Causal Factors Influencing Liver Fluke Disease Prevention Behaviors in Health Region 10: A Structural Equation Modeling Study with Qualitative Behavioral Insights

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Abstract
Despite control programs, liver fluke (Opisthorchis viverrini) prevalence remains at 6.62% in Health Region 10, northeastern Thailand. This study investigated the causal factors influencing prevention behaviors among people with a history of infection using Structural Equation Modeling (SEM) and supplementary qualitative interviews. A cross-sectional survey was conducted among 630 individuals across five provinces (Ubon Ratchathani, Sisaket, Yasothon, Amnat Charoen, and Mukdahan), alongside in-depth interviews with 50 participants.SEM analysis revealed that communication was the strongest predictor of prevention behavior ($\beta = 0.705$, $p < 0.001$), while knowledge had a minimal direct effect ($\beta = 0.022$\$). The model explained 49.23% of the variance in behavior ($R^2 = 0.492$). Economic factors exerted a moderate negative effect ($\beta = -0.139$). Qualitatively, a distinct knowledge–behavior gap emerged: 60% of interviewees continued to consume raw fish primarily driven by taste preference (83%) yet 50% reported that witnessing local illness or death was a more powerful behavioral motivator than abstract health knowledge. Liver fluke prevention in Health Region 10 is driven by local communication infrastructure and visible community consequences rather than knowledge expansion alone. Public health strategies should transition from conventional, knowledge-focused education to spatially targeted communication systems and community-level risk messaging that addresses socio-cultural and structural barrier.

Keywords: Geometric Harmonisation, Inter-Agency Interoperability, Land Parcel Data, Multipurpose Cadastre, Spatial Data Integration

1. Introduction

1.1 Background and Significance

Liver fluke infection caused by *Opisthorchis viverrini* remains one of the most important food-borne parasitic diseases in Southeast Asia. Fish-borne liver flukes, including *O. viverrini*, are recognized as major human health threats in endemic regions and are strongly associated with hepatobiliary morbidity and cholangiocarcinoma [1]. Foodborne trematode infections occur through the consumption of contaminated raw or undercooked freshwater fish, crustaceans, or aquatic plants, and their transmission is closely linked to food hygiene, sanitation, animal reservoirs, and community-level practices [2]. In Thailand, the disease burden is geographically concentrated in the northeastern region, where ecological conditions, freshwater fish consumption patterns, local food culture, and community-level behavioral practices interact to sustain transmission.

Health Region 10, located in northeastern Thailand, represents a major endemic area for liver fluke infection. The region comprises five provinces: Ubon Ratchathani, Sisaket, Yasothon, Amnat Charoen, and Mukdahan. Despite decades of control efforts and the implementation of the Decade Strategic Plan for the Elimination of Liver Fluke and Cholangiocarcinoma during 2016–2025, infection remains above the national elimination target. Regional prevalence has been reported at 6.62%, while Sisaket Province recorded the highest prevalence at 10.41% [3]. Cholangiocarcinoma incidence in this region has also remained high, ranging from approximately 25 to 35 cases per 100,000 population annually.

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From a geoinformatics and spatial public health perspective, this persistent burden indicates that liver fluke prevention is not only a biomedical or educational problem, but also a geographically embedded behavioral and environmental challenge. Risk is distributed across communities where cultural food practices, communication access, economic constraints, environmental exposure, and local health-service systems vary by place. Therefore, understanding the causal factors that shape prevention behavior at the regional level is essential for designing spatially targeted interventions and improving public health resource allocation in endemic areas.

1.2 Research Problem

Although liver fluke control programs in northeastern Thailand have included health education, mass screening, praziquantel treatment, environmental sanitation, and community mobilization, sustained behavioral change remains limited. Raw and undercooked freshwater fish consumption continues to be practiced in many communities, reflecting deeply rooted food traditions and social norms. This persistence suggests that infection control cannot rely solely on individual-level knowledge dissemination.

A central challenge is the gap between knowledge and actual preventive behavior. Previous literature shows that helminth-related malignancy must be understood through complex biological, behavioral, environmental, and contextual pathways rather than through infection knowledge alone [4]. Reinfection among previously treated individuals further indicates that biomedical treatment and health education alone may be insufficient when broader social, cultural, economic, communication, and environmental determinants remain unaddressed. Recent geospatial and environmental health research also emphasizes that *O. viverrini* infection patterns are shaped by interactions among physical environment, social conditions, and healthcare interventions [5].

This problem is particularly relevant because liver fluke prevention requires more than general health messaging. It requires an understanding of how behavioral risk determinants are distributed across administrative and community settings, and how communication systems, environmental exposure, and structural barriers influence prevention behavior in specific geographic contexts. However, most previous studies have focused on prevalence, knowledge, or risk behavior separately, while limited evidence has examined the causal structure linking multiple determinants of prevention behavior across an endemic health region.

1.3 Study Approach and Objective

This study applies Structural Equation Modeling (SEM) to examine the causal relationships among social-cultural factors, communication factors, economic factors, environmental factors, knowledge, and liver fluke prevention behavior among individuals with a history of liver fluke infection in Health Region 10. SEM is appropriate for this study because it allows simultaneous analysis of multiple direct and indirect relationships, including the mediating role of knowledge and the relative strength of each determinant within a single causal model [6]. To strengthen interpretation of the SEM results, supplementary in-depth interviews were conducted with participants from all five provinces in Health Region 10. These qualitative behavioral insights were used to explain the mechanisms underlying the quantitative pathways, particularly why some determinants had stronger effects on prevention behavior than others. This integrated approach provides both statistical estimation and contextual explanation, supporting the development of geographically targeted and behaviorally informed public health interventions. The primary objective of this study was to investigate causal factors influencing liver fluke disease prevention behaviors in Health Region 10 using Structural Equation Modeling, with knowledge examined as a mediating variable. The findings are intended to support spatially responsive health planning, communication-system strengthening, and targeted intervention design for liver fluke control in endemic regions.

