



## PREDICTORS OF DROPOUT IN INTERDISCIPLINARY CHRONIC PAIN MANAGEMENT PROGRAMMES: A SYSTEMATIC REVIEW

Janke OOSTERHAVEN, PT, MSc<sup>1,2</sup>, Harriet WITTINK, PT, PhD<sup>1</sup>, Jurgen MOLLEMA, MSc<sup>1</sup>, Cas KRUITWAGEN, MSc<sup>1,3</sup> and Walter DEVILLÉ, MD, PhD<sup>2-4</sup>

From the <sup>1</sup>Research Group Lifestyle and Health, University of Applied Sciences Utrecht, Utrecht, <sup>2</sup>Amsterdam Institute for Social Science Research, University of Amsterdam, Amsterdam, <sup>3</sup>Julius Centre for Health Sciences and Primary Care, University Medical Centre Utrecht, and <sup>4</sup>National Knowledge and Advisory Centre on Migrants, Refugees and Health (Pharos), Utrecht, The Netherlands

**Objective:** Systematic review to identify predictors for dropout during interdisciplinary pain management programmes.

**Data sources:** PubMed, PsycINFO, CINAHL, Embase, and SPORTDiscus were searched from inception to 22 June 2017.

**Study selection:** Screening, data-extraction and quality assessment was carried out independently by 2 researchers.

**Data synthesis:** Eight studies with low methodological quality were included in this review. Out of 63 potential predictors identified in univariate analyses, significant results were found for 18 predictors of dropout in multiple logistic regression analyses in 4 domains, as described by Meichenbaum & Turk: (i) sociodemographic domain (2); (ii) patient domain (8); (iii) disease domain (6); and (iv) treatment domain (2).

**Conclusion:** This systematic review presents an overview of predictors of dropout. The literature with regard to the prediction of dropout has focused mainly on patient characteristics and is still in the stage of model development. Future research should focus on therapist/therapy-related predictors and the interaction between these predictors. This review suggests future research on this topic, in order to generate better outcomes in interdisciplinary pain management programmes.

**Key words:** dropout; chronic musculoskeletal pain; interdisciplinary pain management programmes; systematic review.

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Correspondence address: Janke Oosterhaven, Research Group Lifestyle and Health, University of Applied Sciences Utrecht, Heidelberglaan 7, NL-3584 CS Utrecht, The Netherlands. E-mail: janke.oosterhaven@hu.nl

Dropout from chronic musculoskeletal pain management programmes is associated with poor treatment outcomes (1–3). Despite this, dropout continues to be a neglected topic even after Turk & Rudy brought relapse and non-compliance to attention as a significant problem in chronic pain management (4). This is remarkable, since the assumption is that, because of the complexity of chronic pain management programmes and the focus on self-care behaviour, dropout is inevitable (4–6).

### LAY ABSTRACT

Dropout from interdisciplinary pain management programmes is reported to be high. This may result in poor treatment outcomes. Therefore, paying attention to the prevention of dropout is important. This systematic review presents an overview of predictors of dropout (mainly patient characteristics) and makes suggestions for future research on this topic.

To date, the literature on dropout in interdisciplinary pain management has largely relied on post-hoc analyses on differences between dropouts and treatment completers in cross-sectional research studies. The importance of dropout is acknowledged considering the dropout rates found in these studies ranging from 5% to 46% (4, 7, 8). However, few longitudinal studies have been performed and, as yet, no systematic review has summarized predictors for dropout. More insight in these predictors is needed to develop strategies to prevent premature treatment dropout. Although various definitions of dropout exist, we used the following definition: “patients with chronic pain, who were referred to a chronic pain management programme, who initiated (participated in the baseline assessments), but discontinued prior to completion of the entire programme” (9).

Since therapy for patients with chronic pain is partly similar to that of patients with mental disorders, we can look at mental health research that has been done on dropout in psychotherapy/cognitive therapy. This literature demonstrated dropout incidences around 20% (19.7–21.9%) and valuable insights with regard to predictors of dropout have been gained (10–13). These predictors can be categorized in 5 domains of barriers to retention in therapy, as suggested by Meichenbaum & Turk (14): (i) sociodemographic (dropouts were younger and less educated (10, 13)); (ii) patient (dropouts were less motivated for treatment, preferred alternative treatments and were diagnosed with a specific disorder such as depression or substance use disorder) (10–13); (iii) disease; (iv) treatment (no pre-determined treatment time limit and outpatient treatments were associated with dropout); and (v) healthcare system/system domain (higher dropout rates were found when the treatment was applied by trainees instead of licensed therapists (10)).

