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Questionnaire-derived Human Sensing for Health Need Assessment

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In this exploratory study, we propose a questionnaire-derived human sensing framework for assessing functional health support demands using perceived health and lifestyle signals. A structured questionnaire was completed by 40 participants. The six functional demands differed significantly (Friedman test, $\chi^2 = 28.023$, $p < 0.001$), with sleep/relaxation and heat reduction showing relatively high mean scores. Spearman correlation analysis with Benjamini–Hochberg false discovery rate (FDR) correction identified 29 significant associations among 60 signal–demand comparisons. Strong associations were observed between dryness/heat sensation and heat reduction ($\rho = 0.733$), fatigue and energy support ($\rho = 0.644$), digestive discomfort and digestive support ($\rho = 0.602$), and poor sleep and sleep/relaxation support ($\rho = 0.547$). These relationships were transformed into an interpretable FDR-supported association network. The findings demonstrate the potential of structured self-reported responses as complementary human sensing information for personalized health support assessment.

1. Introduction

The rapid development of sensing technologies has shifted health monitoring from conventional clinical measurements to continuous, human-centered assessment. Wearable and flexible sensors can acquire physiological and behavioral information under daily-life conditions. Recent advances in materials and structural design have further improved their applicability. Biomimetic hydrogels incorporating cellulose nanocrystals have enhanced wet adhesion for wearable motion sensing,(1) while cellulose nanocrystal- and lignin-reinforced composites have enabled mechanically robust and self-powered sensing.(2) Conductive-pathway optimization and biaxial strain-gauge designs have also improved signal stability and motion-tracking accuracy.(3)

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These developments demonstrate the increasing capability of physical sensors to quantify human physiological and behavioral states.

However, physical sensors mainly measure observable physiological, mechanical, or behavioral variables and may not directly capture subjective perceptions such as fatigue, stress, sleep quality, digestive discomfort, or health-support needs. Self-reported information can therefore provide a complementary human sensing layer. Conventional retrospective questionnaires may be affected by recall bias,[4] whereas ecological momentary assessment (EMA) captures subjective information closer to real-world experiences. The validity of EMA has been increasingly investigated for measuring behaviors and subjective experiences in natural environments.[5] Recent studies have demonstrated associations between EMA and accelerometer-derived measurements[6] and have combined EMA, wearable sensing, and machine learning to investigate affective states and user receptivity.[7] Together, these approaches illustrate the growing convergence of subjective assessment and digital sensing for characterizing human states.

Digital phenotyping further extends this concept by using personal digital devices and sensor-derived behavioral features to characterize health-related states.[8,9] Recent studies indicate that digital health assessment increasingly combines passive sensing with self-reported measures, highlighting their complementary roles in characterizing individual health states.[9,10] From a broader human sensing perspective, structured questionnaire responses can be treated as human-generated signals representing subjective health perceptions and functional demands. Unlike conventional questionnaire-based health assessment, in which responses are primarily summarized as scores or interpreted as predefined constructs, the proposed framework treats individual responses as quantitative sensing variables and examines their data-supported relationships across two information layers. It then transforms these relationships into an interpretable association network. The novelty of this approach lies not in the questionnaire itself but in the methodological transformation of structured subjective responses into quantitative sensing variables, false discovery rate (FDR)-supported signal–demand associations, and an interpretable human sensing network that can complement physical sensing modalities.

Nevertheless, converting multidimensional self-reported information into meaningful health need representations remains challenging. Health recommender systems increasingly use user-specific information, yet the transparent interpretation of relationships between individual characteristics and health needs remains important.[11] Network-based representations provide a potential solution by organizing heterogeneous health variables and their relationships into interpretable structures. Healthcare knowledge graphs have consequently attracted increasing attention for integrating heterogeneous information, representing relationships, and supporting health-related inference and recommendation.[12–14] Knowledge graph-based health recommender systems have also demonstrated the potential of structured relational information to provide individualized health support.[15]

For ordinal questionnaire data, statistical association analysis can provide quantitative evidence before network construction. In particular, Spearman's rank correlation can identify monotonic relationships between perceived health signals and functional health-support

demands without assuming normally distributed data. When multiple signal–demand relationships are examined simultaneously, FDR control can further reduce the likelihood of false-positive associations. A network constructed from FDR-supported relationships may therefore provide a transparent representation of multidimensional subjective sensing information while reducing reliance on predefined mappings.