2. Methods

2.1 Study Design and Spatial Setting

This study employed a cross-sectional analytical design using Structural Equation Modeling (SEM) to examine causal relationships among factors influencing liver fluke disease prevention behaviors. The study was conducted in Health Region 10, northeastern Thailand, a major endemic area for *Opisthorchis viverrini* infection. The study area comprised five provinces: Ubon Ratchathani, Sisaket, Yasothon, Amnat Charoen, and Mukdahan (Figure 1). These provinces represent a geographically connected public health region where liver fluke infection remains persistent despite long-term prevention and control programs. Data were collected between January and June 2024. The regional scope of the study allowed analysis of behavioral determinants across multiple provincial settings within the same health-administrative region.

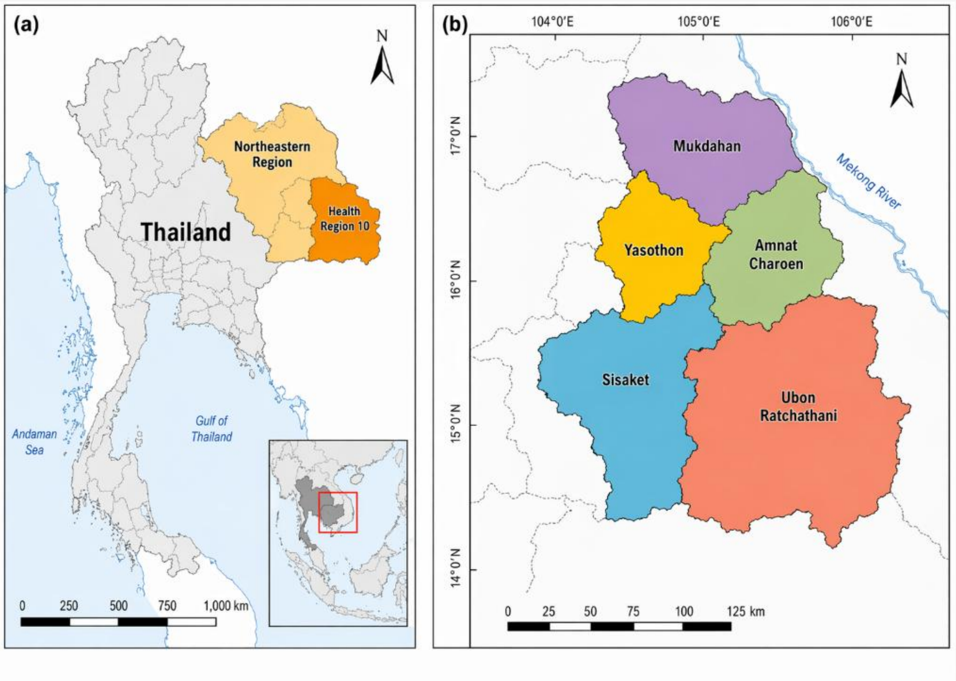

Figure 1: Study area in Health Region 10, northeastern Thailand

This design supports geographically informed public health interpretation by linking individual-level prevention behaviors with regionally distributed social, communication, economic, and environmental determinants. A supplementary qualitative component was also included to provide deeper understanding of behavioral mechanisms underlying the quantitative SEM findings. In-depth interviews were conducted with a subset of participants to explore motivations, barriers, and contextual conditions influencing liver fluke prevention behaviors. These qualitative insights complemented the SEM analysis by explaining how and why specific causal pathways influenced behavior in endemic community settings.

This study is divided into seven stages as shown in Figure 2 as follows: (1) study design and spatial setting definition across Health Region 10; (2) sample size calculation and multi-stage cluster sampling (N = 630); (3) parallel data collection using a structured self-administered questionnaire and supplementary in-depth interviews; (4) quantitative analysis using Structural Equation Modeling (SEM) and qualitative analysis using content analysis; (5) integration of quantitative and qualitative findings with GIS-based spatial interpretation; (6) results and discussion of causal pathways; and (7) conclusions and policy recommendations.

2.2 Study Population and Sample Size

The target population consisted of individuals with a documented history of liver fluke infection residing in Health Region 10. Eligible participants were adults living in one of the five study provinces and having a previous record or history of liver fluke infection. The study focused on this population because individuals with prior infection represent a high-risk group for reinfection and are directly relevant to prevention behavior analysis. The sample size was calculated according to SEM sample size recommendations, which suggest a minimum of 10 observations per estimated model parameter [6]. The proposed structural model contained 42 estimated parameters. After applying a design effect of 1.5 to account for cluster sampling, the required final sample size was 630 participants.

Multi-stage cluster sampling with proportionate stratified allocation was used to ensure representation across the five provinces in Health Region 10. The final provincial distribution was as follows: Ubon Ratchathani, 252 participants (40.0%); Sisaket, 203 participants (32.2%); Yasothon, 75 participants (11.9%); Amnat Charoen, 52 participants (8.3%); and Mukdahan, 48 participants (7.6%). This geographically stratified allocation ensured that the sample reflected the regional distribution of the target population across the health-administrative area.

