The Impact of Unemployment on Dream Content

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This study examines the relationship between employment status and dream content using a data set of 6,478 dream reports collected from Reddit. We used machine learning to analyze thematic differences between unemployed individuals and a control group. The results revealed that the dreams of unemployed individuals demonstrated an underrepresentation of surprise and visual observations alongside an overrepresentation of work-related topics. These patterns suggest that unemployment is associated with distinct alterations in dream content, reflecting reduced cognitive engagement and heightened preoccupation with occupational concerns. This study establishes the feasibility of leveraging large-scale, publicly available data to explore the dream content of subpopulations.

Keywords: dream, social media, classification, content analysis, unemployment

Dreams provide valuable insights into cognition and emotion, often relating to waking concerns and experiences (Weinstein et al., 2018). While previous research has explored the relationship between dreams and emotions (Gilchrist et al., 2007), few studies have examined how broader life circumstances, such as employment status, shape dream content (Schredl et al., 2020). Unemployment affects psychological well-being, and analyzing dream content may reveal cognitive and emotional patterns missed by self-report measures. This study addresses this gap by examining whether thematic differences emerge in the dreams of unemployed individuals compared to a control group, using a novel data set of publicly available dream reports.

Beyond its relevance to unemployment, this study contributes to ongoing discussions in dream theory. By identifying patterns in how waking experiences correspond to dream content, it informs debates on the extent to which dream experiences are continuous with waking life (Domhoff, 2017). Additionally, it highlights the potential

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of large-scale dream analysis as a valuable research tool, extending recent computational approaches (Das et al., 2024) to subgroup comparisons.

Unemployment and Its Psychological and Social Effects

Unemployment represents a profound disruption to an individual's economic stability (Paul et al., 2014), psychological well-being (Wanberg, 2012), and social identity (Schöb, 2013). Meaningful employment is often integral to one's sense of self, providing financial resources and a source of purpose and societal recognition (Brand, 2015). Losing employment can precipitate a crisis of identity, leading to diminished self-worth, which may result in psychological difficulties, including feelings of inadequacy, shame, and despair (Goldsmith et al., 1996). Individuals may not fully return to their baseline levels of life satisfaction even after reemployment (Lucas et al., 2004). Understanding how unemployment affects cognitive and emotional processing is critical, yet self-reported experiences may not fully capture these effects. Dream content offers a unique, indirect lens into the psychological consequences of unemployment, potentially revealing patterns that may not emerge through traditional self-report methods.

Psychological challenges are often exacerbated by social withdrawal and isolation, driven by the stigma of unemployment and the financial limitations that restrict participation in social activities (Powdthavee, 2012). This disengagement exacerbates the individual's sense of alienation and contributes to broader social cohesion issues, weakening the ties that bind communities and potentially amplifying the societal impact of widespread unemployment (Gallie, 1999). Reluctance to self-disclose about unemployment status limits opportunities for providing social support, which is a critical buffer against the adverse effects of job loss (Ibañez & Lopez, 2018).

The societal implications of widespread unemployment are far-reaching, as the erosion of individual self-concept and social ties on a large scale can contribute to increased social instability and economic decline (Shelton, 1985). As more individuals struggle with losing their sense of purpose and place within society, there is a concomitant risk of increased demand on public services, diminished consumer spending, and the potential for social unrest (Saadi-Sedik & Xu, 2020). These challenges are expected to intensify in the context of anticipated future job losses driven by technological advancements and economic transformations (National Bureau of Economic Research, 2018). Addressing the multifaceted consequences of unemployment requires a comprehensive approach that extends beyond economic support to encompass the psychological and social dimensions that underpin individuals' sense of identity and purpose.

The Impact of Work-Related Distress on Dreaming

The continuity hypothesis of dreaming (Hall, 1971) states that dreams are continuous with waking life. Dreams contain the same thoughts, concerns, and interests that occupy waking cognition. Empirical studies analyzing large sets of dream reports have found that thematic consistency in dreams persists over time, aligning with individuals' enduring waking concerns (Bulkeley & Domhoff, 2010). This perspective rejects the idea that dreams are separate from waking life and instead positions them as a continuation of stable cognitive patterns (Domhoff, 2017). However, continuity is selective. Dreams do not indiscriminately incorporate all waking experiences but rather emphasize central personal concerns that are meaningful to the dreamer over time (Domhoff, 2017).