Therefore, in this study, we propose a questionnaire-derived human sensing framework for health-need assessment using an FDR-supported association network. Perceived health and lifestyle signals and six functional health-support demands were collected using a structured questionnaire and quantitatively analyzed. The resulting statistically supported signal–demand relationships were transformed into an interpretable network. Rather than replacing physical sensors or providing clinical diagnoses, the proposed framework complements conventional sensing technologies by converting structured subjective responses into interpretable human sensing information for future personalized and human-centered health applications. From a sensing science perspective, this questionnaire-derived layer provides subjective information that may not be directly observable using conventional physical sensors. In a future multimodal human sensing system, these subjective signals can be synchronized with wearable measurements such as motion, heart rate, skin temperature, and physiological strain, as well as environmental measurements such as ambient temperature and humidity. Such integration can provide complementary subjective and objective information for a more comprehensive representation of human health states.

2. Materials and Methods

2.1 Study design and participants

A cross-sectional questionnaire-based study was conducted from March to August 2026 to investigate the relationships between self-reported health and lifestyle signals and functional health-support demands. A study-specific structured online questionnaire was distributed to adult participants, and 40 valid responses were collected. The present study was designed as an exploratory feasibility study to examine the applicability of the proposed questionnaire-derived human sensing framework rather than as a confirmatory population-level investigation. Participation was voluntary, and the questionnaire was completed anonymously for academic research purposes. Responses with incomplete questionnaire items were excluded from the analysis. After data screening, all 40 responses contained complete questionnaire data and were included in the final analysis.

Basic demographic information included age, sex, body mass index (BMI), pregnancy status, pregnancy planning, or breastfeeding status. Additional information regarding digestive sensitivity, sensitivity to caffeine or other stimulants, the history of herbal allergies, and preference for low-sugar or sugar-free beverages was collected to characterize the study population and provide contextual information for health-need assessment. These variables were used for participant characterization and were not included as primary variables in the

subsequent association-network analysis. The overall study framework, including questionnaire-based data collection, human sensing signal extraction, statistical analysis, and association network construction, is illustrated in Fig. 1.

2.2 Questionnaire-derived human sensing

The study-specific questionnaire consisted of 24 items (Q1–Q24) organized into four sections. Q1–Q4 collected demographic and basic physiological information. Q5–Q14 assessed perceived health and lifestyle signals, including fatigue, cold sensitivity, dryness or heat sensation, poor sleep quality, stress, digestive discomfort, irregular bowel habits, sedentary behavior, late bedtime, and poor concentration. These variables were treated as questionnaire-derived human sensing signals representing subjective health and lifestyle states.

Q15–Q20 assessed six functional health-support demands: energy support, sleep and relaxation, digestive support, metabolic support, heat reduction, and general wellness. Q5–Q14 were evaluated using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), whereas Q15–Q20 were scored from 1 (very low demand) to 5 (very high demand). Higher scores therefore represented stronger perceived conditions or greater functional health-support demands. The questionnaire structure used for the subsequent analysis is summarized in Table 1.

Q21–Q24 collected information regarding digestive sensitivity, caffeine or stimulant sensitivity, herbal allergy history, and preference for low-sugar or sugar-free beverages. These items were used only to describe individual health-related characteristics and preferences, and were not included in the primary signal–demand correlation analysis. Rather than assuming that predefined combinations of questionnaire items represented validated latent health constructs, perceived health and lifestyle signals (Q5–Q14) and functional health-support demands (Q15–Q20) were analyzed as two related layers of questionnaire-derived information. The questionnaire was developed specifically for this exploratory study and was not intended to constitute a validated psychometric instrument. Formal expert content validation, pilot testing, and psychometric reliability assessment were not performed before data collection. Accordingly, the individual questionnaire items were analyzed directly rather than interpreted as validated latent constructs or combined into psychometric composite scores. Accordingly, individual