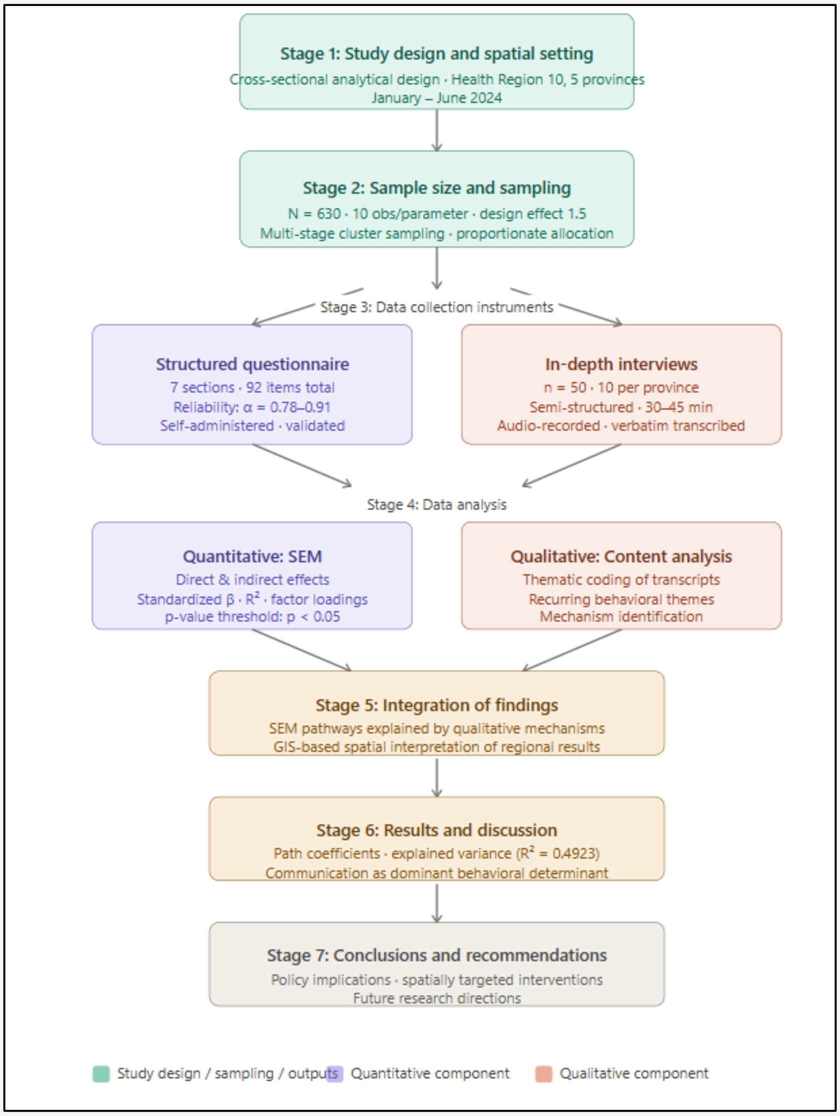

Figure 2: Structural equation modeling for liver fluke disease prevention behaviors study workflow

2.3 Research Instruments

Data were collected using a structured self-administered questionnaire developed to measure individual, social, communication, economic, environmental, knowledge, and behavioral dimensions related to liver fluke disease prevention. The questionnaire consisted of seven sections:

1. Demographic characteristics;
2. Social culture, 10 items, Cronbach's $\alpha = 0.87$;
3. Economic factors, 10 items, Cronbach's 0.84;
4. Knowledge, 20 items, KR-20 = 0.78;
5. Communication, 10 items, Cronbach's $\alpha = 0.91$;
6. Environmental factors, 10 items, Cronbach's $\alpha = 0.82$; and
7. Prevention behaviors, 12 items, Cronbach's $\alpha = 0.89$.

The reliability coefficients ranged from 0.78 to 0.91, indicating acceptable to excellent internal consistency. The instrument was designed to capture both individual-level determinants and community-contextual factors relevant to liver fluke prevention in geographically endemic settings. All sections were pilot-tested prior to full deployment, and item wording was refined based on expert review and cognitive pre-testing with five participants from the target population to ensure clarity, cultural appropriateness, and comprehensiveness of coverage across all measured constructs.

2.4 Statistical Analysis

Descriptive statistics were used to summarize participant characteristics and latent variable scores. Structural Equation Modeling was then applied to examine the hypothesized causal relationships among social culture, communication, economic factors, environmental factors, knowledge, and prevention behaviors. Knowledge was specified as a mediating variable in the structural model. The SEM analysis estimated direct effects, indirect effects through knowledge, and total effects. Standardized path coefficients (β), coefficients of determination (R^2), and factor loadings were calculated. The explanatory power of the model was assessed using R^2 values for endogenous variables. Statistical significance was set at $p < 0.05$. The analytical approach enabled simultaneous estimation of multiple behavioral determinants and their relative contributions to liver fluke prevention behavior. This was appropriate for examining complex prevention behavior in an endemic geographic region where social, communication, economic, and environmental conditions may operate together rather than independently.

2.5 Supplementary Behavioral Interviews

To strengthen interpretation of the SEM findings, supplementary semi-structured interviews were conducted with a purposive sample of 50 participants. Ten participants were selected from each of the five provinces in Health Region 10 to ensure geographic balance across the study area. The interviews explored behavioral motivations, perceived barriers, decision-making processes, communication exposure, cultural food practices, and factors influencing liver fluke prevention behavior. Each interview lasted approximately 30–45 minutes, was audio-recorded with participant permission, and was transcribed verbatim. Content analysis was used to identify recurring themes that explained the quantitative findings, particularly the strong effect of communication on prevention behavior and the weak direct effect of knowledge. The qualitative component provided contextual interpretation of the SEM pathways and clarified behavioral mechanisms that could not be fully captured through questionnaire data alone.

