

## PAIN & AGING SECTION

# What makes life go well? A network topic modeling analysis of well-being practices in adults with chronic pain

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### Abstract

**Objective:** This study leverages natural language processing techniques to identify specific practices older adults with chronic pain adopt to enhance well-being.

**Method:** We applied network topic modeling to open-ended survey responses from 683 adults (57% female) who reported experiencing chronic pain in the Midlife in the United States (MIDUS) study, analyzing responses to the question “What do you do to make your life go well?” Structural equation modeling was used to examine the relationships between identified topics and measures of pain interference and prescription pain medication use, adjusting for sociodemographics and well-being indicators.

**Results:** The analyses revealed 12 key topics, including avoiding stress, maintaining social connections, and practicing spirituality and faith. Notably, maintaining social connections was negatively associated with pain interference ( $\beta = -0.14$ ,  $SE = 0.05$ ,  $P < .05$ ) and prescription pain medication use ( $\beta = -0.11$ ,  $SE = 0.04$ ,  $P < .05$ ).

**Conclusion:** The findings demonstrate the utility of network topic modeling in identifying complex psychosocial dimensions influencing chronic pain management, providing insights into the distinct role of well-being practices in shaping pain outcomes.

**Keywords:** chronic pain; well-being; natural language processing; topic modeling; network psychometrics.

### Introduction

Chronic pain is a pervasive health issue that significantly impacts individuals’ quality of life and well-being, affecting over 30% of people worldwide.<sup>1</sup> The substantial healthcare costs and lost productivity from chronic pain<sup>2,3</sup> are further compounded by a myriad of physical, psychological, and social consequences, including reduced mobility, depression, anxiety, sleep disturbances, and decreased social participation.<sup>4–6</sup> Given the significant burden of chronic pain, identifying factors that contribute to well-being and resilience in this population is crucial.

Decades of research, from foundational studies on the biopsychosocial model to recent meta-analyses, underscore the crucial role of psychological factors in chronic pain outcomes.<sup>4,7–9</sup> Research consistently demonstrates that higher levels of well-being correlate with reduced pain intensity, more effective coping strategies, and better overall functioning among individuals with chronic pain.<sup>10–14</sup> Building on these findings, positive psychological interventions, including gratitude exercises and mindfulness practices, have shown promise in reducing pain intensity and enhancing well-being.<sup>15,16</sup> However, most research has focused on measuring well-being as an outcome rather than examining the specific practices individuals actively employ to enhance their well-being. This distinction between measuring “being well” (the end-state of well-being) and understanding “doing well” (the

active engagement in well-being-promoting behaviors) aligns with contemporary theoretical perspectives that view well-being as a dynamic process rather than a static outcome.<sup>17,18</sup>

While traditional self-report measures (eg, pain intensity and severity) have provided valuable insights into the relationship between well-being and pain,<sup>19,20</sup> they may not fully capture the complex ways individuals actively maintain well-being while living with chronic pain. Qualitative research has provided valuable insights into the lived experiences of individuals with chronic pain, highlighting the intricate interplay between pain, emotions, coping strategies, and social support.<sup>21,22</sup> This work underscores the importance of understanding how individuals actively navigate life with chronic pain, highlighting both their capacity for self-directed management and their unique insights into effective well-being practices. While interventions play a valuable role, individuals with chronic pain often develop personal strategies that reflect their lived experiences and specific needs. This person-centered perspective suggests the value of examining naturally occurring well-being practices that emerge from individuals’ daily experiences of managing chronic pain. However, there remains a need for methods that can systematically analyze these qualitative data to uncover the specific well-being practices individuals engage in and their potential impact on pain outcomes.

Recent advances in natural language processing (NLP) have enabled innovative methods for analyzing complex datasets and uncovering insights that may be overlooked by

Received: 12 June 2024. Revised: 24 October 2024. Accepted: 12 December 2024

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traditional quantitative approaches.<sup>23</sup> Topic modeling, a specific NLP method, has shown potential in identifying latent themes and patterns in textual data, providing insights into how individuals conceptualize and pursue well-being.<sup>24–26</sup> While various sources of textual data exist, including social media posts and clinical documentation, open-ended survey responses from representative samples offer particular advantages for understanding well-being practices. These responses provide direct reflections on specific aspects of well-being, collected within a structured research context. To date, however, research applying topic modeling to such open-ended responses from individuals living with chronic pain remains scarce.