An activity's frequency in dreams may relate to its importance to the dreamer (Hall & Van de Castle, 1966). Given the central role of work in daily life and personal identity, dream content is expected to reference job-related themes frequently. The prevalence of work-related dreams varies across studies and samples. In 1956, 18.7% of women and 27.2% of men reported work-related dreams, while in a 2000 sample, 29.9% of women and 37.6% of men experienced such dreams (Schredl & Piel, 2005). In a more recent study involving 1,695 participants, approximately one in five dreams was related to a current or previous job (Schredl et al., 2020).

There is considerable empirical evidence linking individuals' work-related emotional states with their dream content. Schredl et al. (2020) demonstrated that people who perceive their work as stressful are likelier to have work-related dreams, often reflecting the emotional stress encountered in their occupational environment. This suggests that dream content can serve as a mirror for work-related psychological states. Supporting this, Kroth, Daline, et al. (2002) found significant correlations between low job satisfaction and the occurrence of harmful dream content, including repetitive traumatic themes. Their findings imply that workplace dissatisfaction is directly associated with distressing dream experiences, reinforcing the continuity between waking work-related emotions and dream content.

The connection between occupational distress and dream content is particularly evident in high-stress professions, such as medical ones. For instance, Mealer et al. (2009) reported that 35% of nurses experienced work-related nightmares. Garcia et al. (2021) expanded on this by showing that increased daily stress among nurses significantly heightened the frequency and severity of work-related nightmares, establishing a bidirectional relationship where nightmares further contributed to subsequent stress levels.

Differentiating Work-Related Stress in Dream Narratives

While the relationship between work and dream content is widely acknowledged, this connection requires further specification. Work-related distress can manifest in various forms, including the threat or experience of unemployment, toxic or abusive work environments, and poor work–life balance. It is reasonable to expect that the content of dreams would differ depending on the specific nature of the work-related stress. Similarly, dream content related to work experiences remains relatively underexplored regarding specific themes.

To explore nuances in the continuity between workplace experience forms and dream content, we must look beyond work-related themes' frequency and emotional tone. The continuity hypothesis states that dreams do not simply reflect the experiences of the waking world but, for the most part, express, through enactment, embodiment, and dramatization, waking conceptions (Domhoff, 2017). This means that while unemployment might influence dream content, it may not appear as a direct representation of jobs and work but instead manifest through subtler motifs and narrative structures. Konakawa et al. (2023) noted differences in the will and mobility of the dream ego, corresponding to the waking culture of the dreamer. Similarly, Roesler (2018) argued that dreams are a continuity of the holistic situation of the total psyche, including unconscious aspects.

Most large-scale studies on work-related dreams focus primarily on the emotional tone of dreams rather than on detailed content exploration. However, some research has highlighted relevant thematic patterns. For instance, dreams of being chased have been correlated with low job satisfaction, high job stress (Kroth, Daline, et al., 2002), and feelings of powerlessness (Kroth, Thompson, et al., 2002). Additionally, reports of women's work-related dreams during the COVID-19 pandemic reflect the specific occupational challenges of that time (Barrett, 2020).

Existing research firmly establishes that work-related distress and emotional states are directly reflected in the content and themes of dreams. This connection requires further elaboration, as a more comprehensive and specified analysis of the specific themes and patterns present in work-related dreams could provide invaluable insights into the psychological impact of various employment challenges and experiences. Dream analysis may be particularly useful for understanding the topic of unemployment, as workers are often reluctant to disclose personal information about their employment status and psychological experiences. The sensitive nature of unemployment and the associated stigma often lead individuals to refrain from openly sharing their struggles (Krug et al., 2019), making dream analysis a valuable tool to gain deeper insight into this complex issue.

Current Study Overview and Methodology

Building on existing literature linking work-related distress to dream content, this study examines how unemployment shapes the narratives of dream reports. While prior research has established connections between work-related emotional states and dream content (Schredl et al., 2023), this study seeks to move beyond general emotional tones to analyze the specific narratives and themes present in the dreams of unemployed individuals. By investigating the nuances of dream content, the study aims to provide a more detailed understanding of how unemployment shapes dream experiences.

This study contributes to understanding the psychological impact of unemployment and advances research on factors shaping dream content. While it is well established that dreams reflect aspects of waking life, the precise nature of this continuity remains debated (Domhoff, 2017). Research has demonstrated that specific waking experiences, such as work-related stress, are reflected in dream content. Still, less is known about how broader life circumstances, such as unemployment, influence dreaming. By examining how unemployment is associated with specific alterations in dream content, this study provides insights into how major disruptions to daily life correspond with changes in dream patterns, extending existing discussions on the relationship between waking experience and dreaming.