The mental health literature demonstrated associations between dropout and negative treatment outcomes. An important reported reason for dropout was the patient's low motivation. Since research studies select the most motivated patients, selection bias may affect the generalizability of these studies and may lead to overestimation of treatment effects (10–13). It is not clear if these findings may be transferred to interdisciplinary pain management programmes. For most patients with chronic pain these programmes are their last hope. Systematic research on predictors of dropout in these programmes may reveal specific knowledge on how to address these predictors. This may prevent a lot of frustration, overutilization of the healthcare system and more patients who complete interdisciplinary pain management programmes, which may result in better treatment outcomes.

Therefore, the following research question was addressed in this systematic review: which factors are predictors of dropout of patients with chronic musculoskeletal pain during interdisciplinary pain management programmes?

## METHODS

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (15) and the Cochrane Handbook for Systematic Reviews of Interventions (16) were followed in performing the review. A PROSPERO protocol (registration number: CRD42016039689, <https://www.crd.york.ac.uk/prospero/> (17) was developed *a priori* together with a medical information specialist (JM). Amendments made during the research process were registered in the PROSPERO protocol.

### Literature search and study selection

A comprehensive search strategy was conducted from inception to 22 June 2017 in the following databases: PubMed, PsycINFO, CINAHL, Embase and SPORTDiscus. To achieve maximum sensitivity we applied medical subject headings and title/abstract text searches (Appendix S1<sup>1</sup>). The PubMed search strategy was translated to the other databases. Studies obtained through screening reference lists were added in the top righthand box of the PRISMA flowchart (Fig. 1). The search strategies were reviewed and conducted by an experienced medical information specialist.

Screening was done independently by 2 reviewers (JO, HW). The first step was to screen articles on titles and abstracts. The second step was assessment of the full-texts of the articles for inclusion (JO, HW). For each article, any discrepancy between the 2 reviewers was resolved through discussion. In the first screening stage (titles plus abstracts), studies were included when both reviewers agreed they were eligible for inclusion, or if there was doubt about whether or not to exclude them. In the second screening stage (full-texts), studies were included

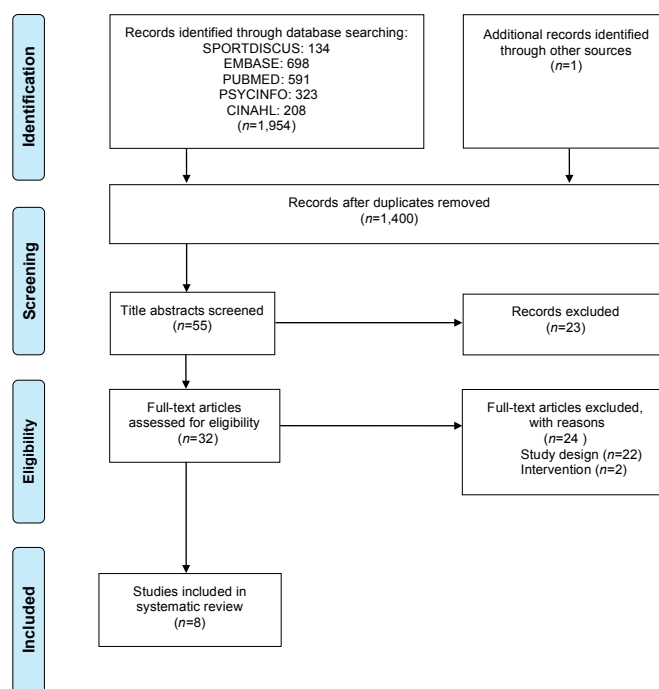


Fig. 1. Flow chart of study selection.

when both reviewers felt they met all the inclusion criteria. The following definition of predictor was used in this systematic review: “a predictive factor is a measurement that is associated with response or lack of response to a particular therapy” (18). Due to the complexity of dropout we focused in this systematic review on studies that applied both univariate analyses and multiple logistic regression analyses. These studies are also known as outcome prediction models (19).