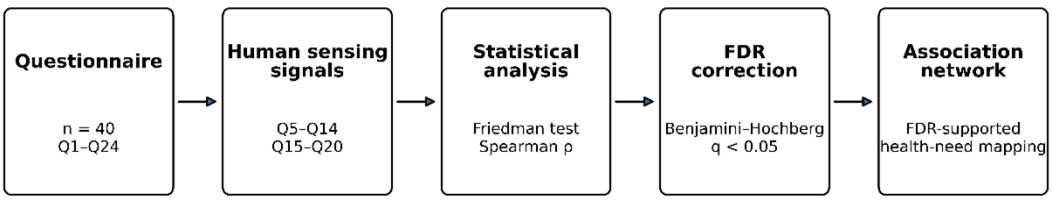


Fig. 1. Overall framework of questionnaire-derived human sensing and FDR-supported health need assessment.

Table 1
Structure and classification of questionnaire items used for questionnaire-based human sensing and health need assessment.

Item	Questionnaire item	Classification	Scale
Q5	I frequently feel fatigued.	Perceived health signal	1–5
Q6	I frequently feel sensitive to cold.	Perceived health signal	1–5
Q7	I frequently experience dryness or a sensation of internal heat.	Perceived health signal	1–5
Q8	My sleep quality is poor.	Perceived health signal	1–5
Q9	I frequently experience high levels of stress.	Perceived health signal	1–5
Q10	I frequently experience digestive discomfort or abdominal bloating.	Perceived health signal	1–5
Q11	My bowel habits are irregular.	Perceived health signal	1–5
Q12	I spend prolonged periods sitting during daily activities.	Lifestyle signal	1–5
Q13	I frequently stay up late.	Lifestyle signal	1–5
Q14	I have recently experienced difficulty concentrating.	Perceived health signal	1–5
Q15	I would like to improve my energy level or receive energy support.	Functional health-support demand	1–5
Q16	I would like to improve my sleep or promote relaxation.	Functional health-support demand	1–5
Q17	I would like to improve my digestive function.	Functional health-support demand	1–5
Q18	I would like support for metabolism or weight management.	Functional health-support demand	1–5
Q19	I would like to reduce sensations of dryness or internal heat.	Functional health-support demand	1–5
Q20	I would like general support for daily health maintenance.	Functional health-support demand	1–5

Note: Q5–Q14 represent questionnaire-derived human sensing signals, whereas Q15–Q20 represent functional health-support demands. Higher scores indicate stronger perceived conditions or greater health-support demands. The individual items were analyzed directly and were not combined into predefined composite health scores.

items were analyzed directly without constructing composite scores or assuming an underlying psychometric scale. This approach enabled the direct examination of the relationships between subjective human sensing signals and corresponding functional health demands.

The two-layer structure of the questionnaire-based human sensing framework and its relationship with the subsequent association analysis are illustrated in Fig. 2.

2.3 Statistical analysis

Descriptive statistics were calculated to characterize the participants and questionnaire responses. Because the questionnaire responses were measured on five-point ordinal Likert scales, medians were calculated as appropriate descriptive statistics. Means and standard deviations (SDs) were additionally reported only to facilitate a descriptive comparison of response levels among the six functional health-support demands and were not used as the basis for inferential testing. Categorical variables were expressed as frequencies and percentages. Inferential analyses of the ordinal data were performed using nonparametric methods, including Spearman's rank correlation and the Friedman test.

