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RESEARCH ARTICLE

Predictability of sleep in insomnia: sleep patterns of patients from a sleep psychology clinic

Dave Laroche [1,2] | Hans Ivers [1,3] | Celyne H. Bastien [1,2] | Annie Vallières [1,2,4]

[1]École de psychologie, Université Laval, Quebec City, Quebec, Canada

[2]CERVO Brain Research Center, Quebec City, Quebec, Canada

[3]Centre de recherche sur la cancer, Université Laval, Quebec City, Quebec, Canada

[4]Centre de recherche du CHU de Québec-Université Laval, Quebec City, Quebec, Canada

Correspondence
Dave Laroche, Pavillon Félix-Antoine-Savard, École de psychologie, Université Laval, Québec City, QC G1V 0A6, Canada.
Email: dave.laroche.2@ulaval.ca

Summary

The present study aims at identifying sleep patterns in insomnia in a clinical sample using three strategies to define poor nights. Sleep diaries and self-reported questionnaires were collected from 77 clinical patients with insomnia. The conditional probabilities of observing a poor night after 1, 2, or 3 consecutive poor nights were computed according to three strategies with same criteria for sleep onset latency, wake after sleep onset, and sleep efficiency, but varying criterion for total sleep time. Latent profile analyses were conducted to derive sleep patterns. Uni- and multivariate analyses were conducted to characterise the sleep patterns identified. A total of 1586 nights were analysed. The strategy used significantly influenced the average percentage of reported poor nights. Two to three sleep patterns were derived per strategy. Within each strategy, sleep patterns differed from each other on sleep variables and night-to-night variability. Results suggest the existence of sleep patterns in insomnia among individuals consulting in psychological clinics. Adding a total sleep time of 6-h cut-off as a criterion to define poor nights increases the accuracy of the strategy to define poor night and allows to identify sleep patterns of poor nights in insomnia.

KEYWORDS

behavioural sleep medicine, insomnia, comorbid, night-to-night variability, predictability, sleep patterns

1 | INTRODUCTION

Poor nights in insomnia are perceived as unpredictable for most individuals with insomnia. Moreover, the night-to-night variability referring to the fluctuation of sleep variables in insomnia is a widely accepted concept (Molzof et al., 2018; Sánchez-Ortuño & Edinger, 2012). Some authors have questioned the unpredictability of poor nights in insomnia, arguing that sleep patterns might be hidden by the night-to-night variability (Perlis et al., 2005; Perlis et al., 2010; Perlis et al., 2014; Vallières et al., 2005; Vallières et al., 2011). Evidence supporting the existence of sleep patterns in insomnia is strong in some studies (Vallières et al., 2005, 2011) while limited in others (Buysse et al., 2010; Perlis et al., 2005, 2014).

Three predictable sleep patterns were identified from two separate research samples of adults with insomnia in Vallières et al. (2005, 2011). These authors found: (1) the high probability pattern (HPP) characterised by a high and constant probability of having a poor night after 1, 2, or 3 consecutive poor nights and associated to ageing, more severe insomnia, and greater mental fatigue; (2) the low probability pattern (LPP) characterised by a low and decreasing probability of

having consecutive poor nights, sleep-maintenance insomnia, and greater physical fatigue; and (3) the unpredictable pattern (UP) characterised by a 50% probability of having a poor night regardless of the number of previous poor nights. No specific predictable patterns were found in Perlis et al. (2010, 2014) but two tendencies were reported. In the first trend (Perlis et al., 2010), the probability that a good night was preceded by a poor night decreased over time while in the second trend (Perlis et al., 2014), individuals with insomnia needed in average 3 consecutive poor nights before experiencing a good or better than average night (Perlis et al., 2014). In a study by Buysse et al. (2010) no sleep patterns were identified.

Divergence among the five studies may be attributed to samples and methods differences. First, the samples in Vallières et al. (2005, 2011) and in Perlis et al. (2010, 2014) were adults with insomnia, medication free, and without comorbid disorders or with comorbid disorders in partial remission. Buysse et al. (2010) included elderly individuals with comorbid disorder in remission. The series of investigated nights also differed among these five studies ranging from 14 nights in Buysse et al. (2010) to 21 nights in the four other studies (Perlis et al., 2010, 2014). Shorter series of nights reduces the probability of observing series of poor nights. Finally, the definition used for poor night sleep was not consistent across studies, which is the basic characteristic to define a pattern. Vallières et al. (2005, 2011) defined poor nights with wake time variables and sleep efficiency (SE) while Perlis et al. (2010, 2014) also considered the participant's sleep improvement in their nights' classification. Buysse et al. (2010) investigated sleep patterns using a correlative approach, assessing inter-night coherence with mixed models. Nights' values were included as covariates and removed from the model if not significant, eliminating the need for defining poor nights.

To minimise result discrepancies, defining the optimal criteria for a poor night is essential. Otherwise, sleep patterns may differ significantly across studies. In previous research, criteria to define a poor night utilised combinations of wake time variables and SE (Perlis et al., 2010, 2014) without considering total sleep time (TST) as an endpoint. However, Vgontzas et al. (2012, 2013) drew attention to TST in insomnia, demonstrating a 6-h cut-off as the primary marker to identify the objective short sleep duration phenotype. Furthermore, a 5-h TST duration could also be used to define a poor night, as it reflects the minimum time for a sleep window frequently recommended in cognitive-behavioural therapy for insomnia (CBT-I; Morin, 1993). The sleep restriction therapy, included in CBT-I, justifies the minimum 5-h sleep window because research shows that a 5-h TST protects against excessive daytime sleepiness (Spielman et al., 2011). In fact, this means that a 5-h TST indicates poor sleep, as it increases sleepiness. For this reason, there is a need to test a 5-h TST criterion. In addition, a TST criterion ensures that short-duration nights are not classified as good, even if sleep onset latency (SOL) and wake after sleep onset (WASO) are <60 min.

There is also a need for the replication of sleep patterns in insomnia among clinical samples, as CBT-I might incorporate the notion of sleep predictability for assessment and cognitive interventions purposes. Existing studies on this topic have utilised research samples; however, trial samples may not accurately represent the patients typically encountered in psychological clinics (Vallières et al., 2021). Clinical cases are often excluded from research samples because of their complexity, which may not fit within the inclusion criteria (Curtis et al., 2019; Hoertel et al., 2012, 2013, 2014; Vallières et al., 2021; Zailinawati et al., 2012; Zimmerman et al., 2002).