Articles were included if: (i) the study population involved patients over 18 years of age, with chronic non-cancer musculoskeletal pain, i.e. chronic pain that is localized in muscles, ligaments, bones, fasciae, bursae or joints. Chronic pain was defined as: “pain that persists longer than 3 months, or pain that extends beyond the expected period of healing” (20); (ii) the study intervention consisted of interdisciplinary pain management programmes. Interdisciplinary was defined as: “clinicians from different specialities working together and communicating with each other on a frequent and scheduled basis about patients to reach a common goal” (21); (iii) the study design was: retrospective- or prospective cohort study or randomized controlled trials (RCTs) with the aim to identify multiple predictors for dropout during treatment and containing both univariate analyses and multiple logistic regression analyses; (iv) the language of the article was limited to: English, Dutch, French or German. Articles were excluded if the study intervention consisted of: (i) dropout during medication trials or (ii) an online intervention.

### Methodological quality assessment

The methodological quality of all included studies was assessed independently by 2 reviewers (JO, HW) with the Quality in Prognosis Studies (QUIPS) tool. This tool is appropriate to assess the risk of bias in prognostic studies and considers 6 domains: study participation, study attrition, prognostic factor measurement, outcome measurement, study confounding, and statistical analyses (Table I) (22, 23).

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**Table I.** Risk of bias due to various factors, and total score study quality (23)

Study	Study participation	Study attrition	Prognostic factor measurement	Outcome measurement	Study confounding	Statistical analysis and reporting	Study quality total score
Howard et al. 2009 (24)	Low	Moderate	Low	Moderate	High	Low	Low
Bendix et al. 1998 (27)	Low	High	Moderate	Moderate	High	Low	Low
Billier et al. 2000 (28)	Low	High	Moderate	Low	High	Low	Low
Carosella et al. 1994 (29)	Low	Moderate	Moderate	Low	High	High	Low
Coughlan et al. 1995 (30)	Low	Low	Moderate	High	High	High	Low
Kvaal et al. 1999 (31)	Moderate	High	Moderate	Low	High	High	Low
Sloots et al. 2009 (32)	Low	Low	High	Moderate	High	Moderate	Low
Richmond & Carmody 1999 (33)	Moderate	High	Moderate	Moderate	High	Low	Low

The reviewers familiarized themselves with the QUIPS through a test session involving 2 excluded studies, before judging the included studies. All ratings were entered into a spreadsheet. Any difference between the 2 reviewers was resolved through discussion and, if needed, a third reviewer was consulted to reach consensus (WD). An overall score of the study quality was based on the recommendations of Hayden and colleagues (23). For each domain the risk of bias was classified as high, moderate or low. Studies were considered of high quality if in all 6 domains a low risk of bias was found and these studies were labelled as an overall low risk of bias study (23).

#### *Data-extraction, data-analyses and data-synthesis*

Several steps were taken to extract and synthesize the data from the included studies, all steps independently by 2 reviewers (JO, HW), followed through a discussion, if needed a third reviewer was consulted to reach consensus (WD). In step 1, an extraction manual was designed to facilitate the data-collection process.

The following information was extracted from the included studies: (i) general information: authors, journal, publication date, country, language; (ii) research design: retrospective-or prospective cohort study or RCT; (iii) research population; (iv) analytical approach: univariate analyses using a variety of methods (for example  $\chi^2$  tests, independent t tests and univariate logistic regression analyses) and multiple logistic regression analyses; (v) all possible factors associated with dropout in univariate analyses and multiple logistic regression analyses with statistical significance and strength of the associations, number of studies that examined the associations.

In step 2 the factors were grouped into 5 domains of Meichenbaum & Turk (14).

For each domain the presence of associations and the direction of the associations of predictors and dropout was determined in univariate analyses and multiple logistic regression analyses (Tables II, III, and Table S2<sup>1</sup> and Table S3<sup>1</sup>).

For data-synthesis in systematic reviews of studies on outcome prediction models there is still no clear methodological procedure for pooling the data. The heterogeneity of the study populations, study interventions, predictors, statistical analyses and statistical reporting and the fact that most predictors were only investigated in one study (24), did not support applying a best-evidence synthesis (25, 26). Therefore, in step 3, only potential predictors from univariate analyses and multiple logistic regression analyses that were judged in at least 2 studies were described in the results. To summarize the results for a predictor that was investigated in more than 1 study the term: (i) "significant" was assigned if  $\geq 75\%$  of the studies showed significant results; (ii) "non-significant" was assigned if  $\geq 75\%$  of the studies showed non-significant results; (iii) "conflicting results" was assigned if the rule of  $\geq 75\%$  studies showing significant or non-significant could not be applied, or if opposite directions of the association were found in studies (e.g., if

dropout was associated with higher pain intensity in one study and with lower pain intensity in another study) (26).