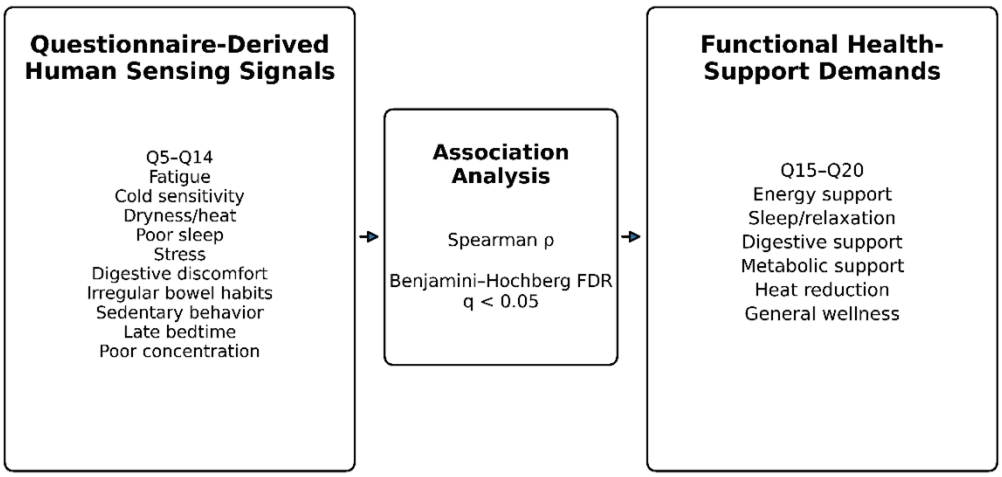


Fig. 2. Two-layer structure of questionnaire-derived human sensing linking perceived health and lifestyle signals to functional health-support demands through FDR-controlled association analysis.

Because Q5–Q20 were measured using ordinal Likert scales, Spearman's rank correlation coefficient (ρ) was used to evaluate associations between perceived health and lifestyle signals (Q5–Q14) and functional health-support demands (Q15–Q20). A total of 60 pairwise signal–demand correlations were evaluated. Statistical significance was defined as $p < 0.05$.

To account for multiple comparisons and reduce the likelihood of false-positive associations, the Benjamini–Hochberg FDR procedure was applied to the 60 correlation tests. Both the original p-values and the FDR-adjusted q-values were considered when interpreting the results. Associations with an FDR-adjusted $q < 0.05$ were regarded as statistically supported relationships for network construction. The distributions of the six functional health-support demands (Q15–Q20) were additionally compared using the Friedman test because these ordinal measurements were obtained repeatedly from the same participants. A two-sided significance level of 0.05 was adopted for statistical testing. Statistical analyses were performed in Python using the pandas, SciPy, and statsmodels libraries, with FDR correction.

2.4 Construction of data-supported health need association network

A data-supported health need association network was constructed to provide an interpretable representation of the relationships between questionnaire-derived human sensing signals and functional health-support demands. The network consisted of two types of node: perceived health and lifestyle signals, derived from Q5–Q14, and functional health-support demands, derived from Q15–Q20.

An edge was established between two nodes only when a positive Spearman correlation remained statistically significant after FDR correction ($q < 0.05$). Edge thickness was

proportional to the magnitude of the Spearman correlation coefficient, allowing stronger associations to be visually distinguished from weaker relationships. Thus, the network topology was determined directly from the statistical results rather than from predefined symptom–demand mappings. The network representation complemented the complete correlation matrix by highlighting FDR-supported pathways linking perceived conditions to functional health-support demands.

The resulting framework transforms questionnaire responses into quantitative human sensing signals and subsequently identifies statistically supported associations between perceived health conditions and functional health-support demands. These associations are further organized into an interpretable health need network, providing a data-supported representation of the relationships among the questionnaire-derived variables. The network represents statistical associations rather than causal or diagnostic relationships and is intended for health need interpretation rather than clinical diagnosis or product-level recommendation.

3. Results and Discussion

3.1 Participant characteristics and response profiles

A total of 40 participants completed all questionnaire items and were included in the analysis. No missing responses were identified. Participants aged 40–49 years constituted the largest age group (67.5%). Regarding sex, 22 participants were male, 17 were female, and one response contained an ambiguous selection and was therefore excluded only from sex-based interpretation. The BMI category of 18.5–24 represented the largest proportion of the study population (55.0%).

The additional questionnaire items revealed several characteristics relevant to health-support assessment. Sixteen participants (40.0%) reported digestive sensitivity or susceptibility to diarrhea, and eight (20.0%) indicated sensitivity to caffeine or other stimulating beverages. In addition, 31 participants (77.5%) preferred low-sugar or sugar-free beverages. These findings illustrate the heterogeneity of individual health-related characteristics and preferences within the study population. Because these variables were collected primarily for participant characterization, they were not interpreted as primary human sensing variables or included in the subsequent signal–demand association analysis. Note that the sample was strongly concentrated in the 40–49-year age group (67.5%). This demographic concentration may affect both the prevalence of perceived health conditions and the relative levels of functional health-support demands observed in the present study.