The present study had two objectives: firstly, to compare three strategies for defining poor nights, and secondly, to replicate the same three sleep patterns in insomnia than Vallières et al. (2005, 2011) within a clinical sample. It was expected that more poor nights would be found with the addition of a TST criterion.

2 | METHODS

2.1 | Participants

The present study used a convenient sample of patients who consulted at the Sleep Psychology Clinic of the Consultation services of the École de Psychologie of Université Laval for sleep complaints. The Sleep Psychology Clinic specialises in the assessment and treatment of sleep disorders and related psychological difficulties. Ethical approval was obtained from the Université Laval Ethics in Research Committee sector psychology and educational sciences (2017-319 R-4/24-03-2022).

Inclusion criteria were: (a) having difficulty falling asleep and/or maintaining sleep; (b) aged ≥18 years; (c) having completed ≥21 days of pretreatment sleep diaries with no more than 3 missing nights. Exclusion criteria were: (a) reporting to have a degenerative neurological disease; (b) having a history of alcohol or drug abuse in the year prior to assessment; (c) having a circadian rhythm sleep–wake disorder.

Every individual included in the study received a formal insomnia diagnosis based on Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition, Text Revision (DSM-IV-TR) (American Psychiatric Association, 2000) or DSM, Fifth Edition (DSM-5) (American Psychiatric Association, 2013) criteria through a complete psychological assessment by professional therapists or supervised trainees. All participants reported clinically significant distress or impairment in social, occupational, educational, academic, behavioural, or other important areas of functioning, as required for an insomnia diagnosis by the DSM-IV-TR (American Psychiatric Association, 2000) and DSM-5 (American Psychiatric Association, 2013).

2.2 | Evaluation protocol

Patients followed a standardised evaluation protocol (Vallières et al., 2021). It included two clinical semi-structured interviews, sleep diary, and four online self-reported questionnaires. The evaluation took place over 3 weeks to a rate of one weekly session for a total of 5 h of assessment.

2.2.1 | Semi-structured interviews

The structured insomnia and sleep disorders interview (Morin, 1993) was used to screen insomnia and other potential sleep disorders. The Mini-International Neuropsychiatric Interview (Lecrubier et al., 1997; Sheehan, 1998) adjusted for the DSM-5 criteria (American Psychiatric Association, 2013) was used for psychiatric disorders.

2.2.2 | Sleep diary

The sleep diary was an online or paper format to be completed daily based on the consensus diary (Carney et al., 2012). The online version of the sleep diary was used for 25.5% of the patients. Sleep variables were drawn or derived from the sleep diary. Patients were instructed to complete their sleep diaries ideally upon waking. Each entry was systematically reviewed by the therapist with the patient during their weekly assessment session. Sleep diary data were visually inspected prior to analysis as in Vallières et al. (2005, 2011) and Perlis et al. (2010, 2014).

2.2.3 | Self-reported questionnaires

The Insomnia Severity Index (ISI; Bastien et al., 2001) is a seven-item questionnaire assessing the severity of insomnia. The ISI has adequate psychometric properties (Bastien et al., 2001). The Dysfunctional Beliefs and Attitudes About Sleep Scale (DBAS-16; Morin et al., 2007) measures with 16 items the endorsement of dysfunctional beliefs and attitudes about sleep and has adequate psychometric properties (Morin et al., 2007). The Beck Depression Inventory-II (BDI-II; Beck et al., 1996) is a 21-item questionnaire assessing depressive symptoms during the past week. Its psychometric properties are well supported (Dozois et al., 1998; Wang & Gorenstein, 2013). The State-Trait Anxiety Inventory (STAI; Spielberger et al., 1983) assesses state Anxiety (20 items) as well as Anxiety Traits (20 items). Its psychometric properties are excellent (Spielberger et al., 1983). Its psychometric properties (Canadian French version) are excellent (Gauthier & Bouchard, 1993).

2.3 | Statistical analyses

Descriptive statistics analyses were computed using the Statistical Package for the Social Sciences (SPSS), version 29.0.0. Subsequent statistical analyses were conducted following four main steps. The four steps aimed at classifying each night as 'good' or 'poor' in each series of nights following the three strategies, to compute the conditional probability of having a poor night following a good night, to verify if there are sleep patterns in participant's sleep, and to characterise the sleep patterns.

In the first step each night was classified as good or poor following three strategies: Strategy 1: SOL and/or WASO ≥60 min with an SE ≤80%; Strategy 2: SOL and/or WASO ≥60 min with an SE ≤80% or when TST ≤300 min; and Strategy 3: SOL and/or WASO ≥60 min with an SE ≤80% or when TST ≤360 min. Strategy 1 was used by Vallières et al. (2005, 2011). The two additional strategies included a TST criterion preventing nights of short duration from being misclassified. Based on each strategy, a time series of binary indicators was created for each individual, with '1' assigned to represent a poor night and '0' representing a good night.

In the second step, the conditional probabilities of a poor night (P) after 1 ($p[P|P]$), 2 ($p[P|PP]$) or 3 ($p[P|PPP]$) consecutive poor nights were computed for each series of nights per strategy with Statistical Analysis System (SAS), version 9.4. One-way analysis of variance (ANOVA) and multiple comparisons test with Bonferroni correction with the alpha set at 0.017 ($\alpha = 0.05/3$ strategies) were computed to compare the three strategies on the percentage of identified poor nights. As the knowledge about whether the preceding night was poor should not alter the likelihood of observing a poor night, the unconditional probabilities over 21 nights were also computed for each individual to verify the presence of dependency between poor nights. If the conditional and unconditional probabilities are unequal (i.e., if $P[P|P] \neq P[P]$), it indicates that poor nights are dependent, meaning that experiencing a poor night increases (or decreases) the likelihood that the next night will also be poor.

