PHC utilization, supporting its mediating function. However, it does not independently reduce financial burden, as the direct path to financial protection is non-significant ($\beta = -0.06, P = 0.078$) and therefore depicted as a dashed line in Figure 1.
- PHC utilization exerts a significant negative effect on financial burden which confirms that greater use of PHC services is associated with reduced OOPE relative to no PHC use.
- The direct significant path from PHC-first entry to financial protection is also shown, indicating that even without full referral adherence, PHC-first entry has a protective effect.
- The indirect effects occur through sequential pathway PHC-first entry → R → U → FP which accounts for 20% of the total effect. FP is in part gained from PHC-first entry and transmitted through referral compliance and increased PHC use.

Figure 1. PHC Pathway Diagram



4. Discussion

The study applied a dual method (Quasi-experimental and SEM) to enhance both causal inference and explanatory depth. The quasi-experimental approach, through the propensity score weighting, simulated counterfactual conditions to estimate the causal impact of PHC-first entry on financial burden and quantifying its protective effect. SEM complemented this by capturing how this protection occurs through the sequential mechanisms R and U. SEM showed good model fit (RMSEA = 0.038, CFI = 0.95, TLI = 0.93, SRMR = 0.041) and validated both direct and mediated pathways. Together, these methods strengthen internal and construct validity: the quasi-experimental analysis establishes whether PHC-first entry protects financially, while SEM explains how that effect is transmitted.

At the patient level, PHC-first entry is significantly associated with a moderate 14–19% reduction in OOPE among diabetes and hypertension patients, likely due to incomplete referral compliance, heterogeneous PHC capacity, and persistent bypassing to higher-level services. These findings suggest that while PHC-first entry improves financial protection for chronic disease patients, its impact remains limited unless coupled with systematic and enforced referral adherence. These findings align with evidence from other LMICs (46) and studies conducted in India 40, China (47, 48), Greece (43), and Bangladesh (49). However, the financial protection effect remains moderate unless reinforced by referral adherence, which enhances the reduction in OOPE to 17–26% and lowers the probability of catastrophic expenditure. Referral adherence functions as a financial protection multiplier, which indicates that PHC-first entry alone does not sufficiently protect patients unless complemented by systematic and enforced referral compliance. This effect is especially pronounced for uninsured and AMG households, which underscores the equity-enhancing potential of PHC gatekeeping for the most vulnerable populations. However, adherence levels remain modest (58–65%), which reflects the partial and uneven implementation of referral-based gatekeeping across insurance schemes.

At the population level, the SEM confirms the full sequence through which PHC-first entry contributes to improved financial protection. PHC-first entry increases referral adherence ($\beta = 0.42$) and PHC utilization ($\beta = 0.27$), while referral adherence further increases utilization ($\beta = 0.33$), thereby the full pathway PHC first entry→ R → U is observed. However, referral adherence alone does not yield financial protection unless it results in sustained PHC utilization, as shown by its non-significant direct effect on financial protection ($\beta = -0.06$; $p = 0.078$).

The SEM shows that financial protection operates through three distinct mechanisms. First, the direct effect of PHC-first entry on financial protection ($\beta = -0.18$) accounts for 54% of the total financial protection effect and translates into an immediate reduction in OOPE of about 14–19%. Second, an indirect effect operates through PHC utilization intensity, which represents 46% of the total effect and is associated with an OOPE reduction of approximately 7–10%. Third, a more complex sequential pathway (PHC-first → referral adherence → utilization → financial protection) accounts for 20% of the total effect and an additional OOPE reduction of nearly 6–8%. In this PHC context, financial protection operates through complementary and partly overlapping pathways. The direct effect (54%) reflects the immediate reduction in OOPE from PHC-first entry, while the indirect effect (46%) captures longer-term gains from sustained PHC use and reduced reliance on costly services. Within this, the sequential pathway (20%), as a subset of the utilization effect, indicates that part of the financial benefit stems from coordinated care and referral adherence. The direct effect produces the greatest OOPE reduction because PHC-first entry replaces an expensive mode of entry (specialist/hospital care with high costs and intensive procedures) with a cheaper one (subsidised PHC), whereas the indirect and sequential pathways act only on the remaining, already-lowered spending by fine-tuning how often and how appropriately services are used, so their marginal savings are smaller.