3.2 Functional health-support demands

The distributions of the six functional health-support demands are shown in Fig. 3. Sleep/relaxation support exhibited the highest mean score (4.10 ± 0.90), followed by heat reduction (4.03 ± 1.07), digestive support (3.92 ± 1.19), general wellness (3.77 ± 1.31), and metabolic support (3.70 ± 1.36). Energy support showed the lowest mean score (3.12 ± 1.16).

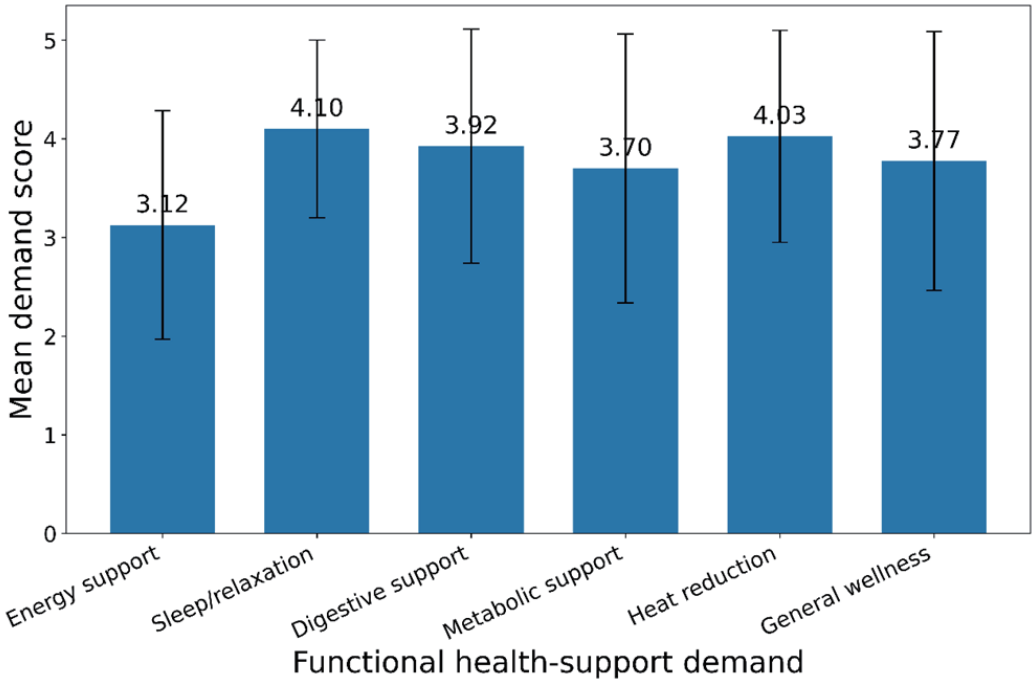


Fig. 3. (Color online) Mean scores of the six functional health-support demands among the participants (n = 40). Error bars represent SDs.

The Friedman test revealed a significant overall difference among the six functional health-support demands (χ^2 = 28.023, p < 0.001), indicating that participants did not express uniform levels of demand across the assessed dimensions. Descriptively, sleep/relaxation and heat reduction had the highest mean scores, whereas energy support had the lowest mean score. Because no post-hoc pairwise comparisons were performed, these descriptive differences should not be interpreted as evidence of statistically significant differences between specific demand pairs.

3.3 Associations between human sensing signals and health-support demands

Spearman correlation analysis was performed to investigate the relationships between perceived health and lifestyle signals (Q5–Q14) and functional health-support demands (Q15–Q20). A total of 60 signal–demand correlations were examined, and the Benjamini–Hochberg FDR procedure was applied to account for multiple comparisons. Of the 31 associations with unadjusted p < 0.05, 29 remained statistically significant after FDR correction (q < 0.05). As shown in Fig. 4, several conceptually corresponding signal–demand pairs exhibited significant positive associations.