In the third step, latent profile analyses (LPA) were conducted using R-4.3.0 to derive profiles (i.e., sleep patterns) of individuals based on their probability to have a poor night after 1, 2, or 3 consecutive poor nights per strategy. Each depicted profile corresponds to a specific sleep pattern. To determine the optimal number of profiles for describing individuals, LPA compared statistical models with one to five potential sleep patterns. The best-fitting model was then determined with the help of Bayesian information criterion (BIC), log-likelihood and entropy criteria. One LPA per strategy was computed leading to one best-fitting model per strategy. As conditional probabilities are random variables with a bounded domain (0–1), standard statistical packages for LPA (based on the normal multivariate distribution) failed to support this distribution. Thus, an LPA package was developed in R by the second author (H.I., statistician) to support the vector beta distribution, based on algorithms described in Ji et al. (2005), Ma and Leijon (2009) and Trianasari et al. (2021). For comparison with LPA results, K-means cluster analyses were also computed using SPSS 29.0.0, like in Vallières et al. (2005, 2011). As with the LPA profiles, each cluster corresponded to a specific sleep pattern. Solutions with two to three clusters were investigated. The final solution was selected based on three criteria: (1) the parsimony of the solution, (2) the sample size of each cluster, and (3) the clinical interpretability of each cluster.

In the fourth step, one-way ANOVAs were computed using SAS version 9.4 to characterise sleep patterns derived from LPA within each strategy. Sleep patterns were compared on age, total scores on self-reported questionnaires, sleep variables, night-to-night variability for each sleep variables and finally, number of comorbid sleep or psychiatric disorders and medications. Night-to-night variability was defined as the difference between one measure and its equivalent

from the previous night. When normality assumptions were not respected, corresponding non-parametric tests were used. When results were significant, multiple comparisons test with Bonferroni corrections ($\alpha = 0.05/3$ strategies) were computed. Sleep patterns within each strategy were also compared on categorical variables (sex, insomnia severity, over-the-counter melatonin intake, and psychotropic medication type) with Pearson chi-square tests.

3 | RESULTS

3.1 | Sample description

Files from 333 individuals having been evaluated between 2015 and 2022 at the Sleep Clinic were reviewed. In all, 256 individuals were excluded: 129 presented too many missing sleep diary data, 89 had no insomnia diagnostic, 18 were children, three had a history of alcohol or drug abuse in the year prior to assessment, and 17 had circadian rhythm sleep–wake disorders. The final sample was composed of 77 individuals with insomnia (49.4% women) with a mean (standard deviation, range) age of 43.6 (13.7, 18–74) years.

Table 1 reports individuals' daily medication intake, comorbid psychiatric and sleep disorders, and diagnosis preponderance. In all, 75.3% of the sample presented at least one sleep disorder comorbid with insomnia, while 54.6% of individuals presented at least one psychiatric disorder comorbid with insomnia. In all, 14% of individuals had both comorbid sleep disorder and psychiatric disorder with insomnia; 16.9% of individuals presented no comorbidities and did not take any medication; and 61.0% of the sample took at least one psychotropic medication daily.

TABLE 1 Re-partition of patients according to their daily medication intake, comorbid psychiatric disorders, sleep comorbid disorders, and diagnosis preponderance.

Daily medication intake				***N* (%)**
Types of medication				
Anxiolytic alone				18 (23.4)
Antidepressant alone				12 (15.6)
Anxiolytic with antidepressant				13 (16.9)
Antidepressant with other medication				3 (3.9)
Other				1 (1.3)
None				30 (39.0)
Total				77 (100)
Diagnoses preponderance	**1st diagnosis *N* (%)**	**2nd diagnosis *N* (%)**	**3rd diagnosis *N* (%)**	**Total**
Sleep diagnoses				
Obstructive sleep apnea	19 (24.7)			19
Nightmare disorder	2 (2.6)			2
Hypersomnolence disorder	1 (1.3)			1
Bruxism	1 (1.3)			1
Restless leg syndrome		2 (2.6)		2
Periodic limb movements disorder			2 (2.6)	2
Total	23 (29.9)	2 (2.6)	2 (2.6)	27
	1st diagnosis *N* (%)	**2nd diagnosis *N* (%)**	**3rd diagnosis *N* (%)**	**Total**
Psychiatric diagnoses				
Major depression disorder	19 (24.7)	3 (3.9)		19
Persistent depression disorder	3 (3.9)			3
Generalised anxiety disorder	11 (14.3)	9 (11.7)	2 (2.6)	22
Social anxiety disorder	5 (6.5)	1 (1.3)		6
Panic disorder	1 (1.3)	1 (1.3)	2 (2.6)	4
Adjustment disorder	1 (1.3)			1
Bipolar disorder	2 (2.6)			2
Post-traumatic stress disorder		1 (1.3)		1
Obsessive-compulsive disorder			2 (2.6)	2
Agoraphobia		2 (2.6)	1 (1.3)	3
ADDAMC		1 (1.3)		1
Total	42 (54.6)	18 (23.4)	7 (6.5)	67

Abbreviations: ADDAMC, anxiety disorder due to another medical condition; *n*, number of individuals; 2nd, second; 3rd, third; 1st, first.

3.2 | Strategies to define poor nights

A total of 1586 nights were analysed. Strategy 1 classified 31.6% of nights as poor while Strategies 2 and 3 classified 40.1% and 49.9%, respectively. Strategies were significantly different on the average percentage of reported poor nights ($F[1, 107] = 53.3$, $p < 0.001$). Multiple comparison tests with Bonferroni corrections showed that the average percentage of poor nights with Strategy 3 was higher compared to both other strategies ($p < 0.001$). The average percentage of poor nights was higher for Strategy 2 than for Strategy 1 ($p < 0.001$).

3.3 | Sleep patterns

3.3.1 | Latent profile analyses

Table 2 shows the model fit indices and sample size per profile of the LPA, while Table 3 presents the re-partition of patients in sleep patterns according to sex and age. For Strategy 1, the three-profile solution yielded optimal model values. The optimal model demonstrated better value of entropy (0.95) compared to the four other models and a better log likelihood than model I and II. In Strategy 2, the two-profile solution yielded optimal model values. The optimal model demonstrated the highest BIC values while also showing a better value of entropy (0.95) than the four other models. For Strategy 3, the three-

TABLE 2 Model fit indices and sample size per profile (%) of the beta latent profiles analysis ($N = 77$).