The present study aims to investigate the relationship between self-reported practices that individuals believe improve their quality of life and pain outcomes (pain interference and pain medication use) within a national sample of US adults living with chronic pain. By leveraging NLP and network topic modeling, we seek to identify latent topics in participants' open-ended responses, providing a nuanced understanding of how individuals conceptualize and pursue well-being in the context of chronic pain. Furthermore, we examine the associations between these well-being practices and pain outcomes, controlling for traditional well-being measures (eg, positive affect, purpose in life) and sociodemographic characteristics.

## Methods

This study employed a novel mixed-methods framework that bridges qualitative and quantitative approaches to understanding chronic pain management. While traditional qualitative methods excel at capturing individual experiences and quantitative methods identify broad patterns, network topic modeling offers a unique middle ground. By integrating constructivist approaches to qualitative research<sup>27</sup> with advanced computational text analysis,<sup>26</sup> this method enables systematic identification of shared patterns while preserving the rich, person-centered nature of qualitative data. This methodological integration aligns with emerging perspectives on mixed-methods research that emphasize maintaining individual voices while generating insights across larger populations.<sup>28</sup>

### Participants

The Midlife in the United States (MIDUS) longitudinal study provided data for this investigation. MIDUS began in 1994–1995, recruiting a nationwide sample of 7108 non-institutionalized, English-speaking adults aged 25–74 through random digit dialing. The study conducted follow-up assessments in 2004–2006 (MIDUS 2) and 2013–2015 (MIDUS 3). In 2011, responding to the Great Recession's impact on health and well-being, researchers launched the MIDUS Refresher study.<sup>29</sup> This Refresher study maintained the original methodology, using random digit dialing to recruit new participants who completed 30-min phone interviews ( $n = 3577$ , response rate 59%) and self-administered questionnaires (73% completion rate). To increase racial diversity, researchers also recruited a supplementary sample of primarily Black participants from Milwaukee County, WI ( $n = 508$ , response rate 47.7%), of whom 59% completed the self-administered questionnaires.

The analytical sample was drawn from 3 primary data sources: MIDUS 2 ( $n = 4963$ ), MIDUS Refresher ( $n = 3577$ ),

and MIDUS Milwaukee Refresher ( $n = 508$ ). Participants were included in the final analytical sample if they met 2 key criteria: (1) reported experiencing chronic pain, defined as “pain persisting beyond the typical healing period and lasting from a few months to several years,” and (2) completed the open-ended response question “What do you do to make your life go well?” The resulting analytical sample comprised 683 participants, with 373 (54.6%) from MIDUS 2, 271 (39.7%) from MIDUS Refresher, and 39 (5.7%) from MIDUS Milwaukee Refresher. MIDUS data collection was reviewed and approved by the Education and Social/Behavioral Sciences and the Health Sciences IRBs at the University of Wisconsin-Madison. The MIDUS data are publicly accessible at: <https://midus.colectica.org/>.

## Measures

### Open-ended responses

The open-ended responses to the question “What do you do to make your life go well?” were used to derive the topics in the network topic model. Several preprocessing steps were taken to prepare the open-ended response data for analysis. First, the responses were converted to lowercase with white-space and punctuation removed. Standard English stopwords (eg, “I,” “the”) and custom stopwords from the open-ended question stem (eg, “make,” “my,” “life”) were removed using the *tm*<sup>30</sup> package in R. This text cleaning process focused the data on the meaningful keywords provided by respondents. The *tm* package was then used to generate unigrams (ie, single-word tokens) from the responses. For example, the sentence “The drummer plays well” contains, after the removal of stopwords, the unigrams “drummer,” “plays,” and “well.” Words were also stemmed, a process that converts words to their root form to consolidate related terms. For example, the words “walking,” “walked,” and “walks” would each be represented by the root word “walk.” This standardization helps identify common concepts even when expressed in different grammatical forms, while maintaining clear semantic relationships between terms.

The degree of sparsity<sup>31</sup> (ie, infrequent word usage across responses) allowed in the analysis was optimized by empirically identifying the number of words that provided the greatest amount of information as measured by the Total Entropy Fit Index (TEFI<sup>26</sup>). TEFI is a relative measure of fit that guides model selection in network analysis. When analyzing textual data, TEFI helps determine the optimal number of topics by evaluating how well different solutions capture the underlying structure of the data. Lower TEFI values indicate better fit, similar to other model fit indices. For example, when comparing solutions with different numbers of topics (eg, 3, 5, 7, or 9), TEFI helps identify which dimensionality best represents the underlying patterns in participants' responses while avoiding both oversimplification and unnecessary complexity<sup>26,32</sup> (see the [Supplemental Material](#) for additional details about the sparsity optimization approach).