## RESULTS

### *Study selection*

The initial search identified a total of 1,954 studies. One additional study was added through screening reference lists (Fig. 1). Without the 555 duplicates, 1,400 studies remained for screening on title and abstract. A total of 32 articles were considered for inclusion, but after full-text screening, only 8 studies were selected for the review. The main reason for exclusion was study design, such as cohort studies with only analyses on differences between completers and dropouts at baseline without prospective or retrospective follow-up and without univariate- or multiple logistic regression analyses of factors that might be predictors for dropout. Two studies were excluded due to the absence of an interdisciplinary approach in the intervention or on the grounds that the intervention under study was an online programme.

### *Study characteristics*

The 8 included studies were conducted between 1994 and 2009. Three studies took place in Europe and 5 studies in the USA. Table S1<sup>1</sup> provides an overview of the studies included in this review. Most studies focused in their main research objective on detecting predictors of dropout in chronic pain management programmes, 3 studies had a prospective cohort design (24, 27, 28), 4 a retrospective cohort design (29–32) and 1 randomized clinical trial (RCT) with a retrospective secondary analysis on dropout (33).

### *Interventions*

Seven studies described outpatient chronic pain management programmes with an interdisciplinary approach (27, 29, 31–33). Three of these studies were outpatient programmes with a focus on return to work, known as functional restoration programmes (24, 27, 29). One study investigated an inpatient programme with an interdisciplinary approach in the UK (30).

**Table II.** Results for (potential) predictors for dropout in simple analysis

(Potential) Predictor	Studies		Non-significant
	n	Significant	
<b>Sociodemographic (19)</b>			
Age	7	27, 28, 29, 30, 32, 33	25
Sex <sup>a</sup>	6	30, 32	24, 27 <sup>b</sup> , 29, 33 <sup>b</sup>
Education	2		36, 37
Social status	3		27 <sup>b</sup> , 29, 33 <sup>b</sup>
Ethnicity	2	32	24
Job code (blue collar vs white collar)	1		24
Pre-treatment work status	2	24	33 <sup>b</sup>
Original job available	1	24	
Pre-treatment case settlement	1		24
Job satisfaction	1		24
Job demand	2	27 <sup>c</sup>	24
Vibrations in job	1	27 <sup>c</sup>	
Supervisor support	1		29
Management control	1		29
Work pressure	1		29
Height	1		27
Weight	1		27
No shows	1		30
Sick leave days	1	27 <sup>c</sup>	
<b>Patient (21)</b>			
Maintenance	1		28
Fear of injury	1		29
Dysthymia	1		29
Pain distress	1		30
Depression <sup>a</sup>	3	28, 24 <sup>d</sup>	24 <sup>e</sup> , 30
Catastrophizing	1		30
MMPI Disability Profile	1	24	
Axis 2 disorder	1	24	
Substance use disorder	1	24	
Anxiety disorder	1	24	
Opioid dependency	1	24	
Any cluster A Dx	1	24	
Any cluster B Dx	1	24	
Any cluster C Dx	1	24	
Any cluster D Dx	1		24 <sup>b</sup>
Self-efficacy	1	30	
Return to work expectation	1	29	
Walk distance	1	30	
Pre-contemplation	1	28	
Action	1	28	
Somatization	1	28	
<b>Disease (21)</b>			
Pain intensity <sup>a</sup>	6	28 39, 30	27 <sup>b</sup> , 24, 31 <sup>b</sup>
Age first low back pain	1		27
Smoking	1		27
ADL scores	1		27
Sport activities	1		27
Aerobic capacity	1		27
Mobility	1		27
Isometric abdominal endurance	1		27
Isometric back endurance	1		27
Compensable body parts	1		24
Area of injury	1		24
Pain site	1	30	
Chronicity	1	30	
Disability	4	24, 28, 29, 33 <sup>c</sup>	
Ability to work	1	27 <sup>c</sup>	
Variability in pain	1	31 <sup>c</sup>	
Meds too long	1	33 <sup>c</sup>	
Length of disability	1	24	
Duration of work disability	1	29	
Pre-treatment surgery	1	24	
Pain behavior	1	33	
<b>Treatment (2)</b>			
Type of institution	1	32	
Phase of treatment	1	32	

<sup>a</sup>Conflicting results. <sup>b</sup>Simple analysis not reported, considered to be non-significant based on description in methods section in original article. <sup>c</sup>Simple analysis not reported, considered to be significant based on description in methods section in original article. <sup>d</sup>Beck Depression Index (BDI) self-report measure of depression. <sup>e</sup>Structured interview for DSMIV major depressive disorder. ADL: activities of daily living; Any cluster A Dx: paranoid; schizoid; schizotypal; Any cluster B Dx: antisocial; borderline; histrionic; narcissistic; Any cluster C Dx: avoidant; dependent; obsessive-compulsive; Any Cluster D Dx: otherwise; MMPI: Minnesota Multiphasic Personality Inventory.