2.6 Ethical Considerations

Ethical approval was obtained from the Institutional Review Board of Ubon Ratchathani University. All participants were informed about the study objectives, procedures, voluntary participation, confidentiality, and the right to withdraw from the study at any time. Written informed consent was obtained from all participants before data collection. Participant confidentiality and data privacy were maintained throughout the study. Personal identifiers were removed from the dataset, and interview transcripts were anonymized before analysis.

3. Results

3.1 Participant Characteristics

Table 1 presents the demographic and geographic distribution of the 630 participants included in the study. The sample was drawn from all five provinces in Health Region 10, northeastern Thailand, enabling regional-level interpretation of liver fluke prevention behavior across an endemic health-administrative area. The sample comprised 328 females (52.1%) and 302 males (47.9%). In terms of geographic distribution, the largest proportion of participants resided in Ubon Ratchathani Province (n = 252, 40.0%), followed by Sisaket Province (n = 203, 32.2%), Yasothon Province (n = 75, 11.9%), Amnat Charoen Province (n = 52, 8.3%), and Mukdahan Province (n = 48, 7.6%). This distribution reflected the proportionate stratified allocation across the five provinces in Health Region 10. Most participants were farmers (n = 478, 75.9%), indicating that the study population was predominantly engaged in rural and agriculture-based livelihoods. All participants reported a history of raw fish consumption and previous liver fluke infection, confirming that the sample represented a high-risk population relevant to prevention behavior analysis. Supplementary interview participants (n = 50) showed similar demographic characteristics and were equally distributed across the five provinces, with 10 participants recruited from each province.

Table 1: Demographic and geographic characteristics of participants (N = 630)

Characteristic	n	%
Gender		
Male	302	47.9
Female	328	52.1
Province of residence		
Ubon Ratchathani	252	40.0
Sisaket	203	32.2
Yasothon	75	11.9
Amnat Charoen	52	8.3
Mukdahan	48	7.6
Occupation		
Farmer	478	75.9

3.2 Descriptive Statistics of Latent Variables

Table 2 summarizes the descriptive statistics of the latent variables included in the structural model. These variables represent individual and contextual determinants of liver fluke disease prevention behavior among participants residing across the five provinces of Health Region 10. Participants demonstrated a high level of knowledge regarding liver fluke transmission and prevention, with a mean score of 18.30 out of 20. Communication also showed a high mean score of 39.92, suggesting substantial exposure to prevention-related messages, communication channels, or community-based information systems. Prevention behavior was likewise high, with a mean score of 49.90 out of 60. In contrast, economic factors showed the lowest relative mean score at 25.90, indicating that economic conditions may function as a structural constraint affecting the implementation of preventive practices. Environmental factors showed a moderate mean score of 30.97, reflecting the continuing relevance of local environmental exposure within the endemic geographic context of Health Region 10. Overall, the descriptive results suggest that although participants had high knowledge and relatively strong prevention behavior, contextual determinants, particularly communication and economic conditions remained important for explaining behavioral variation across the study region.

3.3 Measurement Model and Factor Loadings

Table 3 presents the factor loading summary for the latent constructs used in the SEM analysis. The factor loadings indicate the extent to which the observed indicators represented their corresponding latent variables. The measurement model demonstrated acceptable to excellent indicator quality across the latent variables. Communication showed the highest mean factor loading at 0.820, with loadings ranging from 0.712 to 0.873. This indicates that the communication indicators were highly consistent in representing the communication construct. Prevention behavior also showed strong measurement quality, with a mean loading of 0.726 and a range of 0.478 to 0.835. Social culture demonstrated a high mean loading of 0.760, while economic factors and environmental factors showed acceptable mean loadings of 0.687 and 0.626, respectively. Knowledge had the lowest mean loading at 0.390, with a range of 0.286 to 0.508. Although some knowledge indicators were relatively weak, the construct was retained because knowledge was theoretically important as a mediating variable in the hypothesized causal model. Overall, the factor loading results supported the use of the measurement model for subsequent structural analysis.

3.4 Structural Model, Path Coefficients, and Explained Variance

The structural model examined the direct effects of communication, economic factors, social culture, environmental factors, and knowledge on liver fluke disease prevention behavior. The model also assessed the role of knowledge as a mediating variable. Table 4 shows that the model explained 7.66% of the variance in knowledge ($R^2 = 0.077$) and 49.23% of the variance in prevention behavior ($R^2 = 0.492$). The R^2 value for prevention behavior indicates that the structural model had substantial explanatory power for behavioral outcomes in this endemic regional setting. Communication emerged as the dominant predictor of prevention behavior, showing a very strong positive effect ($\beta = 0.705$, $p < 0.001$). This indicates that participants with stronger communication exposure or access to prevention-related communication systems were more likely to report appropriate liver fluke prevention behaviors. From a geoinformatics-oriented public health perspective, this finding suggests that communication infrastructure may be a key spatially actionable determinant for intervention planning across endemic communities.