					Strategy 1		Sample size per profile, %				
Profile	***m***	**LL[a]**	**AIC[a]**	**AICc[a]**	**BIC[a]**	**Entropy**	**1**	**2**	**3**	**4**	**5**
1	6	42.95	73.91	72.71	59.85	1.00	100.00				
2	13	131.40	236.80	231.40	206.40	0.90	28.57	71.43			
3	20	142.00	244.00	229.00	197.20	0.95	27.27	32.47	40.26		
4	27	162.90	271.80	241.00	208.60	0.85	5.20	29.87	28.57	36.36	
5	34	177.90	287.80	231.10	208.10	0.87	16.88	23.38	5.20	29.87	24.68
					Strategy 2		**Sample size per profile, %**				
Profile	***m***	**LL**	**AIC**	**AICc**	**BIC**	**Entropy**	**1**	**2**	**3**	**4**	**5**
1	6	42.24	72.49	71.29	58.42	1.00	100.00				
2	13	146.10	266.20	260.50	235.80	0.95	64.94	35.06			
3	20	141.30	242.60	227.60	195.80	0.78	20.78	15.58	63.64		
4	27	157.20	260.50	229.60	197.20	0.78	41.56	23.38	5.20	29.87	
5	34	187.10	306.20	249.60	226.60	0.75	41.56	19.48	9.09	6.494	23.38
					Strategy 3		**Sample size per profile, %**				
Profile	***m***	**LL**	**AIC**	**AICc**	**BIC**	**Entropy**	**1**	**2**	**3**	**4**	**5**
1	6	45.96	79.92	78.72	65.86	1.00	100.00				
2	13	123.40	220.80	215.00	190.30	0.90	38.96	61.64			
3	20	199.50	358.90	343.90	312.00	0.98	57.14	10.39	32.47		
4	27	192.80	331.50	300.70	268.20	0.91	40.26	25.97	9.09	24.68	
5	34	224.20	380.30	323.60	300.60	0.87	23.38	19.48	10.39	22.08	26.68

Abbreviations: AIC, Akaike information criterion; AICc, Akaike Information Criterion corrected for small sample size; BIC, Bayesian information criterion; LL, log-likelihood; *m*, the number of free parameters.

[a]Due to the support of the beta distribution, all fit indices are reported as a 'larger is better' format.

profile solution yielded optimal model values. The optimal model demonstrated better BIC values compared to the four other models as well as the best value of entropy (0.98).

Figure 1 illustrates the conditional probability of having a poor night according to strategy and sleep pattern. Two to three sleep patterns were identified per strategy. With Strategy 1 (SOL and/or WASO ≥60 min and SE ≤80%), three sleep patterns (1.1, 1.2, 1.3) were identified. In the sleep pattern 1.1 (21 patients), the conditional probability of having a poor night decreased from 0.66 to 0.55. In sleep pattern 1.2 (25 patients), the conditional probability was high and constant from 0.85 to 0.88, while in sleep pattern 1.3 (31 patients), the conditional probability remained at a low level although it increased from 0.34 to 0.51. The unconditional probabilities of observing a poor night over 21 nights for sleep patterns 1.1, 1.2, and 1.3 were respectively of 0.46, 0.58, and 0.45. With Strategy 2 (SOL and/or WASO ≥60 min and SE ≤80% or TST ≤300 min), two sleep patterns (2.1, 2.2) were identified. In the sleep pattern 2.1 (50 patients), the conditional probability of experiencing a poor night remained around 0.50 while it was high and constant in the sleep pattern 2.2 (27 patients), remaining at 0.83 to 0.85. The unconditional probabilities of observing a poor night over 21 nights for sleep patterns 2.1 and 2.2 were respectively of 0.43 and 0.61. With Strategy 3 (SOL and/or WASO ≥60 min and SE ≤80% or TST ≤360 min), three sleep patterns were identified (3.1, 3.2, 3.3). In the sleep pattern 3.1 (44 patients), the conditional probability of experiencing a poor night slightly increased from 0.45 to 0.54. In the sleep pattern 3.2 (eight patients), it consistently hovered around, from 0.95 to 0.99 while being high and constant around 0.80 in sleep pattern 3.3 (25 patients). The unconditional probabilities of observing a poor night over 21 nights for sleep patterns 3.1, 3.2, and 3.1 were respectively of 0.38, 0.84, and 0.60.

Sleep patterns belonging when derived from LPA were consistent across strategies for 16.9% of the sample. In all, 31.5% of individuals changed sleep patterns belonging to Strategy 1 to Strategy 2, while 24.7% changed from Strategy 2 to Strategy 3. Additionally, 23.4% of individuals changed sleep patterns belonging to Strategy 1 to Strategy 2 and from Strategy 2 to Strategy 3.

3.3.2 | The K-means cluster analyses

The K-means cluster analyses supported a two-cluster solution with Strategy 1 (SOL and/or WASO ≥60 min and SE ≤80%) and Strategy 2 (SOL and/or WASO ≥60 min and SE ≤80% or TST ≤300 min), while supporting a three-cluster solution with Strategy 3 (SOL and/or WASO ≥60 min and SE ≤80% or TST ≤360 min). Each cluster was

TABLE 3 Re-partition of patients in sleep patterns according to sex and age.

	Strategy 1		
Variable	**Pattern 1.1**	**Pattern 1.2**	**Pattern 1.3**
Sex, *n*			
Male	12	13	14
Female	9	12	17
Total	21	25	31
Age, years, mean (SD)	44.05 (14.05)	44.04 (16.04)	43.03 (13.70)
	Strategy 2		
Variable	**Pattern 2.1**	**Pattern 2.2**	
Sex, *n*			
Male	24	15	
Female	26	12	
Total	50	27	
Age, years, mean (SD)	45.12 (13.25)	40.89 (14.35)	
	Strategy 3		
Variable	**Pattern 3.1**	**Pattern 3.2**	**Pattern 3.3**
Sex, *n*			
Male	23	5	11
Female	21	3	14
Total	44	8	25
Age, years, mean (SD)	43.82 (13.14)	42.00 (15.10)	43.84 (14.76)

Abbreviation: SD, standard deviation.
Note: Strategy 1, sleep onset latency (SOL) and/or wake after sleep onset (WASO) ≥60 min and sleep efficiency (SE) ≤80%; Strategy 2, SOL and/or WASO ≥60 min and SE ≤80% or TST ≤300 min; Strategy 3, SOL and/or WASO ≥60 min and SE ≤80% or TST ≤360 min.

mutually exclusive, so that each participant displayed only one sleep pattern. Table S1 shows the central conditional probabilities derived from K-means analyses of observing a poor night according to strategy. For all three strategies, the conditional probability of observing a poor night after 1, 2, or 3 consecutive poor nights was high and constant for one sleep pattern, while it was low and decreasing for another sleep pattern. Strategy 3 also depicted a third strategy in which the conditional probability of observing a poor night after 1, 2, or 3 consecutive poor nights remained around 50%. Sleep pattern belonging when derived from K-means cluster analyses were consistent across strategies for 67.53% of the sample.