## Population

Four studies included patients with chronic low back pain only (27, 29, 32, 33), the other 4 studies included patients with chronic pain in various parts of the body (24, 28, 30, 31). One study conducted a thorough investigation of predictors of dropout with multiple logistic regression analyses in a group of 300 (16%) dropouts from a total sample of 1,845 patients (16%) (24). In 6 studies the dropout group varied from 14 (23%) to 685 patients (16%) (24, 33) and in 2 studies it was unclear how many dropouts were investigated (29, 32).

There were no important differences in sex and in age between 5 of the studies. In 2 studies 70% of the population was female (27, 28) and one study contained a veteran population with 26% females (33). Most studies described patients between 40 and 50 years old, apart from 2 studies, which included patients with a mean age of 35 (29) and 57 years (33).

Reported pain duration varied between a mean of 16 months and 19 years (24, 33) and was not reported in 3 studies (24, 29, 32). The mean pain intensity before treatment ranged from 5 to 8 on a 0–10 NRS scale. One study included only patients with chronic pain who reported worst pain levels of 5 and higher (31).

## Terms and definitions and incidence of dropout

Different terms were used to describe dropout: (i) withdrawal from treatment; (ii) early discharge; (iii) non-completion and treatment dropout. Only 4 studies described a definition of dropout (24, 29, 32, 33). The incidence of dropout ranged from 10% in a study in the UK to 51% in a study in the USA (29, 31). Two studies did not report the percentage of dropout (25, 30).

## Methodological quality

Analysis of the overall agreement with regard to the methodological quality between the reviewers revealed a Cohen's weighted kappa of 0.70 (confidence interval (CI) 0.52; 0.88) indicating substantial agreement (34). All studies were considered to be of low quality according to Hayden's recommendations (23) (Table I). This was due to a serious risk of bias in most studies for study attrition, prognostic factor measurement and statistical analyses and reporting. For most studies the reporting of the first step in the statistical analyses, the univariate analyses were poor in contrast



**Table III.** Results for predictors for dropout in multiple logistic regression analysis

Domain	Predictors
<i>Predictors retained in any multiple logistic regression model</i>	
Sociodemographic	Pre-treatment work status <sup>a</sup> (24) Ethnicity (32) Number of sick days (27)
Patient	Pre-contemplation, Action (28) Opioid dependency, Any cluster B Dx (24) Return to work expectation, Somatization (29) Self-efficacy, Walk distance (30)
Disease	Ability to work (27) Variability in pain (31) Pain behaviour, Meds too long (33) Length of disability (24) Duration of work disability (29) Type of institution, Phase of treatment (32)
<i>Predictors not retained in any model</i>	
Sociodemographic	Age (27, 30, 32, 33) Sex (27, 29, 30, 32, 33) Social status (27, 29, 33) Hand, Vibrations in job (27)
Patient	Job available, Pre-treatment case settlement (24) Pre-treatment work status <sup>a</sup> (33) Depression (24, 28) Anxiety disorder, Any cluster A Dx, Any cluster C Dx, Any cluster D Dx (24) Pain distress, Catastrophizing (30)
Disease	Age first low back pain, smoking, ADL scores, Sport activities, Aerobic capacity, mobility, isometric abdominal endurance, isometric back endurance (27) Vulnerable body parts, Area of injury, Pretreatment surgery (24) Pain FC, chronicity (30) Pain intensity <sup>a</sup> (27, 30, 31) Severity of disability <sup>a</sup> (29)

<sup>a</sup>Conflicting results. ADL: activities of daily living. Any cluster A Dx: paranoid; schizoid; schizotypal; Any cluster B Dx; antisocial; borderline; histrionic; narcissistic; Any cluster C Dx: socially dependent; obsessive compulsive; Any cluster D Dx: otherwise.