These findings reinforce the need to reposition PHC as the central lever for financial protection in Tunisia’s health system. The strong direct effect of PHC-first entry highlights the importance of clearly mandating PHC as the first point of contact through gatekeeping, reduced copayments, and integration into CNAM access and financing model. The indirect pathway indicates that financial protection is further strengthened when patients remain engaged with PHC over time, which in turn requires investing in chronic care programs, family doctor models, and digital PHC follow-up to support continuity of care. The sequential pathway confirms that coordinated referral systems add additional protective effects, suggesting that referral compliance and structured care pathways should be reinforced through electronic referral systems, performance-based provider payment, and quality monitoring. Together, PHC-first entry, sustained utilization, and coordinated referral systems should be jointly prioritized to enhance financial protection and accelerate progress toward UHC in Tunisia.

Another important finding concerns the unequal financial protection gains across insurance groups. The largest OOPE reductions were observed among uninsured and AMG (−35.7% and −28.5% respectively), while CNAM and private insurance beneficiaries experienced weaker effects. This suggests that having formal insurance coverage (CNAM or AG/Mutual) does not automatically translate into stronger financial protection when referral enforcement is weak and bypassing of PHC is common. Two key policy directions are suggested. **First**, PHC-first entry is especially protective for poor and uninsured populations, but its benefits could be extended to insured groups if gatekeeping, referral enforcement, and PHC-based benefits packages are strengthened. The uninsured in Tunisia (17% of the population) are mainly informal workers, near-poor excluded from AMG, and jobless individuals facing administrative or eligibility barriers. They face the greatest financial hardship (35) yet benefit the most when they access through PHC-first entry. Second, PHC-first entry should be explicitly embedded within CNAM and AG/Mutual financing models, benefit packages, and access rules, making PHC the default entry point for all insured groups.

Having a "PHC-first plus gatekeeping plus insurance alignment" model is not the universal norm, even among wealthy countries. If Tunisia adopts a mandatory PHC-first design within a unified insurance and gatekeeping framework, it would be innovative but not without precedent, drawing lessons from the UK (50, 51), the Netherlands (52, 53), some Scandinavian systems (54, 55), and more recent experiences in Indonesia and Rwanda. In this perspective, establishing a single CNAM scheme based on mandatory PHC-first entry, replacing the current three sub-schemes and extending subsidized enrolment to jobless individuals and low-contribution participation for informal workers, would reduce bypassing, improve care coordination, and strengthen financial protection.

To restore the foundational role of PHC as the trusted first entry, Tunisia must move beyond isolated digital initiatives toward a deliberately designed, people-centered digital gatekeeping system. Building on the country's emerging experience with telemedicine (Njda.TN), digital medical records in PHC centers (e.g., governorate of Sfax), and early referral tracking tools, the health system should evolve toward integrated electronic referral platforms, automated tracking, shared patient records, and teleconsultation support. When digital tools are not merely technological add-ons but instruments that reinforce respect for referral pathways, continuity of care, and the primacy of PHC, they become symbols of equity, trust, and financial protection. Such a digitally enabled gatekeeping model would not only curb bypassing; it would help restore the philosophical essence of PHC: the right care, at the right place, at the right time, for the right cost.

Conclusion

Using a dual-method approach combining quasi-experimental analysis and Structural Equation Modelling, this study confirmed both the causal impact and underlying mechanisms through which PHC-first entry enhances financial protection in Tunisia. PHC-first reduces OOPE directly and indirectly through improved referral adherence, sustained PHC utilization, and coordinated care pathways, with the greatest benefits observed among uninsured and vulnerable populations. However, its protective potential depends on aligning referral enforcement, insurance benefits, and PHC capacity enhancements.