Table 2: Descriptive statistics of latent variables (N = 630)

Variable	Mean	SD	Min	Max
Knowledge (K)	18.30	1.76	4.0	20.0
Social culture (S)	19.01	8.43	10.0	50.0
Communication (C)	39.92	8.75	10.0	50.0
Economic factors (E)	25.90	8.54	10.0	50.0
Environmental factors (EN)	30.97	7.71	10.0	50.0
Prevention behavior (B)	49.90	8.47	24.0	60.0

Table 3: Factor loading summary of latent variables

Latent variable	Indicators	Mean loading	Range
Knowledge (K)	20	0.390	0.286–0.508
Social culture (S)	10	0.760	0.591–0.853
Communication (C)	10	0.820	0.712–0.873
Economic factors (E)	10	0.687	0.473–0.777
Environmental factors (EN)	10	0.626	0.400–0.732
Prevention behavior (B)	12	0.726	0.478–0.835

Table 4: Direct effects on prevention behavior ($R^2 = 0.492$)

Path	β (standardized)	Interpretation
Communication → Behavior	0.705***	Very strong
Economic factors → Behavior	−0.139	Moderate negative
Social culture → Behavior	−0.074	Minimal
Environmental factors → Behavior	0.036	Minimal
Knowledge → Behavior	0.022	Minimal

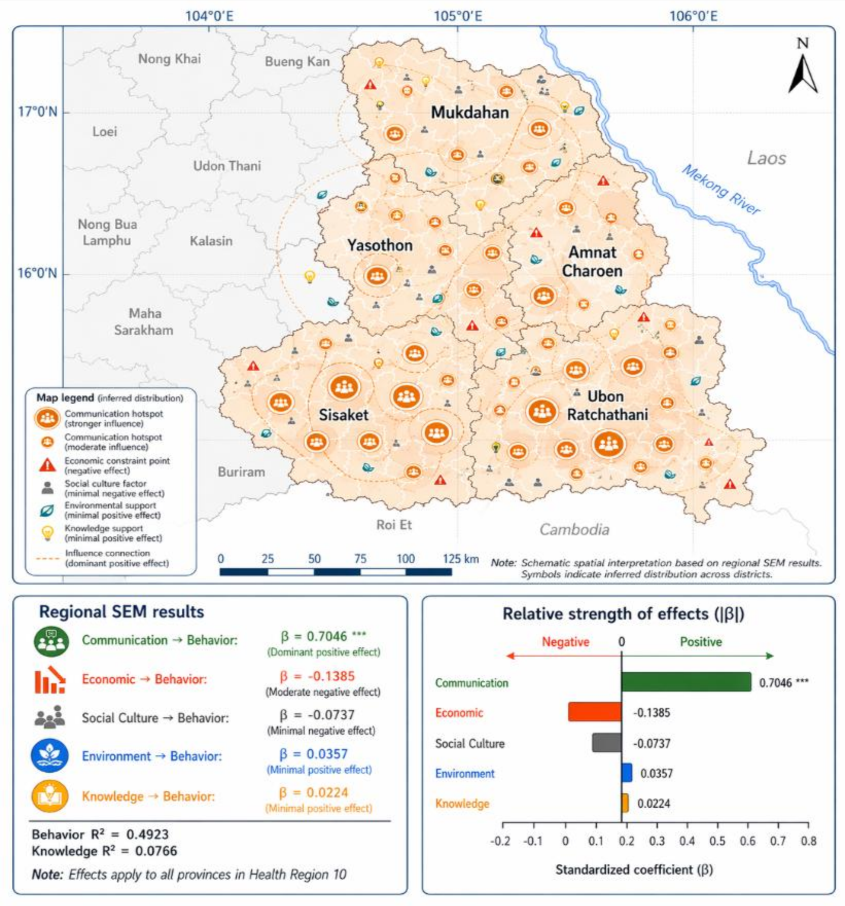

Figure 3: Spatial interpretation of factors influencing liver fluke prevention behavior in Health Region 10

Economic factors showed a moderate negative direct effect on prevention behavior ($\beta = -0.139$), suggesting that economic constraints may reduce the likelihood of adopting or sustaining preventive practices. Social culture showed a minimal negative effect ($\beta = -0.047$), while environmental factors showed a minimal positive effect ($\beta = 0.036$). Knowledge demonstrated only a minimal direct effect on prevention behavior ($\beta = 0.022$), despite the high mean knowledge score observed in Table 2. All indirect effects through knowledge were negligible, with values below 0.01. This indicates that knowledge did not function as a meaningful mediator in the structural model. The findings therefore suggest that liver fluke prevention behavior in Health Region 10 is driven more strongly by communication and structural conditions than by knowledge alone. This result is important for spatially targeted prevention planning because it indicates that improving communication systems and reducing practical barriers may produce greater behavioral impact than expanding knowledge-based education alone.

This GIS-based figure translates the regional SEM results into a spatially interpretable public health framework across the five provinces of Health Region 10. As shown in Figure 3, communication was mapped as the dominant region-wide driver because it exerted the strongest positive effect on prevention behavior ($\beta = 0.705$, $p < 0.001$). Economic constraints were represented as secondary negative barriers ($\beta = -0.139$), whereas social culture, environment, and knowledge showed only minimal direct effects ($\beta = -0.074$, $\beta = 0.036$, and β

= 0.022, respectively). The model explained 49.23% of behavioral variance ($R^2 = 0.492$), indicating that spatially targeted communication infrastructure is a more actionable prevention pathway than knowledge expansion alone.

3.5 Behavioral Insights from Supplementary Interviews

Supplementary interviews with 50 participants provided contextual explanation for the SEM findings, particularly the dominant effect of communication on prevention behavior and the weak direct effect of knowledge. The qualitative findings clarified how region-wide behavioral determinants operated within local community settings across Health Region 10.

3.5.1 Mechanisms underlying the strong communication effect

Communication showed the strongest positive effect on prevention behavior in the SEM model ($\beta = 0.705$, $p < 0.001$). Interview findings revealed three mechanisms explaining this dominance.

First, visible consequences were more influential than abstract biomedical information. Twenty-five interviewees (50%) reported that witnessing illness or death among community members was their primary motivation for changing behavior. One participant stated: “In my village, three people died from liver cancer last year. When I saw their families crying at the funerals, that’s when I really stopped eating raw fish. All the pamphlets about ‘parasites’ didn’t mean anything until I saw real people dying” (Male, 54 years, Ubon Ratchathani). This finding indicates that locally observable consequences transformed disease risk from abstract knowledge into a socially and emotionally salient reality.

