Latent Profile Analysis of Chronic Disease Resource Utilization in Prediabetic Populations and Its Impact on Health-Promoting Behaviors: A Postprint Study

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Abstract

Background Effective utilization of chronic disease resources can facilitate sustained health behavior change and improve health status in individuals with prediabetes; however, current patterns of chronic disease resource utilization in this population remain unclear and warrant further investigation.

Objective To explore latent categories of chronic disease resource utilization among individuals with prediabetes and their relationship with health-promoting behaviors.

Methods Using a consecutive sampling method, individuals with prediabetes who underwent physical examinations at two community health service centers in Nanjing from March to July 2024 were selected as study participants. Data were collected using a general information questionnaire, the Chronic Illness Resources Survey (CIRS), and the Health-Promoting Lifestyle Profile II (HPLP-II). Latent profile analysis was employed to classify chronic disease resource utilization patterns among individuals with prediabetes, and hierarchical regression analysis was used to examine the relationship between resource utilization categories and health-promoting behaviors.

Results A total of 270 questionnaires were collected, of which 263 were valid, yielding an effective response rate of 97.4%. The mean CIRS score for the prediabetes population was (49.1$±8.7), $and the mean HPLP - II score was$(131.1±$17.0). Chronic disease resource utilization among individuals with prediabetes could be classified into three latent categories: low resource utilization-basic dependency type [136 (51.7%)], medium resource utilization-limited support type [105 (39.9%)], and high resource utilization-multifaceted support type [22 (8.3%)]. Hierarchical regression analysis results indicated that after controlling for confounding factors, chronic disease resource utilization category was a significant influencing factor on health-promoting behaviors in individuals with prediabetes ($P<0.001$), explaining 13.8% of the variance.

Conclusion Individuals with prediabetes exhibit three latent categories of chronic disease resource utilization, and resource utilization category is an influencing factor of their health-promoting behaviors. Healthcare professionals may develop targeted interventions based on chronic disease resource utilization categories in the future to enhance health-promoting behavior levels and improve health outcomes.

Full Text

Preamble

Latent Profile Analysis of Chronic Illness Resource Utilization and Its Impact on Health-Promoting Behaviors in Individuals with Prediabetes

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Abstract
Background Effective utilization of chronic illness resources can help individuals with prediabetes adhere to healthy behavior changes and improve their health status. However, the current state of chronic illness resource utilization in this population remains unclear and requires further investigation. **Objective** To explore the latent categories of chronic illness resource utilization among individuals with prediabetes and their relationship with health-promoting behaviors. **Methods** A consecutive sampling method was used to select individuals with prediabetes who underwent physical examinations at two community health service centers in Nanjing from March to July 2024. Data were collected using a general information questionnaire, the Chronic Illness Resource Survey (CIRS), and the Health-Promoting Lifestyle Profile II (HPLP-II). Latent profile analysis (LPA) was performed to classify chronic illness resource utilization, and hierarchical regression analysis was used to examine the relationship between resource utilization categories and health-

promoting behaviors. **Results** A total of 270 questionnaires were collected, with 263 valid questionnaires, yielding a 97.4% valid response rate. The mean CIRS score was (49.1$±8.7), andthemeanHPLP − IIscorewas(131.1±$17.0). Chronic illness resource utilization was categorized into three latent groups: low-resource utilization (basic dependence type) (136 individuals, 51.7%), moderate-resource utilization (limited support type) (105 individuals, 39.9%), and high-resource utilization (multiple support type) (22 individuals, 8.3%). Hierarchical regression analysis showed that, after controlling for confounding factors, the category of chronic illness resource utilization was a significant predictor of health-promoting behaviors in individuals with prediabetes ($P<0.001$), explaining 13.8% of the variance. **Conclusion** There are three latent categories of chronic illness resource utilization in individuals with prediabetes, and these categories significantly influence health-promoting behaviors. In the future, healthcare providers can implement targeted interventions based on the categories of chronic illness resource utilization to improve health-promoting behaviors and enhance health outcomes.

[**Key words**] Prediabetes; Chronic illness resource utilization; Health-promoting behaviors; Latent profile analysis; Hierarchical regression analysis

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1. Subjects and Methods

Prediabetes refers to an intermediate state where blood glucose levels are higher than normal but have not yet reached the diagnostic threshold for diabetes, including impaired fasting glucose, impaired glucose tolerance, and their combination [1]. Data show that the prevalence of prediabetes in China is 35.7%, affecting 388 million people—far exceeding the number of diagnosed diabetes patients [2]. Moreover, this population faces significantly higher risks of cardiovascular and cerebrovascular diseases, microvascular complications, cancer, and dementia compared to those with normal blood glucose levels [3-4]. Fortunately, scientific lifestyle interventions during the prediabetes stage can reverse blood glucose to normal levels. Health-promoting behaviors, as a crucial component of chronic disease prevention, have been proven to prevent and delay the progression of prediabetes and improve health outcomes [5].