Transforming Tunisia's fragmented digital initiatives into a coherent PHC-centered gatekeeping system with e-referral, teleconsultation, and shared patient records, can reduce bypassing and enhance continuity of care. A unified CNAM-administered PHC-first insurance model, replacing the current three sub-schemes and extending subsidized coverage to jobless and informal workers, would further strengthen digital referral compliance, improve financial protection, and reinforce system-wide resilience.

References

1. Ata A, editor Declaration of Alma Ata: International conference on primary health care. Alma Ata, USSR: International Conference on Primary Health Care; 1978.
2. Kluge H, Kelley E, Birtanov Y, Theodorakis PN, Barkley S, Aidossov S, et al. Implementing the renewed vision for Primary Health Care in the Declaration of Astana: the time is now. 2019;20:e158.
3. World Health Organization. Global Health Expenditure Database Geneva: World Health Organization; 2025 [Available from: https://apps.who.int/nha/database/Select/Indicators/en.
4. Wagstaff A, Flores G, Hsu J, Smitz M-F, Chepynoga K, Buisman LR, et al. Progress on catastrophic health spending in 133 countries: a retrospective observational study. 2018;6(2):e169-e79.
5. World Health Organization. Monitoring progress on universal health coverage and the health-related Sustainable Development Goals in the WHO South-East Asia Region 2021 update. 2021.
6. Akbari A, Mayhew A, Al-Alawi MA, Grimshaw J, Winkens R, Glidewell E, et al. Interventions to improve outpatient referrals from primary care to secondary care. 1996;2011(1).
7. Friedberg MW, Hussey PS, Schneider ECJHA. Primary care: a critical review of the evidence on quality and costs of health care. 2010;29(5):766-72.
8. Mosquera PA, Hernández J, Vega R, Martínez J, Labonte R, Sanders D, et al. Primary health care contribution to improve health outcomes in Bogota-Colombia: a longitudinal ecological analysis. 2012;13(1):84.
9. Bitton A, Ratcliffe HL, Veillard JH, Kress DH, Barkley S, Kimball M, et al. Primary health care as a foundation for strengthening health systems in low-and middle-income countries. 2017;32(5):566-71.
10. Khatri R, Endalamaw A, Erku D, Wolka E, Nigatu F, Zewdie A, et al. Continuity and care coordination of primary health care: a scoping review. 2023;23(1):750.
11. Starfield BJGs. Primary care: an increasingly important contributor to effectiveness, equity, and efficiency of health services. SESPAS report 2012. 2012;26:20-6.
12. De Maeseneer J, Willems S, De Sutter A, Van de Geuchte I, Billings M. Primary health care as a strategy for achieving equitable care: a literature review commissioned by the Health Systems Knowledge Network. 2007.
13. Rajan D, Rouleau K, Winkelmann J, Jakab M, Kringos D, Schmets G, et al. Implementing the primary health care approach: a synthesis of the primer. Implementing the primary health care approach: a synthesis of the primer2025.
14. Tangcharoensathien V, Limwattananon S, Patcharanarumol W, Thammatacharee J, Jongudomsuk P, Sirilak SJHp, et al. Achieving universal health coverage goals in Thailand: the vital role of strategic purchasing. 2015;30(9):1152-61.
15. Macinko J, Guanais FC, De Souza MDFMJJoE, Health C. Evaluation of the impact of the Family Health Program on infant mortality in Brazil, 1990–2002. 2006;60(1):13-9.
16. Kringos DS, Boerma WG, Hutchinson A, Saltman RB. Scoring of indicators for the European Primary Care Monitor. Building primary care in a changing Europe [Internet]: European Observatory on Health Systems and Policies; 2015.
17. Souissi S. Perception of Public Health Performance in District Hospitals in Tunisia: 서울대학교 대학원; 2019.
18. Arfa C, Leleu H, Goaied M, Van Mosseveld CJIjohp, management. Measuring the capacity utilization of public district hospitals in tunisia: using dual data envelopment analysis approach. 2016;6(1):9.