3.4 | Depiction of sleep patterns

Table 4 presents the mean values of sleep variables. The three sleep patterns derived from Strategy 1 (1.1, 1.2, 1.3) did not differ significantly on any dependent sleep variables. For Strategy 2, TST was significantly longer in sleep pattern 2.1 compared to sleep pattern 2.2 ($W = 398$, $p = 0.003$). Sleep pattern 2.1 also showed more wake episodes per night than sleep pattern 2.2 ($W = 860$, $p = 0.0398$). For Strategy 3, the only significant difference was the rising time in sleep pattern 3.3 that was later than in sleep pattern 3.2 ($H = 8.668$, $p = 0.004$).

Table 5 presents the mean values of sleep variables night-to-night variability according to the sleep pattern and strategy. Sleep patterns in Strategies 1 and 2 did not lead to any significant difference in the night-to-night variability of sleep variables. Sleep patterns in Strategy 3 differed on the average night-to-night variability of four sleep variables: SOL, $F(2, 74) = 3.933$, $p = 0.024$; early morning awakening (EMA), $F(2, 73) = 7.226$, $p < 0.001$; total wake time (TWT), $F(2, 73) = 3.309$, $p = 0.042$; and rising time, $H = 6.130$, $p = 0.047$. Multiple comparison tests with Bonferroni corrections showed that night-to-night variability of SOL and TWT in sleep pattern 3.3 was higher compared to sleep pattern 3.1, $p = 0.025$ and $p = 0.032$, respectively. Night-to-night variability of EMA was higher in sleep pattern 3.2 ($p = 0.008$) and 3.3 ($p = 0.019$) compared to sleep pattern 3.1. Night-to-night rising time variability was higher in sleep patterns 3.1 ($p = 0.014$) and 3.3 ($p = 0.033$) compared to sleep pattern 3.2.

Table 6 presents the mean scores for self-reported questionnaires according to sleep patterns and strategies. There were no significant differences between sleep patterns for any strategy on insomnia severity, dysfunctional beliefs and attitudes about sleep, as well as on anxiety and depression levels.

4 | CONCLUSION/DISCUSSION

The present study aimed to replicate sleep patterns in insomnia observed by Vallières et al. (2005, 2011) among a clinical sample and to compare three strategies identifying poor night's sleep. Results suggest that two to three sleep patterns can be drawn depending on the strategy used to define a poor night of sleep. Some patterns across the strategies had similar conditional probabilities of observing a poor night, suggesting that some of them were the same. The differences between conditional and unconditional probabilities support that poor nights are dependent and thus can inform on the occurrence of the next one as in previous studies (Perlis et al., 2010, 2014; Vallières et al., 2005, 2011). Sleep patterns differed only for strategies including a TST criterion. Significant differences between sleep patterns on sleep variables and sleep variables' night-to-night variability were mainly found when a 6-h TST cut-off was applied.

Hence, the results on variables characterising a poor night's sleep support the hypothesis that including a TST criterion increases the percentage of identified poor nights. The two strategies using a TST cut-off found the higher percentage of reported poor nights. Therefore, as was hypothesised, the addition of a TST criterion enhances the identification of poor nights. The addition of a TST criterion also led to variations in sleep pattern belonging, remaining constant across the three strategies for a minority of individuals. Using TST seems crucial to avoid classifying a night as good if SE is high, but TST is short. Clearly, misclassification could lead to an underestimation of the percentage of poor nights and, thus, influence the percentage of sleep patterns obtained. Although Perlis et al. (2010, 2014) attempted to