This study uses data scraping to analyze publicly available dream reports and employment status. Large language model techniques are applied to explore the semantic content of these data. While this method has been used in psychological research (Shen & Rudzicz, 2017) to explore concepts such as creativity (Margulis et al., 2022) and music perception (Organisciak et al., 2023), its use in dream content analysis remains novel. This approach allows the collection of large, diverse data sets that reveal complex patterns in dream content differences between groups.

In addition to exploring the link between unemployment and dream content and informing understanding of the link between wake and dream continuity, the study aims to validate further the utility of data scraping in dream science more broadly, building on prior work. Demonstrating the robustness of this approach will contribute to its recognition as a valuable tool for future research in dream science and practical workforce intelligence applications. Ultimately, this research aims to deepen the understanding of the psychological impact of unemployment as reflected in dream narratives while showcasing the potential of digital methodologies to expand the scope of dream science.

Method

Data Source

Reddit is a social news aggregation, content rating, and social network forum. Between January and June 2024, contributors posted 243 million submissions and 1.66 billion comments to the site (Reddit, 2024). As of 2024, there are over 500 million Reddit accounts (Statista, 2024a). Users are generally anonymous. Approximately half of Reddit's user base resides in the United States (Similarweb, 2025), and two in three are male (Statista, 2024b).

Reddit contains more than 1 million subpages, called subreddits, each focusing on its topic. Users join subreddits to enable posts to appear on their feeds. In some cases, joining a subreddit may be a prerequisite to posting on the subreddit. A user's membership of subreddits is publicly visible. Within these self-assembled communities, users share diverse and personal information. This includes experiences and challenges with psychological well-being (Slemon et al., 2021), seeking self-expression, support, and advice (De Choudhury & De, 2014). Reddit allows posts of up to 40,000 characters per comment. It offers rich bodies of text from users in the context of specific topics.

Dream reports used in this study were sourced from the subreddit r/dreams. This subreddit has approximately 401,000 members and an average of 100 weekly posts. Unemployment status was determined by membership in one or more of the following subreddits: r/unemployed (100,670 members), r/unemployment (754,876 members), r/jobs (1,647,307 members), r/recruitinghell (705,312 members), and r/careerguidance (3,802,455 members).

These subreddits were selected because of their high membership overlap with r/unemployed. Overlap is represented through probability multipliers as follows: r/jobs (111.57), r/recruitinghell (92.14), r/career guidance (82.90), and r/unemployment (46.42). Probability multipliers reflect user engagement patterns across subreddits. A score of 2, for instance, indicates that individuals active within the inputted subreddit demonstrate twice the likelihood of participating in the linked subreddit compared to baseline Reddit user behavior. Conversely, a score of 1 signifies no statistically significant difference in engagement, while a score of 0 denotes a complete absence of observed interaction.

Data Collection

Submissions and comments were collected from Reddit using an archive of Reddit data collected by the Pushshift project via Reddit application programming interfaces. All comments and submissions are available from a publicly available data set archived by the Pushshift project (Pushshift, n.d.). Specifically, we extracted two sets of data: complete submission metadata and content from the r/dreams subreddit and metadata of submissions and comments from a set of unemployment-related subreddits: r/unemployed, r/unemployment, r/jobs, r/recruitinghell, and r/careerguidance. The full submissions data from r/dreams include the content of the submission post, the author, and the associated timestamp of the post. The submissions and comments data extracted from the unemployment-related subreddits include the author and timestamp of the post.

The full Reddit historical data set is approximately 3TB and fully compressed, presenting processing challenges to extract relevant information. The data set separates comments and submissions, with each set further separated into monthly files in compressed newline-delimited JSON format. A Python script decompressed each file individually, checked each line for membership in one of the relevant subreddits, and, if relevant, exported that record's data to a separate newline-delimited JSON file. For the r/dreams submissions, submissions were discarded if the text content was shorter than 100 characters or longer than 20,000 characters. These thresholds were chosen after a subjective manual review of the shortest and longest posts.

For the selection of our unemployment sample, we first collected the timestamp of each author's first comment or submission to one of the unemployment subreddits. We searched for dream submissions occurring up to 6 months before this timestamp for each author, intending to capture dreams that predicted unemployment status before the author directly expressed a change in their employment status. In the event of multiple dream submissions for the same author during this period, we kept only the most recent submission. This selection process yielded 3,308 unemployment dream submissions.