### Pain interference

Pain interference was measured using 5 items that asked participants how much pain interfered with different aspects of life (general activity, mood, relations, sleep, and enjoyment) over the past week, on a scale of 0 (no interference) to 10 (complete interference). The reliability of these items was high ( $\alpha = 0.92$ ).

### Frequency of prescription pain medication use

Prescription medication use was measured with a single item, asking participants how often they had used prescription pain medication in the past 30 days, on a scale of 1 (not at all) to 6 (daily).

### Covariates

Covariates included sociodemographic characteristics (age, gender, race, and income), hedonic well-being (positive affect, negative affect, life satisfaction), and eudaimonic well-being (personal growth, and purpose in life). Positive and negative affect were measured using separate 6-item composites. Participants were asked to rate how much of the time during the past 30 days they felt various positive emotions (cheerful, in good spirits, extremely happy, calm and peaceful, satisfied, and full of life) and negative emotions (so sad nothing could cheer them up, nervous, restless or fidgety, hopeless, that everything was an effort, and worthless) on a 5-point Likert scale (1 = All of the time, 5 = None of the time). Scores were computed by calculating the mean across each set of items and coded such that higher scores reflected higher levels of positive or negative affect. Life satisfaction was measured using a 6-item composite asking participants to rate their current life overall, work, health, relationship with spouse/partner, relationship with children, and financial situation on a scale from 0 (the worst possible) to 10 (the best possible). Items were coded such that higher scores reflected higher levels of life satisfaction. Personal growth and purpose in life were measured using 7-item composites. Example items for personal growth included “I have a sense that I have developed a lot as a person over time” and “For me, life has been a continuous process of learning, changing, and growth.” Example items for purpose in life included “I have a sense of direction and purpose in life” and “I enjoy making plans for the future and working to make them a reality.” Both sets of items were rated on a 7-point Likert scale (1 = Strongly agree, 7 = Strongly disagree) and coded such that higher scores reflected higher levels of personal growth and purpose in life. The reliability for each well-being construct was as follows: Positive affect ( $\alpha = 0.91$ ), negative affect ( $\alpha = 0.88$ ), life satisfaction ( $\alpha = 0.68$ ), personal growth ( $\alpha = 0.73$ ), and purpose in life ( $\alpha = 0.73$ ).

### Data analysis

#### Network topic modeling and network topic scores

Network topic modeling<sup>26</sup> was used to identify themes within the open-ended responses on what individuals living with chronic pain do to make their lives go well. The *EGAnet*<sup>26</sup> package in R was used to perform network topic modeling on the unigrams. *EGAnet* uses psychometric network theory with triangulated maximally filtered graphs to estimate topic models. Network topic modeling aims to statistically discover the latent topics and word clusters in an unsupervised manner, without predefined labels, by analyzing patterns of word co-occurrence across the entire corpus to identify groups of words (tokens) that frequently appear together.

Individual responses are characterized by the latent topics and, for any one individual, the open-ended text could be comprised of several words associated with several topics. The propensity to use words for a particular topic is associated with a greater likelihood of discussing the topic for an individual. Similar to factor scores in latent variable modeling, network topic scores quantify individual-level topic

engagement by computing weighted aggregates of topic-specific word frequencies.<sup>33</sup> These scores, implemented within the *EGAnet* framework, employ a formative measurement model where word importance values serve as weights in computing topic composites. Higher scores indicate stronger engagement with particular topics, as measured by the frequency and importance of topic-relevant words in an individual's response.

#### Determining the optimal number of topics

The *EGAnet* package uses the Walktrap community detection algorithm<sup>34</sup> to determine the optimal number of topics (communities) and distribution of variables (words) per topic.<sup>26,35</sup> The Walktrap approach has been shown to perform better than traditional latent Dirichlet allocation approaches to determining the number of topics.<sup>26</sup> In this study, the Walktrap approach was used in conjunction with sparsity-level optimization. Specifically, the optimal number of topics was estimated for each potential sparsity level using the Walktrap algorithm, and the total entropy fit index was computed for each solution. The optimal sparsity level and number of topics were determined based on the solution that provided the best overall total entropy fit index (see the [Supplemental Material](#) for additional details of the sparsity level optimization).

#### Interpretation of the topics

While topic modeling provides a systematic framework for theme identification in textual data, robust interpretation requires integrating quantitative and qualitative analytical approaches. Our methodological framework employed node importance scores—quantitative metrics that capture word-topic relationships through summed network connections<sup>33</sup>—alongside detailed examination of source text content. This dual analytical strategy prioritized high-scoring responses that exemplified each potential topic, enabling the development of empirically-grounded topic labels that aligned with both network-derived statistical patterns and participants' narrative content.