Second, participants emphasized communication infrastructure rather than information volume. Thirty interviewees (60%) reported that regular village broadcasting, repeated reminders, and face-to-face communication from health volunteers were more useful than receiving additional disease facts. A participant explained: “We don’t need more information about the disease. Everyone already knows it’s bad. What we need is regular reminders through the village speaker system something we hear every day so we don’t forget” (Female, 52 years, Yasothon). This suggests that communication acted as a spatially embedded support system, reinforcing prevention behavior through repeated community-level exposure.

Third, interactive communication created practical problem-solving opportunities. Eighteen interviewees (36%) who participated in training sessions reported that interactive formats helped them discuss real-life barriers, receive immediate advice, and translate general health messages into feasible behavioral practices. This mechanism helps explain why communication had a much stronger effect than knowledge alone: communication did not merely transmit information but also created behavioral reinforcement, social accountability, and locally actionable support.

3.5.2 Mechanisms underlying the weak knowledge effect

Despite high knowledge scores (mean = 18.30 out of 20), knowledge showed only a minimal direct effect on prevention behavior ($\beta = 0.022$). Interview findings identified three mechanisms explaining this knowledge–behavior gap.

First, abstract knowledge did not always generate sufficient behavioral conviction. Thirty-five interviewees (70%) acknowledged that liver fluke disease was serious, but 30 interviewees (60%) still reported continued raw fish consumption. One participant stated: “Yes, I know it causes cancer. But lots of things cause cancer air pollution, stress, genetics. Why should I give up something I enjoy when I might get cancer anyway?” (Male, 56 years, Sisaket). This illustrates that knowledge may exist cognitively without becoming a decisive behavioral trigger.

Second, taste preference overrode risk awareness. Among the 30 interviewees who continued consuming raw fish, 25 participants (83%) identified taste as the main reason. One participant noted: “I know it’s risky. My doctor told me to stop. But *koi pla* is so delicious nothing else tastes like it. I try to eat it less often, but I can’t completely stop” (Female, 42 years, Ubon Ratchathani). This finding indicates that prevention behavior was shaped by sensory preference and cultural food attachment, not by knowledge alone.

Third, knowledge was not always activated at the point of decision-making. Although all 50 interviewees had received health education and could correctly answer knowledge questions, many reported that risk knowledge was not salient during social eating situations. One participant explained: “Of course I know about liver fluke. But when I’m at a party and everyone’s eating *koi pla*, I’m not thinking about parasites. I’m thinking about enjoying time with friends” (Male, 49 years, Yasothon). This finding suggests that prevention failure occurred not because knowledge was absent, but because social context and immediate situational cues overpowered risk awareness.

Overall, the qualitative findings strengthen the SEM interpretation by showing that communication influenced behavior through consequence visibility, repeated community reinforcement, and interactive problem-solving. In contrast, knowledge remained weak because it was often abstract, overridden by taste preference, and inactive during real-world eating decisions. These mechanisms support the conclusion that liver fluke prevention in Health Region 10 requires spatially targeted communication systems and community-based behavioral reinforcement rather than knowledge dissemination alone.

3.6 Structural Equation Model

Figure 4 presents the final Structural Equation Model (SEM) of causal factors influencing liver fluke disease prevention behaviors in Health Region 10. The model illustrates standardized path coefficients among social culture, communication, economic factors, environmental factors, knowledge, and prevention behavior, together with the explained variance of endogenous variables.

The structural model confirmed that communication was the dominant direct determinant of prevention behavior, with the strongest standardized path coefficient ($\beta = 0.705$, $p < 0.001$). This pathway indicates that communication systems, including community-based messaging, repeated reminders, and health volunteer interactions, were substantially more influential than knowledge alone in shaping preventive behavior. Economic factors showed a moderate negative direct effect on prevention behavior ($\beta = -0.139$), suggesting that financial and livelihood-related constraints may limit the adoption or continuity of protective practices. In contrast, social culture ($\beta = -0.074$), environmental factors ($\beta = 0.036$), and knowledge ($\beta = 0.022$) showed only minimal direct effects.

The mediating role of knowledge was weak. Although knowledge was included as a theoretical mediator, its direct effect on prevention behavior was minimal, and indirect effects through knowledge were negligible. This result supports the interpretation that behavior change in this endemic region is not primarily driven by information acquisition, but by communication intensity, social reinforcement, and practical enabling conditions. The model explained 7.66% of the variance in knowledge ($R^2 = 0.077$) and 49.23% of the variance in prevention behavior ($R^2 = 0.492$). The substantial explanatory power for prevention behavior indicates that the SEM captured key behavioral determinants relevant to spatially targeted public health intervention planning. Overall, the model demonstrates four critical findings: strong communication-driven behavioral influence, moderate economic constraint, weak knowledge mediation, and substantial behavioral variance explained at the regional level.