In selecting a control sample to compare this against, we sought to eliminate temporal bias by choosing an equivalent number of control dreams from each distinct day in the unemployment dreams set. We count the number of unemployment dreams each day and then randomly select an equal number of control dreams from each day from nonunemployment authors. When sufficient dreams did not exist on that day, we expanded the control selection window to 1 day before and after the target day. This control group selection process was crucial for ensuring the internal validity of our study by mitigating the potential influence of time-related factors on dream content.

Many submissions to r/dreams do not include a particular dream; instead, they offer commentary or discussion. To filter our data set to only the relevant submissions, we manually reviewed each relevant submission from the collected target and control sets, removing those submissions that did not contain a dream. This process yielded 6,478 total dreams, of which 3,235 were unemployment dreams and 3,243 were control dreams. All data were collected from the period of September 1, 2009, to June 30, 2024.

Feature Generation

In order to extract nuanced semantic meaning from submissions, we chose to employ OpenAI's current highest performance document embedding model text-embedding-3-large, a 3,072-dimension vector representing the content of each document.

In addition to testing the 3,072-dimension embeddings directly, we also applied principal component analysis (PCA) to reduce dimensionality across the embeddings, testing varying the number of components between 25, 50, 75, 100, 125, and 150 components.

PCA was employed to reduce the dimensionality of the document embeddings. This step was taken to address the potential for the "curse of dimensionality" (Fan et al., 2018), where high-dimensional data can lead to increased computational complexity and potentially hinder model performance. By reducing the number of features while retaining as much variance as possible (Gewers et al., 2022), PCA can improve both the efficiency and interpretability of subsequent analyses (Jolliffe & Cadima, 2016; Ma & Dai, 2011).

Classification

For binary classification between unemployed and control dreams, we applied logistic regression and random forest models, each implemented using Scikit-Learn 1.3.2 with feature standardization. To identify the optimal hyperparameters for each model, we used a two-stage approach:

1. Hyperparameter optimization (two-fold cross-validation): To identify robust hyperparameters with efficient computational demands, we conducted grid search tuning within a two-fold cross-validation framework. This choice allowed us to explore multiple hyperparameter combinations without excessive computational time and cost. While relatively simple, two-fold provided sufficient data splits to assess initial hyperparameter performance while balancing computational efficiency.
2. Performance evaluation (five-fold cross-validation): After selecting optimal hyperparameters, we conducted five-fold cross-validation to estimate the final model performance. This more extensive cross-validation provided a robust measure of model generalizability and reduced the variance in performance metrics. A five-fold approach strikes a balance by offering a variety of training/testing splits without the redundancy of higher fold numbers, ensuring reliable and interpretable metrics across different feature configurations.

Each cross-validation was randomized with a fixed seed to enhance reproducibility. Through this approach, we aimed to assess both the hyperparameter stability and final model reliability across varying data splits. Chosen optimal hyperparameters for each model are provided in Table 1.

Data Analysis

After selecting an optimal model, we undertook further analysis to understand what information the model used for differentiating unemployment dreams from control dreams. We retrained the optimal model on a single training set and applied the model to the remaining holdout test set. First, to understand the quality of the model for both negative and positive scores, we examined the rate of unemployment dreams across deciles of model score. For classification models such as this, the score outputted by the model is an estimate of the probability of membership in the unemployment class (i.e., in the domain 0% to 100%). We took the top and bottom scoring

Table 1
Classification Performance Metrics for Optimized Models Using Five-Fold Cross-Validation

Model	F_1 score	ROC-AUC	Best model's hyperparameters
Logistic regression	0.5760	0.6062	Inverse regularization strength (C) = 0.001, Regularization penalty = L2
Logistic regression with PCA	0.5691	0.6001	Inverse regularization strength (C) = 0.01, Regularization penalty = L2, PCA components = 150
Random forest	0.5493	0.5749	Max depth of decision tree = none, min samples per leaf = 2, min samples to split node = 2, number of trees in forest = 200
Random forest with PCA	0.5469	0.5736	Max depth of decision tree = 20, min samples to split node = 10, number of trees in forest = 200, PCA components = 100
Random (baseline)	0.4927	0.5000	
Logistic regression	0.5760	0.6062	Inverse regularization strength (C) = 0.001, Regularization penalty = L2

Note. ROC = receiver operating characteristic; AUC = area under the curve; PCA = principal component analysis; max = maximum; min = minimum; C = inverse regularization strength; L2 = regularization penalty.

deciles of all dreams (inclusive of test and training) and compared the prevalence of words between the unemployed and control sets.