Topic interpretation followed a qualitative validation protocol anchored by quantitative node importance scores and source response texts. The analytical process involved 3 researchers conducting independent reviews through sequential stages. Initially, the primary investigator analyzed high-importance words and high-scoring responses for each topic. Subsequently, 2 additional researchers independently evaluated these materials, proposing interpretative refinements. The team employed an iterative consensus-building approach to resolve interpretative discrepancies, following established practices in qualitative research and topic modeling.<sup>36–39</sup> This structured validation procedure ensured topic labels reflected both empirical network associations and underlying narrative content.

#### Researcher positionality and topic validation

The interpretative demands of topic modeling necessitated careful consideration of researcher expertise and validation protocols. The investigative team integrated complementary domains of expertise: Psychometric and mixed-methods research (DC), well-being and social processes (AO), and clinical geriatric pain management (MCR). This methodological triangulation supported robust topic interpretation through the convergence of quantitative, theoretical, and

clinical perspectives. To maintain analytical rigor, the team systematically referenced original participant narratives throughout the interpretative process, emphasizing empirical grounding of thematic constructs (see [Table 2](#)).

### Structural equation model of topics and pain outcomes

Building on the validated topic structure, we implemented structural equation modeling (SEM) to examine associations between topic engagement and pain-related outcomes.<sup>40</sup> The analytical framework employed network topic scores as continuous predictors, with pain interference specified as a latent construct to account for measurement error. Latent topics were represented as composite variables arising from a formative measurement model (see [Figure S1](#)).

To facilitate interpretation, network topic scores, pain interference latent variables, and pain medication use outcomes were standardized to have a mean of zero and a variance of one. This standardization allows regression coefficients ( $\beta$ ) to be interpreted directly as standardized effect sizes—specifically, the standard deviation change in outcomes associated with one standard deviation increase in topic scores, controlling for other model parameters. Models were estimated using the *lavaan* package<sup>41</sup> in R.

## Results

### Descriptive statistics

The analytical sample comprised 683 participants, predominantly female (57%) and White (89%). Mean age was 54.84 years (SD = 12.30). Complete demographic characteristics are presented in [Table 1](#).

### Model optimization parameters

Sparsity optimization procedures yielded an optimal parameter of 0.957, reducing the analyzable lexicon to 129 words. Application of the Walktrap community detection algorithm identified a 12-topic solution as optimal, based on total

**Table 1.** Descriptive statistics.

Data	Count/M (percentage/SD)
N	683
Age	54.84 (12.30)
Gender	
Male	295 (43.19)
Female	388 (56.81)
Income	10.54 (2.13)
Race	
White	562 (89.21)
Black	68 (10.79)
Pain interfered	
Activity	3.78 (3.09)
Mood	3.26 (2.97)
Relations	2.31 (2.80)
Sleep	3.54 (3.13)
Enjoyment	3.75 (3.14)
Prescription pain medication use	
Positive affect	3.23 (0.76)
Negative affect	1.72 (0.72)
Life satisfaction	6.99 (1.47)
Personal growth	39.04 (6.76)
Purpose in life	38.34 (7.13)

M, mean; SD, standard deviation.

Income values are log-transformed to address data skewness and represent the natural logarithm of self-reported income.

entropy fit index criteria. Detailed optimization metrics are documented in the [Supplementary Material](#).

### Network topic structure

The results of the 12-topic model estimated on unigrams are presented in [Table 2](#) and [Figure 1](#). [Table 2](#) provides an overview of each topic, including labels, descriptions, and topic words listed in order of node importance. Additionally, example text from top scorers on each topic is included, showcasing individuals with the highest network topic scores. [Figure 1](#) visually displays the configuration of words to topics, with each topic represented by a distinct color. Based on the importance of words to each topic (see words ordered by node importance in [Table 2](#)) and the context derived from the example text of top scorers, the following descriptive labels were assigned to the 12 topics:

- 1) **Embracing change:** This topic captures individuals' recognition that embracing change and stepping out of one's comfort zone is essential for personal growth and making life go well. "Accept" and "change" were the top words for this topic. The example text from a top scorer highlights a person discussing being ready to accept change, potentially in relation to their personal growth and relationships with others.
- 2) **Living in the moment:** This topic reflects individuals' emphasis on living in the moment by taking life one day at a time. "Take," "day," and "time" are the top words for this topic. The example text from a top scorer emphasizes that taking things one day at a time is an important component of what they do to make their life go well.
- 3) **Maintaining social connections:** This topic highlights the importance of maintaining and prioritizing relationships with family and friends. Top words include "friend," "family," "relationship," "enjoy," "keep," "close," "support," and "appreciate." The text from a top scorer provides a clear picture of a person focused on keeping close to family and friends and putting their family first.
- 4) **Avoiding stress:** This topic focuses on individuals' desire to manage stress effectively and maintain a healthy work-life balance. Top words for this topic include "don't" and "stress." The example text from a top scorer demonstrates an individual who is keen on not letting stress rule their life.
- 5) **Goal-oriented living:** This topic revolves around individuals' emphasis on setting goals, working towards self-improvement, and maintaining a positive outlook. Top words for this topic include "always," "set," and "goals." Text from a top scorer illustrates how setting goals helps make this individual feel like they are working towards something better.
- 6) **Prioritizing family relationships:** This topic captures individuals' focus on expressing love and support for their immediate and extended family members. The top words for this topic include "family members" and "love." The text from a top scorer demonstrates the emphasis on loving their family and friends.
- 7) **Willingness to try:** This topic reflects individuals' willingness to try. The top words for this topic are "thing" and "try" (try, trying, tried, etc.). The topic appears to be about willingness to try and do things in their life.

**Table 2.** Twelve topic network model for individuals experience chronic pain.

Topic	Topic label	Words order by node importance
1	Embracing change	<i>Description:</i> This topic captures individuals' recognition that embracing change and stepping out of one's comfort zone is essential for personal growth and making life go well. <i>Top 12 words (node importance):</i> can (18.5), ive (11.9), year (9.3), chang (9.3), back (8.8), know (8.0), give (7.7), person (7.6), best (7.3), much (7.2), accept (7.0), also (6.7). <i>Example text from top scorer:</i> "I have been highly adaptable and readily accept change. I've learned that it's necessary to step out of one's comfort zone to achieve personal growth. I've become more patient with people and have learned to accept incremental change. I'm not easily discouraged and if something is important to me, I will find a way to accomplish my objectives."
2	Living in the moment	<i>Description:</i> This topic reflects individuals' emphasis on living in the moment by taking life one day at a time. <i>Top 12 words (node importance):</i> day (11.18), time (10.14), take (8.87), spend (8.33), one (8.00), everi (7.72), care (6.75), week (6.72), plan (6.03), physic (5.96), lot (5.50), kid (5.20). <i>Example text from top scorer:</i> "Take things one day at a time, and try to make someone smile. Take time to enjoy nature!"
3	Maintaining social connections	<i>Description:</i> This topic highlights the importance of maintaining and prioritizing relationships with family and friends. <i>Top 12 words (node importance):</i> new (11.79), friend (11.05), active (10.99), famili (8.74), relationship (8.15), mind (7.98), enjoy (7.82), keep (7.82), natur (6.33), close (6.26), support (6.25), appreci (5.72). <i>Example text from top scorer:</i> "Keeping a good close family and friends. Teaching your child to be a good person and good friend to others. Helping neighbors, family with anything needed. Staying close to all of your brothers and sisters and their children. Family comes first in everything keep them close. Travel together as a family. Stay young at heart with the children."
4	Avoiding stress	<i>Description:</i> This topic focuses on individuals' desire to manage stress effectively and maintain a healthy work-life balance. <i>Top 8 words (node importance):</i> will (11.22), don't (8.29), right (8.07), like (7.09), good (5.97), stay (5.46), let (5.25), stress (5.17). <i>Example text from top scorer:</i> "I don't let stress rule my life. Enjoying the small joys in life makes it fun. I work hard, but don't take it home. I love my family above my job. Having fun is worth the time and money spent. Learning skills makes the day go and work easier. I don't do enough."
5	Goal-oriented living	<i>Description:</i> This topic revolves around individuals' emphasis on setting goals, working towards self-improvement, and maintaining a positive outlook. <i>Top 12 words (node importance):</i> always (16.71), find (13.79), someth (13.11), look (9.52), use (9.37), goal (8.23), talk (7.73), abl (7.17), set (7.16), situat (6.54), listen (6.53), even (6.44) <i>Example text from top scorer:</i> "I set goals and always feel like I am working towards something better, even if they are small goals. I try to be good to people and send out good energy because I do believe in karma."
6	Prioritizing family relationships	<i>Description:</i> This topic captures individual' focus on expressing love and support for their immediate and extended family members. <i>Top 5 words (node importance):</i> husband (8.25), children (7.85), grandchildren (6.83), love (6.37), wife (6.37). <i>Example text from top scorer:</i> "Love and pray to my God. Love and enjoy my husband, family (children, grandchildren, added children, brothers, sisters in laws also) friends. Helping my husband with his health and trying to do the things to keep myself healthy."
7	Willingness to try	<i>Description:</i> This topic reflects individuals' willingness to try. <i>Top 12 words (node importance):</i> thing (20.22), tri (12.49), help (10.68), feel (9.35), import (8.79), people (7.91), need (7.57), think (7.18), problem (6.89), done (6.45), ask (5.83), get (5.81) <i>Example text from top scorer:</i> "Work hard to meet my goals. Try to help others so that they might help me if I need it. Try to keep things stable at home and with my parents. I try to listen to other people's problems and to give advice if I think I have good advice to give. Try to compromise with my wife on the big stuff and not sweat the little things."
8	Treating others with kindness and respect	<i>Description:</i> This topic highlights individuals' belief in being a good person and treating others with kindness, respect, honesty, and understanding, as they would want to be treated themselves. <i>Top 7 words (node importance):</i> other (9.71), treat (9.60), respect (8.29), kind (7.05), honest (5.91), want (5.57), understand (5.32) <i>Example text:</i> "Try to be a good person and treat others as I would want to be treated myself."
9	Finding balance in work and play	<i>Description:</i> This topic captures individuals' desire to maintain a balance between working hard and enjoying life. <i>Top 4 words (node importance):</i> work (9.12), hard (8.04), play (5.81), job (5.16) <i>Example text from top scorer:</i> "I work hard and play hard. I am respectful of others and try to have concurrence from others that my decisions may effect. Most importantly, I give thanks to God and try to keep the faith. I also try very hard to greet each day with a smile and always thin and speak optimistically."