The strongest association was observed between dryness/heat sensation (Q7) and heat reduction demand (Q19), with a Spearman correlation coefficient of ρ = 0.733 (FDR-adjusted

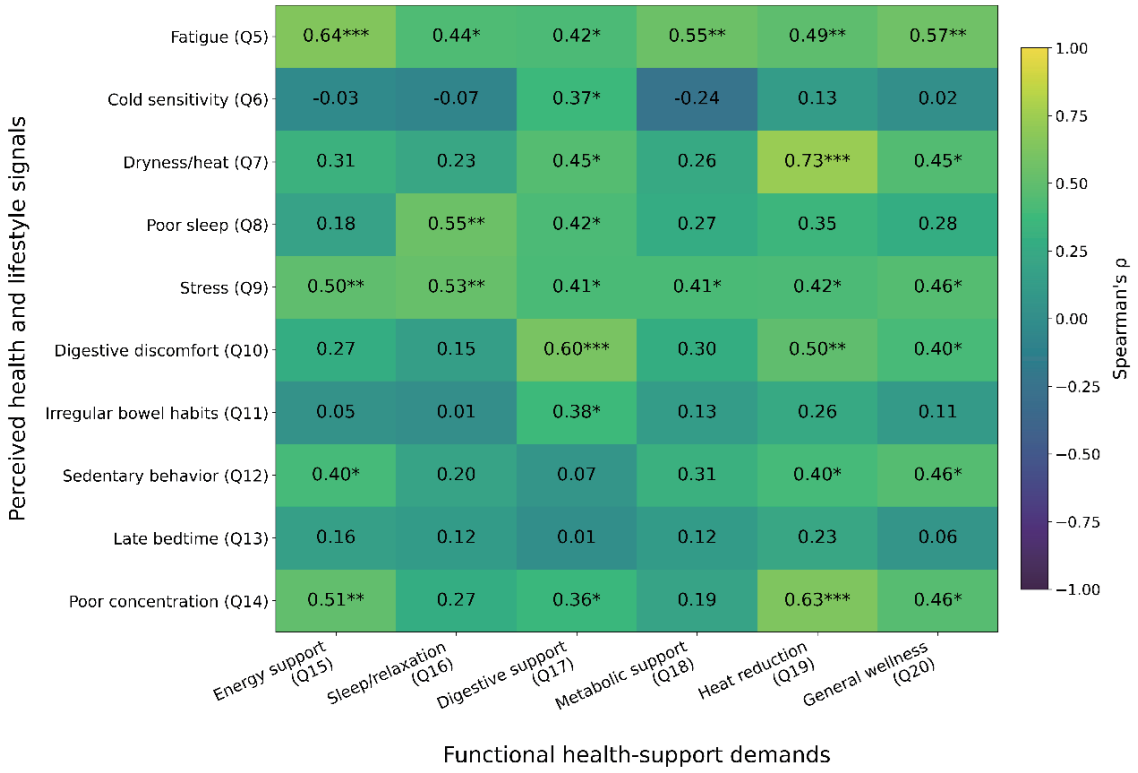


Fig. 4. (Color online) Spearman correlation heatmap between questionnaire-derived perceived health and lifestyle signals (Q5–Q14) and functional health-support demands (Q15–Q20) among 40 participants. Values represent Spearman's rank correlation coefficients (ρ). Statistical significance was determined after Benjamini–Hochberg FDR correction: $q < 0.05$, $q < 0.01$, and $q < 0.001$.

$q = 4.49 \times 10^{-6}$). Fatigue (Q5) was strongly associated with energy support (Q15) ($\rho = 0.644$, $q = 2.22 \times 10^{-4}$), while digestive discomfort (Q10) was positively associated with digestive support (Q17) ($\rho = 0.602$, $q = 6.03 \times 10^{-4}$). Poor sleep quality (Q8) was also significantly associated with sleep and relaxation support (Q16) ($\rho = 0.547$, $q = 0.00221$).

In addition to these conceptually direct relationships, several signals were associated with multiple functional demands. For example, fatigue was also associated with general wellness ($\rho = 0.567$) and metabolic support ($\rho = 0.551$), while poor concentration showed a strong association with heat reduction demand ($\rho = 0.627$). Unlike the more conceptually direct relationships, such as fatigue–energy support and poor sleep–sleep/relaxation support, the association between poor concentration and heat reduction demand is less intuitive. It may reflect overlapping subjective experiences, correlated self-perceptions, or unmeasured contextual factors within the present sample rather than a direct physiological relationship. Therefore, this cross-domain association should be regarded as exploratory and requires independent validation before physiological or clinical interpretation.