**Data extraction, data-analyses and data-synthesis**

Several steps were taken to extract and synthesize the data from the included studies, all steps independently by 2 reviewers (HW, HW), followed through a discussion, if needed a third reviewer was consulted to reach consensus (WD). In step 1, an extraction manual was designed to facilitate the data-collection process. The following information was extracted from the included studies: (i) general information: authors, journal, publication date, country, language, (ii) research design: retrospective- or prospective cohort study or RCT; (iii) research population: (iv) number of multiple logistic regression analyses using a variety of methods (for example  $\chi^2$  tests, independent t tests and univariate logistic regression analyses) and multiple logistic regression analyses; (v) all possible factors associated with dropout in the analyses; (vi) conflicting results; (vii) “conflicting results” was assigned if the rule of  $\geq 75\%$  studies showing significant or non-significant could not be applied, or if opposite directions of the association were found in studies (e.g.,

included in this review investigated age as a potential predictor for dropout in univariate analyses. Six out of 7 studies showed significant associations for younger age as a predictor for dropout (27–30, 32, 33).

**Patient domain**

Conflicting results were found for depression as a potential predictor for dropout. The results of the univariate analyses revealed 2 studies with a significant association of depression with dropout. One study indicated that low depression scores were associated with dropout (28) and another study showed that higher scores on depression scales were associated with dropout (24). Two studies found a non-significant association with dropout (24, 33).

**Disease domain**

For 2 potential predictors in the disease domain conflicting results in the direction of the association with



dropout were found in univariate analyses: for disability (27, 31, 33) and pain intensity (27–31) (Table II). Although significant results were identified for severity of disability and mean pain intensity with dropout in univariate analyses, the direction of the association differed. Only 3 studies showed significant results for pain intensity in association with dropout (28–30). The direction of the association differed in these 3 studies, in one study lower pain intensity (28) and in 2 studies a higher pain intensity was found to be significantly associated with dropout (29, 30).

#### *Results for predictors for dropout in multiple logistic regression analyses*

In total 48 of 63 potential predictors were studied for an association with dropout in multiple logistic regression analyses. Of these 48 potential predictors, 26 were not retained in any multiple logistic regression analyses, for 4 predictors conflicting results were found and for 18 predictors significant results were identified in: (i) the sociodemographic domain (2); (ii) patient domain (8); (iii) disease domain (6); and (iv) treatment domain (2). Table III presents an overview of the number of predictors retained and not retained by the multiple logistic regression models (35). Most predictors were found in only a single study (24). Only one predictor, severity of disability, was found in 3 studies (24, 28, 33). Only 2 studies reported results for the performance of the multiple logistic regression models. The Hosmer–Lemeshow test demonstrated in both studies *p*-values above  $>0.5$  indicating a good fit (28, 30). No multiple logistic regression models were externally validated using independent samples.

#### *Sociodemographic domain*

In multiple logistic regression analyses conflicting results were found for age and pre-treatment work status as potential predictors for dropout. Younger age was not retained in 4 models (27, 30, 32, 33) and was retained in 2 multiple logistic regression models as a predictor for dropout (28, 29). Not working pre-treatment was not retained as a predictor for dropout in one study (33) and was retained in another study (24).

#### *Patient domain*

In the patient domain 7 potential predictors that were investigated in univariate analyses in association with dropout were not retained in multiple logistic regression analyses (24, 28, 30). For 8 predictors of dropout significant results were identified in multiple logistic regression models: pre-contemplation, action (28), opioid dependency, any cluster B Dx (24), return to

work expectation, somatization (29), self-efficacy and walk distance (30).

#### *Disease domain*

For pain intensity and disability conflicting results were demonstrated. In one study lower pain intensity (28) was found to be significantly associated with dropout. In 3 other studies higher pain intensity was identified as a potential predictor for dropout (29–31). Only one of these 3 studies showed significant results in association with dropout in multiple logistic regression analyses (29). Two studies demonstrated that more severe self-reported disability was a significant predictor for dropout (24, 33). Another study found that lower pain disability was significantly associated with dropout (28).

## DISCUSSION

The aim of this systematic review was to identify predictors of dropout of patients with chronic musculoskeletal pain during interdisciplinary pain management programmes. Eight studies with potential predictors for dropout were determined. In total 63 potential predictors were identified in univariate analyses in the 4 domains of retention, as described by Meichenbaum & Turk: (i) sociodemographic domain (19); (ii) patient domain (21); (iii) disease domain (21); and (iv) treatment domain (2). Ten potential predictors (age, sex, social status, education, ethnicity, job demand, depression, pre-treatment work status, pain intensity, and severity of disability) were studied in more than one study and multiple regression analyses revealed conflicting results for almost all these potential predictors.