(continued)



understanding, as they would want to be treated themselves. Top words for this topic include “treat,” “other,” “respect,” and “kind” (stem for kindness, kind, etc.). As the top scorer notes, they try to be good and treat others how they would want to be treated.

- 9) **Finding balance in work and play:** This topic captures individuals’ desire to balance working hard and enjoying life. The top words for this topic include “work,” “hard,” “play,” and “job.” The few words associated with this topic appear to be about working hard and enjoying one’s life (play hard). A top scorer notes that they “work hard and play hard.”
- 10) **Engaging in meaningful daily activities:** This topic reflects individuals’ emphasis on engaging in meaningful activities (eg, exercising, reading, volunteering, eating, church) that contribute to their physical, mental, and spiritual well-being. Top words for this topic include “exercise” (root for exercise, exercising, etc.), “read,” “volunteer,” “eat,” and “church.” A top scorer describes engaging in multiple activities of daily life as important to them.
- 11) **Practicing spirituality and faith:** This topic focuses on individuals’ reliance on their spiritual beliefs and faith to guide their lives. Top words for this topic include “god,” “bless,” “believe” (root for believing, believes, etc.), “faith,” and “pray.” A top scorer provides a detailed description of their spirituality and faith.

- 12) **Cultivating a positive mindset.** This topic captures individuals’ desire to maintain a positive attitude and surround themselves with positivity. The topic words include “learn,” “maintain,” “health,” “attitude,” “sense,” “positive,” and “self.” A top scorer notes they try to keep a positive attitude and keep positive people around.

### Topic associations with pain outcomes

Structural equation modeling analyses revealed distinct patterns of association between network-derived topics and pain-related outcomes, with acceptable measurement model fit indices for pain interference (Table 3). Demographic covariates exhibited differential associations: Advancing age was associated with increased medication use but not pain interference; female gender was associated with elevated medication use relative to males; and Black participants reported higher pain interference compared to White participants, though medication use remained comparable between racial groups. Higher income levels were inversely associated with both pain interference and prescription medication use. Among well-being indicators, negative affect was positively associated with both outcome measures, while positive affect was inversely associated with pain interference only. Notably, after adjustment for these sociodemographic and well-being covariates, maintaining social connections