During the behavior change process, individuals with prediabetes are influenced by multi-level resources including individual, family, and social factors. Chronic illness resource utilization, a concept proposed by Glasgow et al. [6] based on the social-ecological model, refers to patients' use of multiple resources for disease management, including personal coping strategies, healthcare teams, family and friends, neighborhood communities, media and policy, and organizational institutions. Previous studies have found that effective utilization of chronic illness resources can help patients establish and maintain healthy behaviors [7-8]. Qualitative research has revealed that individuals with prediabetes utilize surrounding resources to varying degrees during behavior change [9-10]. Accurately understanding resource utilization patterns in this population can help healthcare professionals develop more precise prevention support strategies and promote personalized and scientific prediabetes management. However, quantitative investigations of chronic illness resource utilization among individuals with prediabetes are currently lacking both domestically and internationally. Latent profile analysis can classify individuals based on their response patterns to observed variables, facilitating subsequent targeted interventions [11]. Therefore, this study employed latent profile analysis to identify latent categories of chronic illness resource utilization among individuals with prediabetes and explored the impact of these categories on health-promoting behaviors, providing a reference for developing interventions to enhance resource utilization and health-promoting behaviors.

1.1 Study Subjects

Using consecutive sampling, we selected individuals with prediabetes who underwent physical examinations at two community health service centers in Nanjing from March to July 2024 as study participants. Inclusion criteria were: (1) meeting the 2023 Chinese Expert Consensus on Prediabetes Intervention diagnostic criteria [1]; (2) age $\geq$ 18 years; (3) clear consciousness and no communication barriers. Exclusion criteria were: (1) comorbid malignant tumors or severe organic diseases; (2) diagnosed mental or psychological disorders; (3) pregnant women. This study was approved by the Nanjing Medical University Ethics Committee [Approval No.: NMU Ethics Review (2022) 662], and all participants voluntarily provided informed consent.

According to Kendall' s principle [12], this study included 22 variables, requiring a sample size 5-10 times the number of variables. Considering a 20% attrition rate, a minimum of 132 participants was needed. The actual study included 263 participants.

1.2 Study Instruments

1.2.1 General Information Questionnaire

Designed by the researchers based on literature review and discussion with team members, this questionnaire included gender, age, marital status, education level, employment status, average monthly family income, BMI, family history of diabetes, smoking status, and alcohol consumption. BMI was calculated by professionally trained community physicians based on measured height and weight. Smoking status was determined by whether participants had smoked in the past year, and alcohol consumption was defined as drinking at least once per week in the past year.

1.2.2 Chronic Illness Resource Survey (CIRS)

Developed by Glasgow et al. [13] and translated into Chinese by Zhong et al. [14], this questionnaire comprises 19 items across six dimensions: healthcare team (3 items), family and friends (2 items), personal coping (3 items), neighborhood community (5 items), media and policy (3 items), and organizational institutions (3 items). Each item uses a 5-point Likert scale from "never" to "very often" (1-5 points), with total scores ranging from 19-95. Dimension scores are evaluated using item means, with higher scores indicating better resource utilization. Scores <3 indicate suboptimal resource utilization, while $ $3 indicate relatively ideal utilization. The Cronbach' s α coefficient was 0.870 in this study.

1.2.3 Health-Promoting Lifestyle Profile II (HPLP-II)
Developed by Walker et al. [15] and translated into Chinese by Teng et al. [16], this scale includes 52 items across six dimensions: health responsibility (9 items), interpersonal relationships (9 items), stress management (8 items), nutrition (9 items), physical activity (8 items), and spiritual growth (9 items). Each item uses a 4-point Likert scale from "never" to "always" (1-4 points), with total scores ranging from 52-208. Higher scores indicate better health-promoting behaviors. The Cronbach' s α coefficient was 0.935 in this study.

1.3 Data Collection and Quality Control

Before data collection, trained research team members explained the study purpose, significance, and questionnaire completion methods to participants, obtained their informed consent, and distributed questionnaires for self-completion. Researchers promptly answered questions during completion. All questionnaires were collected on-site and checked for completeness. Missing items were supplemented by participants, and questionnaires with patterned responses or identical answers were deemed invalid.

1.4 Statistical Analysis

Latent profile analysis was conducted using Mplus 8.3 software. Starting from a single-class model, we progressively increased the number of classes until optimal model fit was achieved. Model fit indices included: (1) Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample size-adjusted BIC (aBIC), where smaller values indicate better fit; (2) Entropy values ranging from 0-1, with values closer to 1 indicating more precise classification (Entropy 0.8 suggests >90% classification accuracy); (3) Lo-Mendell-Rubin (LMR) and Bootstrapped Likelihood Ratio Test (BLRT) for model comparison, where $P<0.05$ indicates the K-class model fits better than the K-1 class model [11].