The persistence of the four principal signal–demand relationships after correction for 60 simultaneous comparisons strengthens the evidence that these associations are unlikely to result solely from multiple-testing effects. Because perceived conditions and functional demands were assessed independently rather than combined into predefined composite scores, the observed relationships provide empirical support for treating structured self-reported responses as questionnaire-derived human sensing signals.

Not all conceptually plausible relationships were supported statistically. For example, sedentary behavior (Q12) showed only a modest association with metabolic support (Q18) ($\rho = 0.307$) and did not remain significant after FDR correction. This finding further supports deriving signal–demand relationships from observed data rather than assigning them solely on the basis of conceptual expectations.

3.4 FDR-supported health need association network

To provide an interpretable representation of the correlation results, the statistically supported positive associations were extracted from the complete correlation matrix and organized into the health need association network shown in Fig. 5. Only associations that remained significant after Benjamini–Hochberg FDR correction ($q < 0.05$) were retained as network edges. Perceived health and lifestyle signals were represented as source nodes, whereas functional health-support demands were represented as target nodes. Edge thickness was proportional to the magnitude of Spearman's rank correlation coefficient (ρ).

The resulting network contained 29 FDR-supported positive associations and revealed both direct and cross-domain signal–demand relationships. The strongest association was observed between dryness/heat sensation and heat reduction demand ($\rho = 0.733$), followed by fatigue and energy support ($\rho = 0.644$), poor concentration and heat reduction ($\rho = 0.627$), digestive discomfort and digestive support ($\rho = 0.602$), and fatigue and general wellness ($\rho = 0.567$). Poor sleep was also strongly associated with sleep/relaxation support ($\rho = 0.547$). These findings indicate that some perceived conditions correspond closely to conceptually related functional demands, whereas others are associated with multiple health-support dimensions.

Compared with the complete correlation heatmap in Fig. 4, the network provides a more interpretable representation of statistically supported signal–demand pathways. Whereas the heatmap displays all 60 pairwise correlations, the network selectively retains only FDR-supported positive associations and makes it easier to identify individual signals connected to multiple functional demands. Thus, its added value lies primarily in relational interpretability rather than in providing an independent predictive model or additional statistical test. Importantly, the network topology was derived directly from FDR-adjusted statistical relationships rather than predefined symptom–demand mappings. This data-driven transformation from questionnaire responses to an association network represents the central contribution of the proposed questionnaire-derived human sensing framework. It enables multidimensional subjective responses to be organized into interpretable health-need information without assuming predefined composite health scores.