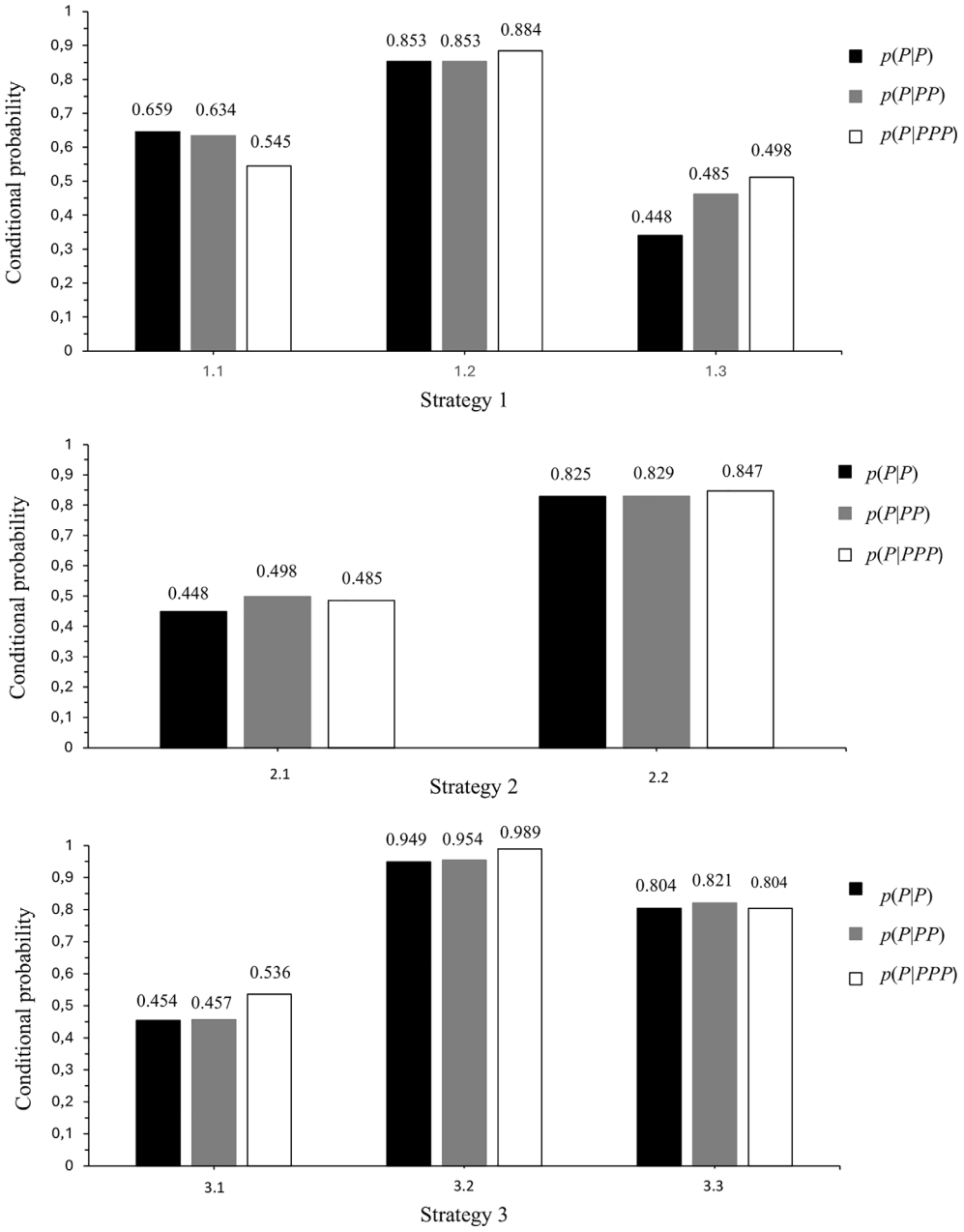

FIGURE 1 Conditional probability of having a poor night for sleep patterns according to the strategy. $p(P|P)$ = conditional probability of observing a poor night after 1 poor night, $p(P|PP)$ = conditional probability of observing a poor night after 2 consecutive poor nights, $p(P|PPP)$ = conditional probability of observing a poor night after 3 consecutive poor nights, *x*-axis shows the conditional probabilities, *y*-axis shows the sleep pattern for each strategy to dichotomise poor nights.

better reflect clinical reality by classifying nights as good when the overall sleep was better than the individual's average, TST remained unconsidered. It potentially resulted in an underestimation of the percentage of poor nights, especially for individuals consistently displaying very poor nights of sleep.

Observed sleep patterns derived from LPAs partially replicate those reported in the Vallières et al. (2005, 2011) studies. First, the HPP pattern identified by Vallières et al. (2005, 2011) seems to be present in each strategy as one sleep pattern per strategy (1.2, 2.2, and 3.3) exhibits a high and constant conditional probability of having poor nights' sleep over time. The UP pattern found by Vallières et al. (2005, 2011) seems also present within sleep patterns 2.1 and 3.1, both exhibiting a consistent conditional probability around 50% of experiencing a poor night. The consistency of sleep patterns in insomnia across strategies supports their existence. The sleep pattern 1.1 displayed a relatively high and decreasing conditional probability, which might constitute a slight variation of the UP pattern as the conditional probability decrement remains low and is still close to 50%. These combined results suggest that the HPP and the UP patterns might be more representative of the clinical population.

Two remaining sleep patterns appear new: 1.3 and 3.2. Sleep pattern 1.3 describes sleepers for whom the probability of having a poor night was low but increased over time. It then seems that for some individuals, the probability of having a poor night increases with sleep debt. The increasing sleep debt could be insufficient to promote sleep onset in these individuals as suggested in the literature (Fuller et al., 2006; Schwartz & Roth, 2008). Still, homeostatic and circadian misalignment (Franken & Dijk, 2024) might be more acute in these

TABLE 4 Mean values of sleep variables according to the sleep patterns and the strategy.

	Strategy 1		
Sleep variable, mean (SD)	**Pattern 1.1**	**Pattern 1.2**	**Pattern 1.3**
Bed time, hh:mm:ss	01:07:13 (01:20:31)	00:51:03 (00:42:22)	01:03:20 (00:59:24)
Rising time, hh:mm:ss	07:41:18 (01:23:22)	07:17:58 (01:10:12)	07:17:23 (01:11:07)
Number of wake episodes	1.95 (1.72)	1.68 (1.83)	1.30 (0.79)
SOL, min	51.98 (34.28)	45.43 (40.21)	40.46 (43.60)
WASO, min	39.39 (29.56)	34.96 (29.53)	34.85 (23.05)
EMA, minutes	37.73 (47.65)	32.24 (32.87)	29.81 (19.00)
TWT, min	127.99 (76.15)	114.24 (67.13)	105.04 (62.13)
TIB, min	501.70 (74.04)	497.51 (61.31)	493.72 (70.54)
TST, min	374.12 (101.00)	383.89 (90.15)	388.68 (72.99)
SE, %	74.17 (13.99)	76.72 (15.62)	78.98 (11.21)
	Strategy 2		
Sleep variable, mean (SD)	**Pattern 2.1**	**Pattern 2.2**	
Bed time, hh:mm:ss	00:59:04 (00:50:07)	01:02:53 (01:18:07)	
Rising time, hh:mm:ss	07:17:41 (01:12:37)	07:35:58 (01:16:47)	
Number of wake episodes	1.69* (1.28)	1.42* (1.77)	
SOL, min	45.24 (41.40)	45.18 (37.73)	
WASO, min	37.19 (21.68)	34.15 (34.77)	
EMA, min	33.41 (30.51)	31.55 (37.87)	
TWT, min	115.35* (70.27)	112.32* (63.38)	
TIB, min	501.11 (70.54)	489.75 (63.20)	
TST, min	385.76 (88.45)	378.33 (82.57)	
SE, %	77.05 (13.33)	76.71 (14.04)	
	Strategy 3		
Sleep variable, mean (SD)	**Pattern 3.1**	**Pattern 3.2**	**Pattern 3.3**
Bed time, hh:mm:ss	01:00:43 (01:02:31)	00:34:14 (00:18:19)	01:08:15 (01:06:00)
Rising time, hh:mm:ss	07:19:52* (01:16:29)	06:44:11* (00:28:47)	07:44:18* (01:15:24)
Number of wake episodes	1.43 (1.33)	1.30 (0.75)	2.00 (1.78)
SOL, min	38.73 (27.36)	56.45 (61.79)	53.03 (49.03)
WASO, min	30.69 (21.67)	47.75 (26.52)	41.98 (33.09)
EMA, min	35.60 (35.03)	36.55 (23.97)	26.54 (32.10)
TWT, min	104.57 (50.99)	140.75 (77.27)	122.92 (86.92)
TIB, min	496.71 (73.59)	487.55 (46.03)	500.92 (64.93)
TST, min	392.33 (89.05)	346.80 (64.34)	378.64 (85.96)
SE, %	78.82 (10.51)	71.64 (15.25)	75.30 (17.08)