19. World Health Organization. Strengthening health financing systems in the Eastern Mediterranean Region towards universal health coverage: health financing atlas 2018. Strengthening health financing systems in the Eastern Mediterranean Region towards universal health coverage: health financing atlas 20182019.
20. Nasri K, Amara M, Helmi I, editors. The landscape of social protection in Tunisia2022: Economic Research Forum (ERF).
21. Makhloufi K, Ventelou B, Abu-Zaineh M. Have health insurance reforms in Tunisia attained their intended objectives? International Journal of Health Economics Management. 2015;15(1):29-51.
22. Ismaïl S, Zaouali N. Santé et assurance maladie en Tunisie: les enjeux de la réforme de 2004. Eastern Mediterranean Health Journal. 2022;28(6).
23. Rao KD, Sheffel AJSs, medicine. Quality of clinical care and bypassing of primary health centers in India. 2018;207:80-8.
24. Institut National de la Statistique. Enquête Nationale sur le Budget, la consommation et le niveau de vie des ménages. In: Statistique INdl, editor. Tunsie2023.
25. Akin JS, Hutchinson PJHP, Planning. Health-care facility choice and the phenomenon of bypassing. 1999;14(2):135-51.
26. Kruk ME, Nigenda G, Knaul FMJAjoph. Redesigning primary care to tackle the global epidemic of noncommunicable disease. 2015;105(3):431-7.
27. Abdelaziz AB. Quarante ans des Soins de Santé de Base en Tunisie: De la «Santé pour Tous» à la «Couverture-Santé Universelle». La Tunisie Médicale. 2021;99(1):12.
28. Ali FH, Njah M, Milot DM, Hassouni KJLTM. Successes and Challenges Related to Community Participation in Primary Health Care and Health Programs in the IGAD Region: A Scoping Review. 2025;103(2):167.
29. Ben Romdhane H, Tlili, Faten, Skhiri, Afef, Zaman, Shahaduz and Phillimore, Peter Health system challenges of NCDs in Tunisia. International journal of public health. 2015;60(Suppl 1):39-46.
30. Abdelaziz AB, Nouira S, Chebil D, Azzaza M, Barhoumi T, Salem KB. La Médecine de Famille (Médecine Générale): Quelles spécificités académiques et professionnelles? La Tunisie Médica. 2021;99(1):29.
31. BelHaj Yahia M. Le système de santé en Tunisie: une crise qui perdure. Confluences Méditerranée. 2023;125(2):137-52.
32. Zakhama L. 40 years of Primary Health Care in Tunisia. Findings and Perspectives. La Tunisie Medicale. 2021;99(1):1-4.
33. Abdelaziz AB. Evaluation de la politique des Soins de Santé Primaires au Maghreb. Retour d'expériences des Experts-Leaders* en Tunisie. La Tunisie Médicale. 2021;99(1):59.
34. Abu-Zaineh M, Arfa, Chokri, Ventelou, Bruno, Ben Romdhane, Habiba and Moatti, Jean-Paul. Fairness in healthcare finance and delivery: what about Tunisia? Health policy Planning. 2014;29(4):433-42.
35. Ismaïl S, and Arfa, Chokri. Effects of out-of-pocket medicine's spending on catastrophic expenditure and impoverishment in Tunisia. Value in Health Regional Issues 2022;30:109-18.