Results

Results of Classification Models and Performance Metrics

The highest-performing model was the logistic regression model without PCA ($C = 0.001$ and L2 regularization), yielding an F_1 score of 0.58 and receiver operating characteristic (ROC)-area under the curve (AUC) of 0.61. The results of all models are summarized in Table 1.

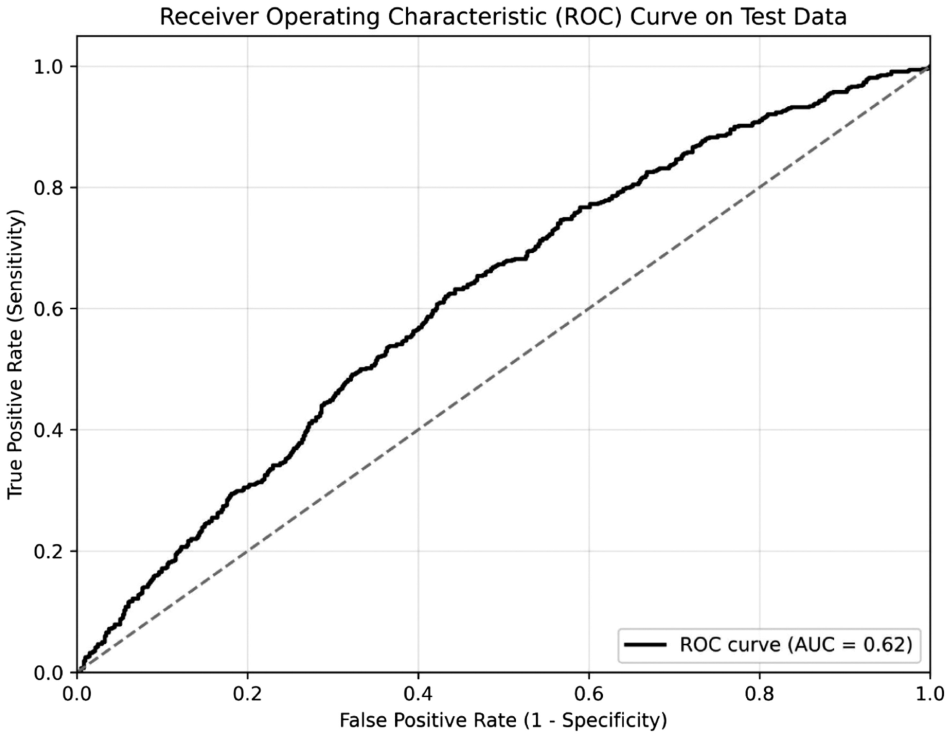
The model's performance was further evaluated using a ROC curve, which measures the trade-off between the true-positive rate (sensitivity) and false-positive rate across various threshold settings (see Figure 1), after retraining the best model on 80% of the data set and applying it to the remaining 20% holdout. The AUC was 0.62, indicating that the model has a moderate ability to distinguish between unemployment and control dream reports, performing better than random chance (AUC = 0.5).

An important observation from the ROC curve is its smoothness, which suggests that the model's sensitivity and specificity change gradually across different decision thresholds. The smooth ROC curve suggests that the model handles the variability and potential noise in dream content effectively, capturing patterns that are broadly applicable across different samples. This stability could indicate better generalization and less overfitting to the training data and implies that highest- and lowest-scoring dreams have the most substantial differences in differentiating characteristics of their content.

Themes Distinguishing Unemployed and Control Groups

To isolate the dream content driving the differentiation between unemployed dreams and control dreams, we examined the dreams scored highest and lowest by the top-performing classification model, choosing the top and bottom decile of

Figure 1
ROC Curve for the Logistic Regression Model Without PCA



Note. ROC = receiver operating characteristic; PCA = principal component analysis; AUC = area under the curve.

dreams by model score. The top 30 words differentiating each set were isolated. These words, reviewed in the context of the dream reports themselves, were qualitatively grouped into eight themes. Descriptions of differentiating content themes are shown in Table 2.