Abbreviations: EMA, early morning awakening; SD, standard deviation; SE, sleep efficiency; SOL, sleep onset latency; TIB, total time in bed; TST, total sleep time; TWT, total wake time; WASO, wake after sleep onset.
*$p < 0.017$.

individuals. As Vallières et al. (2011) suggested, homeostatic impairment might also be what characterises HPP. Another explanation might be that individuals showing sleep pattern 1.3 misperceive their sleep. Vallières et al. (2011) suggested that individuals with HPP might overestimate their SOL and their TWT while underestimating their TST. Individuals with sleep patterns 1.3 might on the contrary underestimate their SOL and their TWT while overestimating their TST. These individuals might perceive alterations in their sleep only over time when ineffective coping strategies are reinforced. The sleep pattern 3.2 represents the poorest sleepers with a constant and very high conditional probability of experiencing a poor night. This sleep pattern might correspond to a sort of very HPP (VHPP) as it might also encompass the HPP. As the number of individuals in the VHPP was quite low, any assumption should be carefully set forward.

TABLE 5 Mean values of sleep variables' night-to-night variability according to the sleep pattern and the strategy.

	Strategy 1		
Sleep variable, mean (SD)	**Pattern 1.1**	**Patten 1.2**	**Pattern 1.3**
Bed time, min	67.22 (80.52)	51.05 (42.37)	57.30 (59.40)
Rising time, min	65.93 (59.12)	57.15 (41.68)	66.20 (53.40)
SOL, min	33.80 (51.99)	51.39 (49.86)	37.74 (38.54)
WASO, min	32.07 (24.70)	34.44 (23.72)	29.47 (17.21)
EMA, min	29.96 (25.27)	24.50 (26.89)	24.50 (19.89)
TWT, min	63.07 (43.94)	68.06 (49.43)	68.06 (43.52)
TIB, min	103.91 (59.89)	86.89 (43.04)	105.33 (71.10)
TST, min	114.02 (62.17)	103.17 (44.27)	120.83 (71.96)
SE, %	14.84 (9.63)	16.16 (9.10)	15.43 (9.42)
	Strategy 2		
Sleep variable, mean (SD)	**Pattern 2.4**	**Pattern 2.5**	
Bed time, min	59.06 (50.12)	62.88 (78.12)	
Rising time, min	67.93 (51.00)	54.42 (50.80)	
SOL, min	36.83 (44.70)	49.01 (48.79)	
WASO, min	29.60 (19.79)	35.86 (24.07)	
EMA, min	24.96 (21.96)	28.02 (26.79)	
TWT, min	64.75 (44.35)	71.05 (46.89)	
TIB, min	105.31 (63.21)	87.18 (52.44)	
TST, min	120.33 (66.39)	100.23 (48.38)	
SE, %	15.05 (9.97)	16.19 (9.42)	
	Strategy 3		
Sleep variable, mean (SD)	**Pattern 3.1**	**Pattern 3.2**	**Pattern 3.3**
Bed time, min	60.72 (62.52)	34.23 (18.32)	68.25 (65.98)
Rising time, min	65.85* (51.85)	30.47* (19.13)	68.98* (51.02)
SOL, min	28.89* (29.56)	52.13 (48.65)	59.06* (62.13)
WASO, min	28.51 (19.12)	30.71 (22.38)	37.90 (24.41)
EMA, min	18.38* (13.39)	46.07* (40.74)	33.81* (26.74)
TWT, min	56.84* (29.26)	65.62 (40.86)	84.98* (62.10)
TIB, min	100.30 (62.60)	64.44 (44.75)	107.62 (57.39)
TST, min	109.98 (57.39)	83.08 (47.29)	127.65 (68.68)
SE, %	13.68 (5.91)	14.08 (8.35)	18.98 (13.44)

Abbreviations: EMA, early morning awakening; SD, standard deviation; SE, sleep efficiency; SOL, sleep onset latency; TIB, total time in bed; TST, total sleep time; TWT, total wake time; WASO, wake after sleep onset.
*$p < 0.017$.

Contrary to Vallières et al. (2005, 2011) sleep patterns in the present study do not differ on clinical dependent variables. This is likely because the present clinical sample is more homogeneous regarding clinical variables and most individuals had more severe sleep and psychiatric issues compared to those included in previous studies (Buysse et al., 2010; Perlis et al., 2010, 2014; Vallières et al., 2005, 2011).

The results of K-means cluster analyses on the presence of sleep patterns in insomnia appear to be consistent with those of the LPAs. The K-means analyses support the existence of the HPP as one sleep pattern within each strategy described a high and constant probability of observing a poor night after 1, 2, or 3 consecutive poor nights. Results supported the existence as well of the UP but only in Strategy 3 that included the 6-h TST cut-off criterion. Contrary to LPAs, K-means cluster analyses allowed the replication of the LPP within the three strategies. As the two methods of statistical analysis produced inconsistent results regarding the presence of the LPP, it is unclear whether the sleep patterns in the present study align with the Vallières et al. (2005, 2011) findings on the LPP. These divergent results may be due to the different approach inherent to each statistical analysis. Contrary to the LPA, which is a modal based approach,

TABLE 6 Mean scores to self-reported questionnaires according to the sleep pattern and the strategy.

	Strategy 1		
Sleep variable score, mean (SD)	**Pattern 1.1**	**Pattern 1.2**	**Pattern 1.3**
Depression (BDI-II)	16.59 (12.53)	17.13 (12.00)	14.37 (9.22)
Insomnia severity (ISI)	18.84 (3.96)	17.64 (4.94)	18.07 (3.43)
Sleep quality (PSQI)	8.80 (3.45)	7.33 (2.73)	8.17 (3.13)
State-anxiety (STAI-S)	11.34 (2.75)	11.63 (2.42)	12.49 (2.32)
Trait anxiety (STAI-T)	50.82 (13.02)	44.44 (12.71)	45.10 (12.10)
Dysfunctional beliefs and attitudes about sleep (DBAS-16)	n\a	9.00 (n\a)	5.33 (1.16)
	Strategy 2		
Sleep variable score, mean (SD)	**Pattern 2.1**	**Pattern 2.2**	
Depression (BDI-II)	15.83 (10.96)	16.12 (11.16)	
Insomnia severity (ISI)	18.43 (3.97)	17.67 (4.32)	
Sleep quality (PSQI)	8.27 (3.09)	7.56 (3.06)	
State-anxiety (STAI-S)	43.16 (12.16)	39.42 (11.35)	
Trait anxiety (STAI-T)	46.64 (12.72)	45.63 (12.69)	
Dysfunctional beliefs and attitudes about sleep (DBAS-16)	5.00 (1.41)	7.50 (2.12)	
	Strategy 3		
Sleep variable score, mean (SD)	**Pattern 3.1**	**Pattern 3.2**	**Pattern 3.3**
Depression (BDI-II)	14.85 (10.76)	17.38 (11.76)	17.00 (11.34)
Insomnia severity (ISI)	18.61 (4.31)	18.00 (2.56)	17.54 (4.19)
Sleep quality (PSQI)	8.23 (3.28)	6.38 (3.25)	8.23 (2.54)
State anxiety (STAI-S)	41.89 (11.65)	40.38 (14.50)	42.30 (11.94)
Trait anxiety (STAI-T)	45.61 (11.20)	49.50 (15.97)	46.30 (13.10)
Dysfunctional beliefs and attitudes about sleep (DBAS-16)	7.00 (1.73)	n\a	4.00 (n\a)