**Table 3.** Structural equation modeling of pain outcomes.

Predictor	Pain interference			Pain medication		
	$\beta$	SE	P	$\beta$	SE	P
Topic 1: Embracing change	0.030	0.053	.564	0.030	0.048	.529
Topic 2: Living in the moment	0.053	0.048	.273	0.013	0.044	.767
Topic 3: Maintaining social connections	-0.144	0.048	.003	-0.105	0.045	.020
Topic 4: Avoiding stress	0.023	0.047	.618	0.047	0.042	.270
Topic 5: Goal oriented living	0.031	0.048	.519	-0.015	0.044	.728
Topic 6: Prioritizing family relationships	0.014	0.046	.757	0.017	0.043	.696
Topic 7: Willingness to try	-0.069	0.053	.197	-0.012	0.048	.803
Topic 8: Treating others with kindness and respect	0.010	0.043	.814	0.026	0.039	.500
Topic 9: Finding balance in work and play	-0.027	0.044	.539	-0.019	0.041	.636
Topic 10: Engaging in meaningful daily activities	0.026	0.045	.561	0.043	0.041	.295
Topic 11: Practicing spirituality and faith	0.018	0.044	.687	-0.062	0.042	.138
Topic 12: Cultivating a positive mindset	0.077	0.045	.085	0.008	0.042	.855
Positive affect	-0.173	0.078	.027	0.003	0.070	.967
Negative affect	0.631	0.083	<.01	0.292	0.072	<.01
Life satisfaction	-0.156	0.040	<.01	-0.051	0.035	.149
Personal growth	0.006	0.009	.467	-0.002	0.008	.793
Purpose in life	-0.009	0.009	.267	0.006	0.008	.450
Age	0.003	0.004	.434	0.019	0.003	<.01
Female	0.142	0.088	.107	0.229	0.081	<.01
Black	0.400	0.150	.008	0.228	0.129	.078
Income	-0.049	0.020	.017	-0.039	0.019	.043
Model fit statistics						
$\chi^2(df)$	201 (89), $P \leq .01$					
CFI	0.962					
RMSEA	0.043 [0.035, 0.051]					
SRMR	0.013					
N	683			683		

Rx, prescription; SE, standard error; P, P value;  $df$ , degrees of freedom;  $\beta$ , path coefficient; CFI, comparative fit index; RMSEA, root-mean-square error of approximation; SRMR, standardized root-mean-square residual.

Pain interference, pain medication use, and network topic scores were all standardized; The measurement model for pain interference showed an acceptable model fit (CFI = 0.979, TLI = 0.958, SRMR = 0.02); No fit statistics are shown for the medication use structural equation model because the model is just-identified (ie, there are as many parameters as observed covariances estimated).

emerged as inversely associated with both pain interference ( $\beta = -0.14$ ,  $SE = 0.05$ ,  $P < .05$ ) and prescription pain medication use ( $\beta = -0.11$ ,  $SE = 0.04$ ,  $P < .05$ ), suggesting potential protective effects of social connectivity in chronic pain management.

## Discussion

This study leveraged network topic modeling to analyze open-ended responses to the question, “What do you do to make your life go well?” in a nationally representative sample of US adults with chronic pain. The identified topics captured important well-being practices, including accepting change, living in the moment, maintaining social connections, avoiding stress, goal-oriented living, prioritizing family relationships, willingness to try, treating others with kindness and respect, finding balance in work and play, engaging in meaningful daily activities, practicing spirituality and faith, and cultivating a positive mindset. Several of these topics aligned with previous thematic analyses<sup>42</sup> and established well-being constructs like social engagement and connection.<sup>43</sup> This suggests that the topics effectively extracted meaningful facets of living the good life grounded in respondents’ own words and values. Notably, the SEM results indicated that these topics were predictive of lower pain interference and reduced need for pain medication, particularly for those who discussed the importance of maintaining strong social ties. These findings were significant even after accounting for the effects of hedonic and eudaimonic well-being on pain outcomes.

A key contribution of this study is distinguishing between actively “doing well” versus simply “being” or “feeling” well. Our analyses demonstrate that social connectivity functions as a significant protective mechanism against adverse pain outcomes, corroborating and extending previous empirical work on social support in chronic pain management.<sup>21,22</sup> While physical manifestations of chronic pain can impede traditional social interactions,<sup>44</sup> the robust relationship between social connection topics and reduced pain outcomes suggests the potential resilience of social engagement mechanisms in chronic pain contexts. This finding aligns with established occupational therapy frameworks emphasizing meaningful activity participation as a core component of pain management efficacy.<sup>45</sup>

## Limitations and future directions

Several methodological limitations warrant consideration in contextualizing the present findings. First, the derived topic labels represent preliminary interpretative frameworks of NLP-identified semantic clusters rather than definitively validated constructs. While these topics demonstrate internal coherence, they may not fully capture the multidimensional nature of individual narratives. Moreover, the source data, collected without specific consideration for topic modeling applications or chronic pain contexts, potentially constrains the depth of extractable insights. Nevertheless, the emergence of interpretable topic structures supports the utility of network topic modeling approaches for analyzing pre-existing qualitative datasets. Future research should aim for more targeted data collection that can robustly support network topic modeling, including carefully crafted open-ended questions about pain management strategies, longitudinal assessments of strategy implementation, and systematic comparison of topic prevalence across different pain conditions. Such study

designs would enable a more comprehensive understanding of how individuals develop and maintain well-being practices while living with chronic pain on a daily basis.