Compared to control dreams, unemployed dreams showed a higher prevalence of themes related to domestic relationships, professional concerns, negative emotions, and meta-commentary on the dreaming experience. Unemployed dreams were also differentiated from control dreams by an underrepresentation of physical and spatial aspects, visual observations, movement and temporal elements, and surprise.

The prevalence of specific themes was compared between the two groups: unemployed individuals and the control group. Dreams were tokenized using the Python package Natural Language Toolkit 3.8.1's word_tokenize and removing Natural Language Toolkit stopwords. Tokenized words were utilized as-is without lemmatization. The prevalence of dreams with at least one token from the word group was calculated in the unemployed individuals versus the control group, yielding the percent of dreams in each group containing any word from the word group. A chi-square test was used to determine whether the differences in prevalence were statistically significant. The theme of professional life was found to have a significantly higher prevalence in the unemployed group compared to the control group. The themes of

Table 2
Descriptions of Differentiating Content Themes

Theme	Keywords	Description	Example
Professional life	Work, college, job, graduated	These words describe professional life, including tertiary education and the workplace.	"This dream actually started with me going back to work for a company at which I was formerly employed. I left them 2 years ago, but I was back working with them again for whatever reason, and I knew that the stakes were high and I had to do well at this job." (Classified as unemployed)
Surprise	Different, remember, weird, know	These words imply a narrative or description that includes elements of surprise, change, or introspection.	"It begins with me and my dad jogging on a hilly path … On our way, I stopped running and noticed that the path to the hill was different than earlier. I was shocked and in disbelief at what I saw." (Classified as control)
Visual perception	Saw, see, looked, eyes, look	These words relate to sensory perception and cognition, emphasizing the act of seeing and observing.	"I walked upstairs to the attic. The attic I entered looked old and creepy. In my search for the comic books, I walked past a large mirror. When I looked into it, I saw an insanely creepy man standing behind me, looking me directly into my eyes. It was at this point I started screaming in my dream." (Classified as control)
Dreaming	Dreams, vivid, last, night	These words describe the experience of dreaming. It reflects the frequency with which the user describes their reflections on the dream, as well as the dream content itself.	"Right before my alarm went off this morning, I had a very vivid nightmare that my dad tried to strangle me." (Classified as control)
Domestic relationships	Relationship, husband, baby, boyfriend, married, dog, anyone, together, ex, wife	These words relate to personal relationships, especially within the domestic sphere.	"I dreamt about my husband getting into an altercation with my ex. As a result my ex stabbed my husband in the back when he turned away. They were in the backyard and I was inside with the two kids." (Classified as unemployed)
Temporal	Suddenly, go, first, went, starts, time	These words suggest narratives that involve sequences of events, actions, or transitions between locations or states.	"I drove under the overpass and suddenly I found myself in an enormous neighborhood with cookie-cutter style mansions. Perfect green lawns, shuttered windows, and unscathed asphalt were a common sight. I looked behind me and couldn't even see the highway I just drove underneath. I immediately fell under a state

(*table continues*)

Table 2 (*continued*)

Theme	Keywords	Description	Example
			of confusion. I looked for street signs and house numbers but nothing was identifiable. There was no sense of direction. I kept driving around trying to find my way out of the neighborhood but it seemed like it just kept going and going." (Classified as control)
Negative emotions	Want, feel, death, anxiety, died, suicide	These words indicate a focus on internal emotional states, concerns, or reflections.	But he just kept laughing and kept telling me I was dead. And it felt more real than anything I've ever felt, I was having a full blown panic attack and could feel my emotions and anxieties, everything. (Classified as unemployed)
Spatial	Room, house, place, bed, door, inside, outside, world, around, world	These words relate to physical locations, both specific (room, bed) and general (house, place). They refer to settings or environments.	"It always starts with me at my grandparents house, just roaming around inside, either getting ready or looking for something. After a little while I always walk out the front door, which always is covered in a blinding light outside. Most of the time, the house is empty." (Classified as control)

surprise and visual observations appeared less frequently in the unemployed group than the control group. Chi-squared values, significance values, and prevalence in the control group and unemployed group are shown for all themes in Table 3.