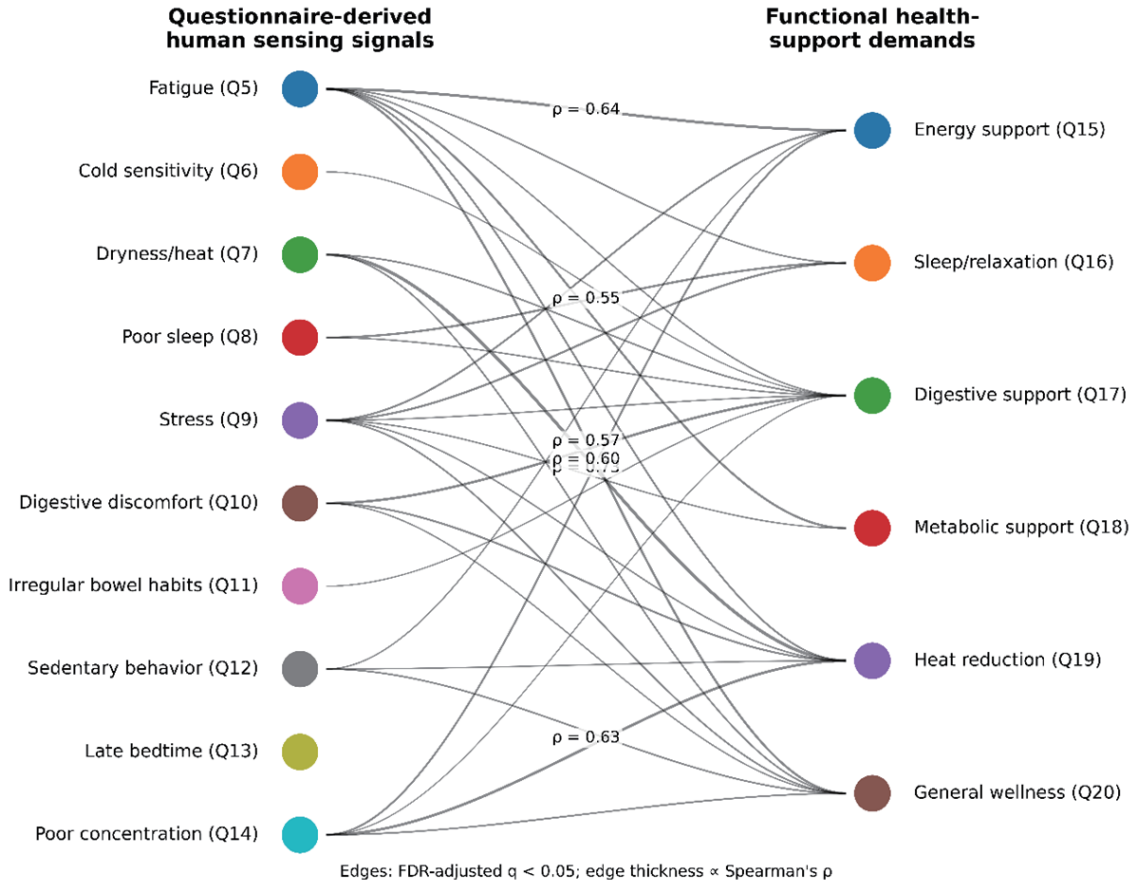


Fig. 5. (Color online) FDR-supported association network between questionnaire-derived perceived health and lifestyle signals and functional health-support demands. Only positive associations remaining significant after Benjamini–Hochberg FDR correction ($q < 0.05$) are shown. Edge thickness is proportional to Spearman's rank correlation coefficient (ρ). Correlation coefficients are labeled for selected strong associations ($\rho \geq 0.55$); $n = 40$.

The network should not be interpreted as a causal or diagnostic model but as an exploratory representation of statistical relationships between questionnaire-derived human sensing signals and perceived functional health-support demands. Several limitations should be considered. First, the relatively small sample size ($n = 40$), particularly in relation to the 60 signal–demand comparisons, may affect the stability and precision of the estimated correlations and network topology. Although FDR correction reduced the likelihood of false-positive findings, it does not eliminate sampling variability associated with a small cohort. Second, both variable layers were self-reported by the same participants during the same questionnaire session; therefore, common-method variance and shared response tendencies cannot be excluded. Third, the study-

specific questionnaire had not undergone formal content validation, pilot testing, or psychometric reliability assessment. Finally, 67.5% of the participants were aged 40–49 years, which limits generalization to younger and older populations. Future studies should therefore validate the framework in larger, independent, and age-balanced cohorts, incorporate expert questionnaire validation and psychometric evaluation, and integrate questionnaire-derived signals with objective physiological, wearable, and environmental sensor measurements. Such multimodal validation will help determine whether the observed signal–demand relationships remain stable across measurement modalities and demographic subgroups.

4. Conclusion

In this study, we demonstrated the feasibility of a questionnaire-derived human sensing framework for assessing functional health-support demands. The six demands differed significantly (Friedman test, $\chi^2 = 28.023$, $p < 0.001$), while descriptive statistics showed relatively high mean scores for sleep/relaxation and heat reduction. Among 60 signal–demand correlations, 29 remained significant after Benjamini–Hochberg FDR correction. Strong associations were identified between dryness/heat sensation and heat reduction ($\rho = 0.733$), fatigue and energy support ($\rho = 0.644$), digestive discomfort and digestive support ($\rho = 0.602$), and poor sleep and sleep/relaxation support ($\rho = 0.547$). These relationships were transformed into an interpretable FDR-supported association network. Although limited by the small sample size, the proposed framework demonstrates the potential of structured self-reported responses as complementary human sensing information. Future studies should validate the framework in larger populations and integrate questionnaire-derived signals with objective sensor measurements.

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include information and communication security, software supply chain security, blockchain technology, post-quantum cryptography, IoT security, AI, explainable AI (XAI), medical signal and image processing, mobile and wireless networking, and applied cryptography.
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