These conflicting findings are in line with findings known from the mental health literature for the following predictors: younger age and being diagnosed with a depression (10–12, 27–30, 32, 33). Similar reasons were found in the literature for chronic musculoskeletal pain and mental health, for why younger age may predict dropout from treatment: practical implications, such as having a day-time job or having young children, which may be in conflict with an intensive interdisciplinary treatment programme (10, 29, 33). It is known that patients with severe depression, anxiety and low motivation are often excluded from studies about mental health. This may also be the case for studies in this review (13).

Furthermore, this systematic review revealed conflicting findings for pain intensity and disability in association with dropout. An intriguing finding was that one study showed the opposite results for the direction of the association of pain intensity and

disability with dropout compared with other studies. The patients who dropped out in this study had lower levels of pain intensity and reported less disability than the completers (28). However, with regard to the unusually high dropout rate of 51% compared with 10–23% in the other studies (24, 30–33), the results of this study may be related to unique elements in this study (poor selection for treatment or inexperienced therapists). Therefore, we may conclude that higher levels of pain intensity and higher severity of disability are predictors for dropout in patients with the QUPS through a test session involving 2 excluded studies, before judging the included studies. All ratings were entered into a spreadsheet. Any difference between the 2 reviewers was resolved through discussion and, if needed, a third reviewer was consulted to reach a consensus that would not be based on the recommendations of Hoedeman and colleagues (23). For each domain the risk of bias was classified as high, moderate or low. Studies were considered of high quality if in all 6 domains a low risk of bias was found and these studies were included in study design and differences in type of chronic pain treatment (28, 31–33)). The 3 types of interventions identified in this review differed in main programme goal (return to work vs pain management), duration of the programme (4–20 weeks) and selection criteria for the study population. Depending on in which country the study was performed (USA or in Europe as indicated in Table 1), differences in the organization of the healthcare system and referral and funding patterns might have also caused differences in study populations.

The reviewers for this review were not blinded for the results of the included studies. All ratings were entered into a spreadsheet. Any difference between the 2 reviewers was resolved through discussion and, if needed, a third reviewer was consulted to reach a consensus that would not be based on the recommendations of Hoedeman and colleagues (23). For each domain the risk of bias was classified as high, moderate or low. Studies were considered of high quality if in all 6 domains a low risk of bias was found and these studies were included in study design and differences in type of chronic pain treatment (28, 31–33)). The 3 types of interventions identified in this review differed in main programme goal (return to work vs pain management), duration of the programme (4–20 weeks) and selection criteria for the study population. Depending on in which country the study was performed (USA or in Europe as indicated in Table 1), differences in the organization of the healthcare system and referral and funding patterns might have also caused differences in study populations.

Several steps were taken to extract and synthesize the data from the included studies, all steps independently by 2 reviewers (JO, HW), followed through a discussion, if needed a third reviewer in which the country the study was performed (USA or in Europe as indicated in Table 1), differences in the organization of the healthcare system and referral and funding patterns might have also caused differences in study populations. The following information was extracted from the included studies: (i) general information: authors, journal, publication date, country, language; (ii) research design: retrospective or prospective cohort study or RCT; (iii) research population; (iv) analytical approach: univariate analyses using a variety of methods (for example  $\chi^2$  tests, independent t tests and univariate logistic regression analyses) and multiple logistic regression analyses; (v) all possible factors associated with dropout in univariate analyses and multiple logistic regression analyses with statistical significance and strength of the associations; the finding that the methodological quality was considered to be low in all 8 studies (24, 27, 30, 31, 32, 33) and assessment was a difficult process caused by the lack of consistent and clear reporting of study- and dropout characteristics. Due to a serious risk of bias in most studies from study attrition and statistical reporting and analysis the internal validity of the evidence found in these prediction models there is still no clear methodological procedure for pooling the data. The heterogeneity of the study populations, study interventions, predictors, statistical analyses and statistical reporting and the fact that most predictors were only assessed in a few studies, made it difficult to apply a meta-analysis of dropout. The methodological quality of the potential predictors from univariate analyses and multiple logistic regression analyses that were judged in at least 2 studies were described in the results. To summarize the results for a predictor that was investigated in more than 1 study the term 'internal validity of this review' was used. The large differences in dropout rates (10–51%) found in this systematic review of 16 studies can be explained by the variation in definitions that were used to describe dropout. A high risk of bias was found for the statistical analysis and reporting in 4 out of 8 studies in this review. Judgement of the statistical results in univariate analyses was most often based on the description in the methods sections of the original articles, as the results were not reported. The statistical analyses in these studies followed a more data-driven approach, which often tend to give a too optimistic estimate of performance of the prediction model and may cause overfitting of the data (36). Only 3 studies reported statistical analyses based on a conceptual framework (28, 29, 31).