The observed null associations between theoretically relevant topics (“engaging in meaningful activities” and “cultivating a positive mindset”) and pain outcomes merit particular attention, given their established centrality in pain management protocols.<sup>10,15</sup> Two primary methodological factors may explain these findings: Measurement limitations inherent in open-ended response analysis, and potential discrepancies between reported and implemented well-being practices. Further investigation using targeted assessment protocols could elucidate these relationships.<sup>46</sup>

Additionally, a significant limitation of this study is the absence of measures assessing self-efficacy and pain-related beliefs, 2 constructs central to understanding pain management outcomes. Self-efficacy—an individual’s belief in their ability to execute behaviors to produce desired outcomes—has been consistently linked to better pain adaptation and reduced disability.<sup>47,48</sup> Similarly, pain catastrophizing and other maladaptive pain beliefs significantly influence pain experiences and management strategies.<sup>49,50</sup> The relationship between our identified topics, particularly “Maintaining Social Connections,” and pain outcomes might be mediated or moderated by these psychological factors. For example, social connections might enhance pain management through building self-efficacy or reducing catastrophizing thoughts. Future research should explicitly examine how well-being practices interact with self-efficacy and pain beliefs to influence pain outcomes. Such studies could help elucidate the mechanisms through which social connections and other well-being practices affect pain management.

Furthermore, the generalizability of our findings across diverse populations and cultural contexts remains an important consideration. Our sample included only a limited number of non-White Americans, highlighting the need for more diverse samples to ensure that the insights gained are representative of the broader population and to identify any group-specific factors that may influence the relationship between well-being practices and pain outcomes. Future research should prioritize the inclusion of underrepresented groups to capture the full spectrum of experiences and perspectives related to chronic pain and well-being.

The structural equation modeling analyses, while revealing significant associations between topic prevalence and pain outcomes, require careful interpretation within their methodological constraints. The cross-sectional design precludes causal inference and directional conclusions, necessitating longitudinal investigations to elucidate temporal dynamics between well-being practices and pain management outcomes. Future research protocols should incorporate time-series analyses of wellness strategy implementation (eg, mindfulness practices, physical activity) and systematic assessment of individual difference variables (personality dimensions, coping repertoires). Additionally, more granular measurement of pain medication utilization patterns—including pharmacological categories, dosing schedules, and integration of complementary therapies—would provide critical insights into pain management optimization, particularly given contemporary developments in therapeutic approaches.<sup>51</sup> This methodological refinement should explicitly differentiate between discrete wellness practices and broader well-being

constructs encompassing psychological, social, and functional domains.

The network topic modeling approach used in this study has potential applications beyond the analysis of open-ended survey responses. For example, This analytical framework could be systematically applied to unstructured data sources, including social media narratives from chronic pain communities<sup>52</sup> and electronic health record documentation.<sup>53</sup> Integration of these diverse data streams could enhance understanding of naturalistic pain management experiences and inform intervention development through methodologically rigorous, ecologically valid approaches.

## Conclusions

This investigation advances the methodological framework for examining well-being practices in chronic pain populations through the integration of network topic modeling techniques with open-ended response data. The computational text analysis revealed distinct behavioral patterns and coping strategies, with social connectivity emerging as a particularly salient dimension in pain management outcomes. Our findings demonstrate the analytical value of methodological convergence, combining qualitative depth with quantitative precision to elucidate the multifaceted relationship between well-being practices and chronic pain experiences. This integrated analytical approach provides an empirical foundation for identifying implementable pain management strategies, while establishing a methodological template for future investigations of adaptive functioning in chronic pain contexts.

## Author contributions

Dakota W. Cintron: Conceptualization, Methodology, Formal Analysis, Writing—Original Draft, Writing—Review & Editing. Anthony D. Ong: Conceptualization, Writing—Review & Editing. Carrington M. Reid: Writing—Review & Editing.

## Supplementary material

Supplementary material is available at *Pain Medicine* online.

## Funding

This research was supported, in part, by Grant P01-AG020166 from the National Institute on Aging to conduct a longitudinal follow-up of the MIDUS (Midlife in the United States) investigation. The original study was supported by the John D. and Catherine T. MacArthur Foundation Research Network on Successful Midlife Development. Dr Reid is supported by the following grants (P3AG022845, K24AG053462) from the National Institute on Aging. The data for this study are publicly available online at <https://midus.colectica.org/>.

*Conflicts of interest:* The authors have no conflicts of interest to declare.

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