36. Ayadi IaZ, Salma. Out-of-pocket health spending and equity implications in Tunisia. Middle East Development Journal. 2017;9(1):1-21.
37. Arfa CaA, Hédi Tunisia: good practice in expanding health care coverage. Lessons from reforms in a country in transition 2008.
38. Giusti M, Persiani N. The experience of Tunisian public healthcare system toward decentralization to the reduction of health inequalities in low-, middle-income countries. International Journal for Equity in Health. 2024;23(1):271.

39. Megdiche M, Lassoued F, Hadj Amor S, Rahay H, Aounallah Skhiri H. The path to Family Medicine in Tunisia. Strategic analysis. La Tunisie Medicale. 2021;99(1):80-8.
40. Huang J, Wang L, Liu S, Zhang T, Liu C, Zhang YJITJoHCO, Provision,, et al. The path analysis of family doctor's gatekeeper role in Shanghai, China: a structural equation modeling (SEM) approach. 2021;58:00469580211009667.
41. Shadish WR, Cook TD, Campbell DT. Experimental and quasi-experimental designs for generalized causal inference: Houghton, Mifflin and Company; 2002.
42. Anderson-Cook CM. Experimental and quasi-experimental designs for generalized causal inference. Taylor & Francis; 2005.
43. Jesus GS, Pescarini JM, Silva AF, Torrens A, Carvalho WM, Junior EP, et al. The effect of primary health care on tuberculosis in a nationwide cohort of 7· 3 million Brazilian people: a quasi-experimental study. 2022;10(3):e390-e7.
44. Shahnazi H, Araban M, Karimy M, Basiri M, Ghazvini A, Stein LJBME. A quasi-experimental study to improve health service quality: implementing communication and self-efficacy skills training to primary healthcare workers in two counties in Iran. 2021;21(1):369.
45. Van Zyl LE, Ten Klooster PMJFip. Exploratory structural equation modeling: Practical guidelines and tutorial with a convenient online tool for Mplus. 2022;12:795672.
46. Sugunan A, Rajasekharan Pillai K, George A. Effectiveness of interventions to contain out-of-pocket-expenditure in lower-middle income countries: A systematic review and synthesis. The International Journal of Health Planning Management 2023;38(4):918-35.
47. Singh D, Prinja S, Bahuguna P, Chauhan AS, Guinness L, Sharma S, et al. Cost of scaling-up comprehensive primary health care in India: Implications for universal health coverage. Health policy planning. 2021;36(4):407-17.
48. Kumar K. A public-private partnership based model for regulating out-of-pocket expenditures to strengthen primary care system. The International Journal of Health Planning Management. 2022;37(5):2964-91.
49. Hasan MZ, Mehdi GG, Tisha KI, Rabbani MG, Ahmed MW, Paul S, et al. Costs of outpatient services at selected primary healthcare centers in Bangladesh: A cross-sectional study. PloS one. 2025;20(1):e0317317.
50. Bordbar N, Shojaei P, Ravangard R, Bastani P, Joulaei H, Kavosi Z. Evaluation of the world countries health referral system performance based on world health organization indicators using hybrid multi-criteria decision-making model. Value in Health Regional Issues. 2022;28:19-28.
51. Brekke KR, Nuscheler R, Straume OR. Gatekeeping in health care. Journal of health economics. 2007;26(1):149-70.
52. Kulu-Glasgow I, Delnoij D, de Bakker D. Self-referral in a gatekeeping system: patients' reasons for skipping the general-practitioner. Health policy. 1998;45(3):221-38.
53. Stevens FC, van der Horst F, Hendrikse F. The gatekeeper in vision care. An analysis of the co-ordination of professional services in The Netherlands. Health Policy. 2002;60(3):285-97.
54. Rotar AM, Van Den Berg MJ, Schäfer W, Kringos DS, Klazinga N. Shared decision making between patient and GP about referrals from primary care: Does gatekeeping make a difference? Plos one. 2018;13(6):e0198729.
55. Gérvas J, Ferna MP, Starfield B. Primary care, financing and gatekeeping in western Europe. Family practice. 1994;11(3):307-17.