Since this study relied primarily on self-reported measures, common method bias might occur. We used Harman' s single-factor test [17] to assess this—if the first factor' s variance contribution was <40%, it indicated no serious common method bias. Normally distributed continuous data were expressed as ($\bar{x}\pm s$), compared between two groups using independent samples t-test and among multiple groups using one-way ANOVA. Non-normally distributed continuous data were expressed as M(P25, P75) and compared using Kruskal-Wallis H test. Categorical data were expressed as frequencies and percentages, compared using ^{2} test or Fisher' s exact test. Hierarchical regression analysis was used for multivariate analysis, with P<0.05 considered statistically significant.

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2. Results

2.1 Basic Characteristics of the Prediabetes Population

A total of 270 questionnaires were distributed, with 7 excluded as invalid, resulting in 263 valid questionnaires (97.4% valid response rate). Among the 263 participants, 110 (41.8%) were male and 153 (58.2%) female; ages ranged from 22-83 years, with a mean age of (64.3\$±10.1)*years*; 241(91.6$^{\{2\},139(52.9}$\{2\}\$, and 25 (9.5%) \$ 30.0*kg*/*m*^\{2\}; 67(25.5±8.7), *andthemeanHPLP*−*IIscorewas*(131.1±\$17.0).

2.2 Common Method Bias Test Results

The common method bias test revealed 16 factors with eigenvalues >1, with the first factor explaining 23.496% of variance (<40%), indicating no serious common method bias.

2.3 Latent Profile Analysis of Chronic Illness Resource Utilization

Using the six CIRS dimensions as observed variables, we analyzed latent profiles of chronic illness resource utilization. Starting with Model 1, we progressively established 1-4 latent class models (Table 1). As the number of profiles increased, AIC, BIC, and aBIC values decreased. Although Model 4 had the smallest information fit indices, its LMR (P) value was 0.708, suggesting poor fit. Model 3 showed smaller information fit indices than Model 2, with Entropy of 0.838 and significant LMR and BLRT values. Considering these results, Model 3 demonstrated the best fit. In discriminant analysis, the average probability of participants belonging to their assigned class ranged from 90.1%-94.6% (all >90.0%), indicating high reliability and accuracy.

Based on Model 3, mean scores for each CIRS dimension across the three classes are shown in Figure 1 [Figure 1: see original paper]. Classes were named according to dimensional score patterns. Class 1 (C1) had scores <3 across all CIRS dimensions, indicating suboptimal utilization of personal coping, healthcare team, family/friends, neighborhood community, media/policy, and organizational resources. This was named **Low Resource Utilization-Basic Dependence Type** (136 individuals, 51.7%). Class 2 (C2) had scores <3 in healthcare team and organizational institution dimensions but >3 in other dimensions, named **Moderate Resource Utilization-Limited Support Type** (105 individuals, 39.9%). Class 3 (C3) had scores >3 in all dimensions except organizational institutions, suggesting these individuals could access supportive resources through multiple channels, named **High Resource Utilization-Multiple Support Type** (22 individuals, 8.3%).

Significant differences were found among the three classes in gender, education level, employment status, average monthly family income, family history of diabetes, and smoking status (P<0.05). No significant differences were observed in age, marital status, BMI, or alcohol consumption (P>0.05) (Table 2).

2.4 Comparison of HPLP-II Scores Across Resource Utilization Classes

Significant differences existed in total HPLP-II scores and all dimension scores among the three classes (P<0.05). Post-hoc comparisons revealed that the High Resource Utilization-Multiple Support Type had the highest scores, followed by the Moderate Resource Utilization-Limited Support Type, with the Low Resource Utilization-Basic Dependence Type scoring lowest (P<0.05) (Table 3).

2.5 Relationship Between Resource Utilization Categories and Health-Promoting Behaviors

2.5.1 Comparison of HPLP-II Scores by Participant Characteristics Significant differences in HPLP-II scores were found by gender, education level, employment status, average monthly family income, BMI, family history of diabetes, and smoking/alcohol consumption status (P<0.05). No significant differences were observed by age or marital status (P>0.05) (Table 4).

2.5.2 Hierarchical Linear Regression Analysis A hierarchical linear regression analysis was conducted with HPLP-II score as the dependent variable (entered as actual values). Model 1 included gender, education level, employment status, average monthly family income, BMI, family history of diabetes, smoking status, and alcohol consumption. Model 2 added chronic illness resource utilization categories. All variance inflation factors were <5, indicating no multicollinearity. Results showed that chronic illness resource utilization category significantly influenced HPLP-II scores (P<0.05), explaining 13.8% of variance (Table 5).