Abbreviations: BDI-II, Beck Depression Inventory-II; DBAS-16, Dysfunctional Beliefs and Attitudes About Sleep Scale-16 items; ESS, Epworth Sleepiness Scale; ISI, Insomnia Severity Index; n\a, not available; PSQI, Pittsburgh Sleep Quality Index; SD, standard deviation; STAI-S, State and Trait Anxiety Inventory-State anxiety; STAI-T, State and Trait Anxiety Inventory-Trait anxiety.

the K-means cluster analysis is a grouping analysis based on distance measurement. The LPA determines the optimal number of profiles (sleep patterns) by comparing multiple models with indices, making it a more reliable measure than K-means cluster analysis. The fact that sleep pattern belonging varies considerably between strategies with LPA compared to K-means cluster analysis shows the sensitivity of the measure. Therefore, results from LPA are preferred.

The fact that most of individuals were medicated raise the question of whether medication intake is helpful to reduce insomnia over time, as it was not associated with lower probability of having a poor night sleep. The probability of having a poor night remaining high for most individuals suggests that medication intake does not reduce enough, if at all, poor night sleep in insomnia. Pharmacotherapy appears to have some beneficial effects in the treatment of insomnia, but evidence of its efficacy remains limited, especially for long-term use (Riemann et al., 2023). Medications are often used to improve sleep while reducing comorbid symptoms. Most medication prescribed for insomnia is not actually indicated for its treatment (Table 1) and thus might only be helpful in the treatment of the comorbid disorders, leaving insomnia to evolve on its own. The apparent lack of effect in reducing poor night sleep in insomnia in the present study may also be due to an ineffective combination of prescribed and over-the-counter (OTC) medications by individuals. As the use of OTC medication was not collected in this study, it is challenging to further comment on this matter.

The present study possesses strengths and limitations. One major strength is to use a clinical sample including individuals likely to be excluded from research samples. Using mixture modelling, such as LPA, is another strength as it does not rely on arbitrary predetermined values, like in K-means cluster analysis. This study is also the first to compare different statistical approaches and poor night's definitions to derive sleep patterns in insomnia. However, the study has some limitations. First, medical conditions were not available, while some of them might influence sleep and explain sleep patterns found. Second, results are limited by the sample size, which might have caused a reduction in statistical power decreasing the probability of finding significant differences between sleep patterns. In fact, the main reason for excluding individuals was missing data, especially from sleep diaries. Missing data mainly explains why conditional probabilities were limited to 4 nights. Specifically, the probability of having 1 poor night

after 1, 2, or 3 poor nights requires a maximum of 4 consecutive nights in the series. As the length of the sequence increases, the probability of missing data also rises, as it is more challenging to observe a sequence of 3 or 4 consecutive nights of insomnia compared to a single night. An uninterrupted night series would permit the computation of the conditional probability of observing a poor night after 'X' consecutive poor nights. The number of probabilities that can be computed would then be equal to the number of nights included in the series.

Future research should aim to reproduce sleep patterns using a 6-h TST cut-off score to define poor night specifically among the clinical population. The inclusion of individuals with medication intake and several medical, sleep, or psychiatric comorbidities would favour generalisation of the results among the clinical population. It might also be interesting to add objective sleep measures to verify whether sleep patterns in insomnia are exclusive to self-report sleep, which would support the hypothesis that sleep patterns in insomnia are due to sleep misperception rather than circadian rhythm and homeostatic impairment. Objective measurement would also allow to quantify sleep misestimation according to sleep patterns in insomnia.

In conclusion, results suggest that Strategy 3, which includes a 6-h TST cut-off, is the most efficient strategy for identifying sleep patterns. Strategy 3 better dichotomised poor and good nights and enabled the replication of the HPP and the UP when derived from both LPA and *K*-means cluster analysis. Future research should adopt it, as it allows for the classification of nights with low SE and long SOL or WASO, as well as nights of short duration (TST ≤360 min). As artificial intelligence (AI) and technology (such as applications and websites) become increasingly used to address insomnia, identifying sleep patterns with binary series pave the way to recommendations based on AI. Being able to predict individuals' sleep will help clinicians monitor treatment outcomes, address cognitive distortions regarding individuals' ability to sleep well, and normalise their experiences. Additionally, sleep patterns in insomnia could lead to the discovery of previously unknown insomnia subtypes or phenotypes.

AUTHOR CONTRIBUTIONS

Dave Laroche: Conceptualization; methodology; data curation; investigation; writing – original draft; writing – review and editing; project administration; formal analysis. **Hans Ivers:** Conceptualization; methodology; formal analysis; software; supervision; validation; writing – review and editing. **Celyne H. Bastien:** Conceptualization; methodology; supervision; validation; visualization; writing – review and editing; resources. **Annie Vallières:** Conceptualization; methodology; data curation; supervision; validation; visualization; writing – review and editing; resources.

CONFLICT OF INTEREST STATEMENT

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DATA AVAILABILITY STATEMENT

The data underlying this article cannot be shared publicly in order to protect the privacy of the individuals who participated in the study. Data will be shared upon reasonable request to the corresponding author under the condition of obtaining ethical approval.

ORCID

Dave Laroche https://orcid.org/0009-0002-9245-7915
Annie Vallières https://orcid.org/0000-0002-9433-7880

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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