Discussion

This study demonstrates the potential of digital methods to use publicly available data for dream research on subpopulation differences. We examined the relationship between employment status and dream content for 6,478 dream reports. Significant

Table 3
Statistical Differences in Theme Prevalence Between Unemployed and Control Dreams

Theme	Prevalence in unemployed	Prevalence in control	χ^2	p
Professional life	.151	.111	21.92	<.001
Surprise	.596	.632	8.63	.003
Visual perception	.480	.509	5.23	.022
Dreaming	.615	.594	3.06	.080
Domestic relationships	.376	.362	1.34	.247
Temporal	.636	.625	0.81	.367
Negative emotions	.375	.365	0.63	.426
Spatial	.580	.586	0.07	.795

differences were found between the dream content of unemployed individuals and the control group, with dream reports of unemployed individuals containing lower prevalence of surprise and visual perception and higher work-related language.

The dreams of unemployed individuals contained significantly fewer words indicative of surprise, change, or introspection. According to the cognitive-evolutionary model of surprise (Meyer et al., 1997), in order to experience surprise, individuals need to actively process and compare incoming information to their expectations (Reisenzein et al., 2019). Therefore, the relative absence of surprise in the dreams of unemployed individuals could point toward a more passive cognitive style. Similarly, there was a significant underrepresentation of words related to visual observations in the dreams of unemployed individuals. This group used fewer words that emphasize the act of seeing, observing, and interacting with their dream environment through visual perception.

The present study found a significant overrepresentation of professional themes in the dreams of unemployed individuals, aligning with the continuity hypothesis (Hall, 1971). Unemployed individuals experience high stress levels linked to joblessness (Gedikli et al., 2023), meaning work is a more intense concern in their waking lives. Previous research (Schredl et al., 2020) identified fewer work-related dreams in individuals with reduced work hours. While seemingly conflicting, this divergence can be attributed to differences in the perceived importance of job loss. Schredl et al. (2020) included a large portion of retirees (60.6%) and homemakers (11.2%), to whom unemployment would be less undesirable. This suggests that the heightened distress associated with active job seeking, rather than unemployment in general, may contribute to the increased prevalence of work-related dreams.

Reduced visual perception and lower surprise levels indicate a continuity of mindset between waking and dreaming. This continuity has been demonstrated in smaller, clinical samples. For example, Roesler (2018) analyzed longitudinal dream series in psychotherapy patients, finding that dream content corresponded with the dreamer's psychological state and personality structure. Roesler observed that changes in dream themes over time were associated with therapeutic progress, suggesting that dreams express a person's broader psychological condition rather than merely reflecting recent waking events.

While the continuity hypothesis has primarily been applied to thematic content, the present study suggests that waking disengagement may extend into dream cognition, reduced visual perception, and lower levels of surprise. This finding indicates that the dream structure itself is shaped by broader psychological states, such as disengagement from waking life. This interpretation aligns with Roesler (2018), who argues that dreams reflect the dreamer's holistic psychological state, including unconscious dynamics. By identifying systematic differences in dream engagement, this study suggests a possible extension of continuity theory, which considers how major life circumstances shape not just what people dream about but how they experience their dream environment.

The lack of engagement with the dream environment characterizing the content of unemployed dreams parallels the concept of decreased employee engagement in the workplace. Employee engagement is defined within human resource management (HRM) as the involvement and enthusiasm of employees in their work and workplace (Schaufeli et al., 2002). An engaged employee works with passion toward their organization's goals, while an unengaged employee will participate but without energy or commitment (Chandani et al., 2016). Employee engagement often decreases in the time period before the onset of unemployment (Li et al., 2016), whether the unemployment is because of involuntary turnover, burnout, or voluntary resignation.

The focus on employee engagement in the HRM and business field has increased in recent years (Shahid, 2019). This is primarily because of a growing body of research demonstrating its links to employee outcomes such as well-being (Fairlie, 2017) and performance (Deepalakshmi et al., 2024), as well as overall organizational success indicators such as talent retention (Harter et al., 2002), financial metrics, and customer satisfaction (Chi & Gursoy, 2009). Employee surveys are typically used to research employee engagement at a group level but have been criticized in terms of validity (Garrad & Hyland, 2020) and the time burden they place on employees and organizational leadership (de Waal, 2014).

The present study indicates that employee dream content analysis may offer a more direct, less burdensome route to group-level employee engagement measures for large populations. While the emotional content of dreams has been linked to work-related stress (Schredl et al., 2020), the present study further details this link, tying dream content to an additional HRM metric of strategic relevance. We propose that large-scale dream analysis may provide insights into population-wide changes in employee engagement, with disengagement with the dream environment indicating decreased engagement with waking work experiences. Applying large-scale dream analysis to defined subpopulations would enable organizations to monitor and address employee engagement challenges through interventions such as improved working conditions.