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3. Discussion

3.1 Characteristics of Latent Classes of Chronic Illness Resource Utilization

This study identified three latent classes of chronic illness resource utilization among individuals with prediabetes: Low Resource Utilization-Basic Dependence Type, Moderate Resource Utilization-Limited Support Type, and High Resource Utilization-Multiple Support Type, demonstrating significant heterogeneity in resource utilization patterns.

The Low Resource Utilization-Basic Dependence Type accounted for 51.7% of participants—the largest group—with all CIRS dimension scores below the critical value, indicating suboptimal resource utilization across all domains. This aligns with findings from Ge et al. [18] and may be attributed to the asymptomatic nature of prediabetes [19]. Without obvious symptoms, individuals often underestimate their health risks and lack intrinsic motivation for behavior change, resulting in insufficient perception and low willingness to utilize preventive resources. Healthcare professionals should strengthen diabetes health education to enhance prevention awareness, improve self-management capabilities and health responsibility, and encourage active resource utilization.

The Moderate Resource Utilization-Limited Support Type comprised 39.9% of participants, with scores above the critical value in all dimensions except healthcare team and organizational institutions. This differs from findings in coronary heart disease patients where healthcare team utilization was optimal [20]. The discrepancy may stem from prediabetes being an early disease stage. While community health service centers are the primary setting for prediabetes management in China, surveys indicate insufficient attention to prediabetes at the community level, with lower rates of health education, pharmacological treatment, and lifestyle intervention compared to diabetes management [21-22]. Relevant authorities should standardize community-based prediabetes management to promote effective utilization of healthcare resources.

The High Resource Utilization-Multiple Support Type represented 8.3% of participants, with scores above the critical value in all dimensions except organizational institutions. This mirrors previous research [23], likely because few social organizations or groups currently focus on diabetes prevention, resulting in low accessibility of organizational resources. Healthcare professionals should actively promote the establishment of diabetes prevention-related social organizations to expand health resource coverage and accessibility.

3.2 Demographic Differences in Resource Utilization Categories

Significant demographic differences existed across resource utilization categories. Compared to moderate and high resource utilization groups, the low resource utilization group had higher proportions of males, individuals with junior high school education or below, average monthly family income <5,000 yuan, employed individuals, those without family diabetes history, and smokers.

Traditional gender norms may contribute to men' s higher confidence in self-managing diseases and reluctance to show vulnerability, resulting in less active resource seeking [24]. For this group, healthcare providers should create open, non-judgmental communication environments to encourage expression of health needs, reduce resistance to health resources, and enhance utilization willingness. Individuals with lower education levels may have weaker health literacy and resource utilization capabilities. Those with lower income or employment status often face financial and time constraints that limit resource utilization [26]. Healthcare professionals can help develop low-cost, flexible health management plans, such as community health screenings and telemedicine services, to reduce time and economic burdens. Additionally, smokers and those without family diabetes history often have insufficient risk perception and preventive motivation, affecting resource needs and utilization [27-28]. Risk education should be strengthened to improve awareness and promote active resource utilization. Future clinical practice should prioritize these high-risk subgroups with targeted support to improve resource utilization.

3.3 Relationship Between Resource Utilization Categories and Health-Promoting Behaviors

Achieving favorable health outcomes requires long-term adherence to health behavior changes in prediabetes [29]. This study found significant differences in health-promoting behaviors across resource utilization categories. Hierarchical regression analysis revealed that, after controlling for demographic variables, chronic illness resource utilization categories explained 13.8% of variance in health-promoting behaviors, consistent with Liu et al.' s findings among rural elderly [30]. According to Bandura' s social cognitive theory [31], individual behavior results from interactions between internal factors and external environments. The Low Resource Utilization-Basic Dependence Type lacks adequate resources across all domains, resulting in low behavior change motivation and difficulty maintaining long-term healthy behaviors. In contrast, moderate and high resource utilization groups have greater external support, higher self-efficacy, and stronger behavior change intentions, leading to better health behaviors. Therefore, healthcare interventions should assess resource utilization patterns and develop personalized strategies, particularly strengthening resource support for low and moderate resource utilization groups to improve behavior initiation and long-term adherence, thereby enhancing overall health status.

3.4 Limitations

This cross-sectional study cannot establish causal relationships between resource utilization categories and health-promoting behaviors. Additionally, participants were recruited from only two community health centers in Nanjing, and the high resource utilization group was relatively small, potentially introducing information bias. Future multi-center, large-sample longitudinal studies are needed to further explore these causal relationships.

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LEI Yang and LIN Zheng were responsible for quality control, overall article oversight, and supervision.

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Note: Figure translations are in progress. See original paper for figures.