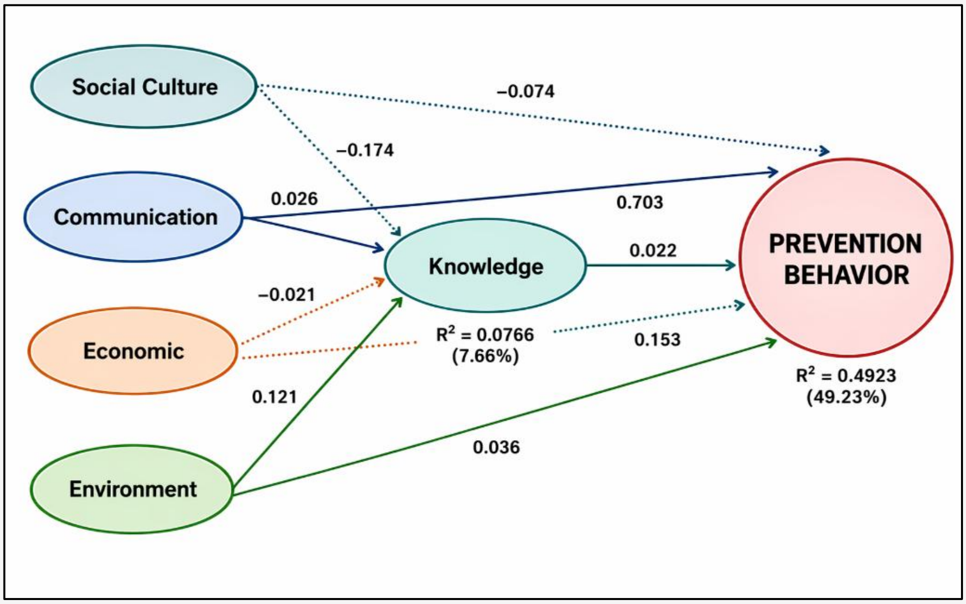

Figure 4: Structural equation model of causal factors influencing liver fluke prevention behaviors

4. Discussion

4.1 Key findings and Theoretical Implications

The principal finding of this study is that communication infrastructure was the dominant causal determinant of liver fluke prevention behavior in Health Region 10 ($\beta = 0.705$, $p < 0.001$; $R^2 = 0.492$). This finding is consistent with Social Cognitive Theory, which emphasizes that behavioral acquisition and maintenance depend on observational learning, social reinforcement, and environmental enabling conditions rather than individual knowledge alone [7]. The strong communication effect supports the view that prevention behavior is shaped by community-level information systems rather than isolated educational inputs. The weak direct effect of knowledge ($\beta = 0.022$), despite high mean knowledge scores, parallels evidence from O. viverrini-endemic communities showing that raw fish consumption persists even among highly knowledgeable populations [8] and that misconceptions and socially embedded eating behaviors maintain infection risk independently of knowledge levels [9]. These findings indicate that the knowledge–behavior gap is a consistent and regionally robust phenomenon in liver fluke prevention. The moderate negative effect of economic factors ($\beta = -0.139$) provides an important structural explanation for prevention failure, consistent with geospatial evidence that O. viverrini infection risk is partly shaped by socioeconomic conditions distributed across communities [5].

4.2 Implications for Public Health Practice

The findings indicate that liver fluke prevention in Health Region 10 should be redesigned from a knowledge-centered model toward a spatially targeted communication-and-support model. Although knowledge remains necessary as a foundation for disease prevention, the weak direct effect of knowledge on prevention behavior ($\beta = 0.022$) suggests that additional information alone is unlikely to generate substantial behavioral change. In contrast, the strong communication effect ($\beta = 0.705$, $p < 0.001$) indicates that prevention programs should prioritize the systems through which risk messages are repeatedly delivered, socially reinforced, and translated into daily practice.

First, communication infrastructure should become the primary operational target. Public health agencies should strengthen village broadcasting systems, health volunteer networks, household-level communication, and locally trusted communication channels. Rather than delivering one-time educational messages, interventions should use repeated reminders, locally meaningful narratives, community testimonials, and interactive problem-solving formats. This approach is consistent with Health GIS and disease surveillance perspectives, which emphasize spatial monitoring, data integration, and geographically organized public health response systems [10] and [13].

Second, prevention programs should reduce structural barriers that limit behavior change. The negative effect of economic factors ($\beta = -0.139$) suggests that high-risk populations may not be able to act on prevention messages when screening costs, treatment access, protein alternatives, or work-related time constraints remain unresolved. Therefore, liver fluke prevention should be integrated with subsidized screening and treatment, affordable safe-food alternatives, and community-level economic support mechanisms. District and sub-district systems should be used to identify communities where economic constraints may reduce prevention feasibility.

Third, interventions should make disease consequences visible and socially meaningful. The qualitative findings showed that witnessing illness or death among community members motivated behavior change more strongly than abstract biomedical facts. Public health campaigns should therefore use community-based narratives, survivor or family testimonials, peer support groups, and locally observable examples of cholangiocarcinoma consequences. This does not mean replacing scientific information, but translating it into socially and emotionally salient communication that can influence real-world decisions.

From a geoinformatics perspective, these implications support a shift from asking, “Do people know?” to asking, “Where are communication gaps, structural barriers, and behavioral support needs concentrated?” GIS-based planning can help identify priority districts, allocate village health volunteer coverage, monitor communication reach, and coordinate community-level prevention activities [13][14] and [15]. This aligns with IJG evidence showing that effective disease management requires local operational systems, cooperation mechanisms, and continuous information use rather than isolated health messages [11]. Similar geographically organized service-monitoring approaches have also been applied to prevention and outbreak response systems [12].

Overall, the practical implication is clear: knowledge should remain part of prevention, but it should no longer be treated as the core intervention mechanism. For Health Region 10, the most actionable strategy is to strengthen spatially targeted communication infrastructure, reduce economic barriers, and embed prevention messages within local social systems. Such a strategy is also consistent with spatial epidemiological evidence showing that liver fluke-related hepatobiliary abnormalities and cholangiocarcinoma risks are geographically patterned and require area-specific planning [14] and [15].