While the present study suggests that dream content may provide insight into workforce engagement, its practical applications remain preliminary. Rather than viewing dream content as an intervention target, these findings suggest that shifts in dream content might function as a passive, large-scale indicator of workforce disengagement. Employers already monitor behavioral signs such as absenteeism and declining productivity; dream trends could offer an additional, nonintrusive signal that cognitive disengagement occurs before it manifests in workplace behaviors.

Limitations

The present study demonstrates a novel approach to exploring the dream content of subpopulations at scale using publicly available dream report data from Reddit, alongside user subreddit participation. This approach has two key limitations. First, Reddit users do not share every dream. Previous research shows that emotionally intense dreams are more likely to be shared (Curci & Rimé, 2008), which suggests the sample in this study may be biased toward emotionally intense dreams.

Second, the inferred unemployment status of participants is based solely on their participation in specific subreddits. It was inferred that users active in r/unemployed and similar subreddits were unemployed at the time of their dream report. Users not active in these subreddits were considered not unemployed and, therefore, were an appropriate control group. However, this assumption may not always hold. It is possible that some users in the unemployment subreddit were no longer unemployed when they posted their dreams or that some individuals in the control group were unemployed but did not participate in the unemployment subreddits. This misclassification of employment status introduces a potential source of error in the analysis.

Future Research

Previous studies using Reddit have supplemented online data with targeted surveys to confirm user attributes (Proferes et al., 2021) and, therefore, minimized the second limitation of the present study. A logical next step would be to collect additional work history data from r/dreams users through surveys or direct inquiries. Temporal synchronization of dream reports with actual employment histories would not only improve the accuracy of the current research but also open new avenues for exploration.

For example, it remains unknown how dream content evolves through the multiple stages of unemployment. The psychological experiences of the initial awareness of job loss, whether voluntary or involuntary, job seeking, and eventual reemployment are likely to influence dream content differently. A longitudinal approach would be beneficial for understanding how dream content evolves as individuals transition between these different occupational statuses. This research has the potential to provide valuable insights into the psychological stressors associated with job loss and employment instability.

Temporal synchronization would also help explore dream content as a predictor of future unemployment. Dreams often contain information that is not easily accessible through other means, either because the individual is not consciously aware of it or because they have chosen not to disclose it (Hartmann, 2010). There is reason to hypothesize that specific dream themes related to unemployment may preempt the onset of actual unemployment and potentially even the employee's awareness of looming unemployment. Subjective well-being drops up to a year before unemployment starts (Clark et al., 2008), suggesting that dreams may show change at that point as well.

This predictive capability of dreams would apply to workforce intelligence efforts. Previous research has leveraged large social media data sets to forecast changes in unemployment rates. For example, emotional tones in Twitter posts have been used as leading macroeconomic performance indicators (Proserpio et al., 2016). Bokányi et al. (2017) found that daily patterns of Twitter activity correlated with unemployment rates, suggesting using digital footprints to augment official unemployment data. Dream content analysis offers a potentially earlier signal, detecting shifts in emotional and cognitive states before they manifest as behavioral or verbal indicators. In this way, large-scale dream collections may contribute to forecasting changes in unemployment rates and prompting the preparation of societal-level interventions.

Conclusions

This study highlights the value of large-scale dream content analysis for understanding the relationship between employment status and dream content. By leveraging publicly available data and employing machine learning techniques, we were able to identify significant differences in the dream narratives of unemployed individuals compared to a control group. The findings suggest that an individual's disengagement with the workforce is mirrored in disengagement with the dream world.

The methodology of the present study has significant applications for both dream science and HRM. For dream researchers, this study highlights the potential of combining large-scale anonymous dream reports with real-world data about dreamers' waking lives, such as employment status. For HRM professionals, this study provides a practical path to integrating dream content analysis into workforce intelligence.

The use of large-scale dream content analysis has the potential to reshape our understanding of the workforce, introducing employees' unconscious processing as an integral part of strategic decision making. Despite the theoretical interest in dreams in HRM (Schiavone, 2013), their application as a data source for business-relevant insights remains underutilized.

While further research is needed to refine these techniques, this study highlights the promising potential of leveraging publicly available data in subpopulation dream content analysis. Demonstrating the feasibility of this approach opens avenues for future investigations into theoretical advancements in dream science and practical applications for understanding workforce dynamics.

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