4.3 Strengths and Limitations

This study has several strengths. First, it applied a comprehensive SEM framework to examine multiple determinants of liver fluke prevention behavior simultaneously, including social culture, communication, economic factors, environmental factors, knowledge, and prevention behavior. This allowed estimation of direct effects, indirect effects, and relative explanatory power within a single structural model. Second, the sample size was adequate for SEM analysis, with 630 participants recruited from all five provinces in Health Region 10 using proportionate stratified allocation. Third, the measurement instruments showed acceptable to excellent reliability, with coefficients ranging from 0.78 to 0.91. Fourth, supplementary interviews with 50 participants added explanatory depth to the quantitative findings by clarifying why communication had a strong effect while knowledge had only a minimal direct effect.

Another strength is the regional and spatial relevance of the study. By covering Ubon Ratchathani, Sisaket, Yasothon, Amnat Charoen, and Mukdahan, the study provides evidence that is directly applicable to Health Region 10 as a public health planning unit. The integration of SEM results with GIS-based spatial interpretation also strengthens the usefulness of the findings for geographically targeted intervention planning, particularly in endemic areas where behavioral risk, communication access, and structural constraints vary across communities. This is important because foodborne trematode control still faces global evidence gaps in mapping, surveillance, and local implementation capacity [16].

However, several limitations should be acknowledged. First, the cross-sectional design limits causal inference. Although SEM estimates directional pathways based on theory and model specification, longitudinal or intervention studies are needed to confirm causal effects over time. Second, self-reported prevention behavior may be affected by recall bias or social desirability bias, especially because raw fish consumption is a culturally sensitive behavior. Third, the model explained 49.23% of the variance in prevention behavior, leaving 50.77% unexplained. This suggests that additional factors—such as taste preference, habit strength, peer pressure, food availability, household decision-making, and unconscious eating routines—may also influence prevention behavior.

Fourth, the GIS-based interpretation presented in Figure 3 is an inferred spatial interpretation of regional SEM results, not a measured district-level statistical model. Province- or district-specific coefficients were not estimated in this study. Therefore, the spatial symbols should be interpreted as a planning-oriented visualization of region-wide behavioral mechanisms rather than as exact local effect estimates. Future studies should validate this schematic interpretation using district-level spatial data, infection surveillance records, environmental exposure indicators, and longitudinal behavioral follow-up [16][17] and [18]. Previous GIS-based studies in Thailand have demonstrated the value of spatial statistical analysis for identifying liver fluke risk areas, but further integration with behavioral modeling remains necessary [17].

Finally, although the findings are highly relevant to Health Region 10, generalization to other endemic regions should be made cautiously. Other provinces may differ in infection ecology, food culture, local communication systems, economic conditions, and public health infrastructure. Evidence from other northeastern Thai settings confirms that *O. viverrini* infection remains shaped by localized behavioral and contextual risk factors, supporting the need for validation across different endemic areas [18]. Despite these limitations, the study provides a strong evidence base for redesigning liver fluke prevention policy. The combined SEM, interview, and GIS-oriented interpretation demonstrates that effective prevention requires not only knowledge dissemination, but also spatially organized communication systems and structural support mechanisms tailored to endemic communities.

5. Conclusion

This study demonstrates that liver fluke disease prevention behavior in Health Region 10 is driven primarily by communication infrastructure rather than knowledge expansion alone. Communication showed the strongest direct effect on prevention behavior ($\beta = 0.705$, $p < 0.001$), while knowledge had only a minimal direct effect ($\beta = 0.022$), despite high knowledge scores among participants. The model explained 49.23% of the variance in prevention behavior ($R^2 = 0.492$), indicating that the identified determinants provide a strong empirical basis for intervention design.

The integrated SEM and interview findings show that behavior change operates through visible consequences, repeated community communication, behavioral support systems, and social norm reinforcement. In contrast, the knowledge–behavior gap persists because taste preference overrides risk awareness, abstract knowledge lacks emotional salience, and knowledge is often not activated during real-world eating decisions.

From a geoinformatics perspective, the findings support a shift from generalized health education toward spatially targeted communication systems. Prevention strategies should prioritize village broadcasting networks, health volunteer communication, community testimonials, interactive problem-solving, and district-level monitoring of communication reach. Economic and structural barriers should also be reduced through affordable screening, accessible treatment, safe-food alternatives, and locally coordinated support mechanisms.

Overall, the challenge is not simply to generate more knowledge, but to deliver prevention communication through the right channels, in the right places, and with sufficient repetition to influence everyday behavior. For Health Region 10, an effective liver fluke prevention strategy should be communication-centered, spatially organized, and structurally supported. This approach offers a practical pathway for strengthening endemic disease control and for advancing GIS-informed public health intervention planning in similar high-risk regions.

Further recommendations for policy and practice are proposed based on these findings. First, provincial health offices in Health Region 10 should establish communication monitoring dashboards that integrate village-level broadcasting reach, health volunteer activity records, and infection surveillance data, enabling evidence-based allocation of communication resources across endemic districts. Second, liver fluke prevention messaging should be systematically embedded within existing primary health care programs and community health volunteer frameworks rather than delivered as standalone campaigns, ensuring sustained behavioral reinforcement through channels that communities already trust. Third, pilot interventions applying a communication-centered behavioral model should be prioritized in the highest-prevalence districts particularly in Sisaket Province (prevalence 10.41%) to generate rigorous local evidence on the effectiveness of repeated community communication, consequence visibility strategies, and interactive problem-solving formats. Fourth, culturally appropriate safe-food alternatives to raw freshwater fish should be developed and promoted in collaboration with local communities, reducing behavioral risk without undermining food culture or social practices associated with traditional cuisine. Future research should validate these findings using district-level spatial statistical models, longitudinal cohort designs, and multi-region comparative studies across other endemic provinces in Thailand and Southeast Asia, to strengthen the generalizability of evidence for communication-centered liver fluke control programs.

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