The results in this review may suggest that dropout is entirely a patient characteristic (see predictors in the sociodemographic, patient and disease domains). However, as demonstrated in the mental health literature, the experience level of therapists and the therapeutic alliance may be important moderators in association with dropout (10, 12, 13). In this literature it has been recommended that it may be more relevant to focus on the interaction between patient-related predictors and therapist/therapy-related predictors and not on a single key predictor alone (10, 12, 13). Judging the available evidence in this review, strong limitations concerning the external validity may be raised. A factor that will influence the generalizability of the multiple logistic regression models for dropout presented in this review is related to the differences in chronic pain treatments in the studies. The evidence found for predictors in the 3 different interventions first has to be validated outside the context in which it was gathered (19). For example, most predictors associated with dropout were found in a large prospective cohort study within a functional restoration programme in the USA. These findings may not be generalized to other contexts (24). Another factor that may limit the generalizability of the predictors found in the RCT (33) is the fact that RCTs are known to attract very highly motivated patients, which does not reflect patients with low treatment motivation, who are often seen in daily clinical practice. It is remarkable that none of the multiple logistic regression models that were identified in this review were tested in independent samples. Currently, there is little information available on the performance of the multiple logistic regression models. Three parameters can be described to gain more insight in the performance of the logistic regression models: calibration, discrimination and clinical usefulness (37, 38). Only calibration was described with the goodness-of-fit for 2 multiple logistic regression models in 2 studies (28, 30). Due to the aforementioned limitations, the decision was made not to perform a best-evidence synthesis (25, 26), but to systematically generate a broad overview of all potential predictors found in the literature associated with dropout in chronic pain management programmes. The

For each domain the presence of associations and the direction of the associations of predictors and dropout was determined in univariate analyses and multiple logistic regression analyses from study attrition and statistical reporting and analysis. The internal validity of the evidence found in these prediction models there is still no clear methodological procedure for pooling the data. The heterogeneity of the study populations, study interventions, predictors, statistical analyses and statistical reporting and the fact that most predictors were only assessed in a few studies, made it difficult to apply a meta-analysis of dropout. The methodological quality of the potential predictors from univariate analyses and multiple logistic regression analyses that were judged in at least 2 studies were described in the results. To summarize the results for a predictor that was investigated in more than 1 study the term 'internal validity of this review' was used. The large differences in dropout rates (10–51%) found in this systematic review of 16 studies can be explained by the variation in definitions that were used to describe dropout. A high risk of bias was found for the statistical analysis and reporting in 4 out of 8 studies in this review. Judgement of the statistical results in univariate analyses was most often based on the description in the methods sections of the original articles, as the results were not reported. The statistical analyses in these studies followed a more data-driven approach, which often tend to give a too optimistic estimate of performance of the prediction model and may cause overfitting of the data (36). Only 3 studies reported statistical analyses based on a conceptual framework (28, 29, 31).

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literature with regard to the topic of dropout is still in the stage of model development, this is defined as type 1A studies, according to the TRIPOD statement (37). Since no internal or external validation was considered in the studies included in this systematic review, the results should be interpreted with care.

### Strengths

Since Turk & Rudy addressed the topic of dropout in the early 1990s, little high-quality research has become available, as shown by this systematic review. The majority of research on dropout in interdisciplinary pain management programmes for chronic musculoskeletal pain has relied on the investigation of differences between dropouts and programme completers at baseline or univariate analyses of one variable associated with dropout. To our knowledge this is the first systematic review on dropout in chronic musculoskeletal pain patients in the rehabilitation setting. A strength of this review is that it provides an overview of predictors of dropout in chronic musculoskeletal pain: 63 potential predictors of dropout in univariate analyses and 48 out of 63 potential predictors were investigated in multiple logistic regression analyses.

### Implications and future directions

Dropout is still a neglected topic in daily practice and in research in interdisciplinary pain management. Learning from the abundant amount of research that has been done in the mental health literature recommendations for future directions can be specified. One direction could be to perform exit interviews with dropouts to investigate reasons for dropout. Based on these reasons for dropout, strategies may be developed to prevent dropout in future (39). Another direction is to address factors that are predictive for dropout in clinical assessment and to make a distinction whether predictors are modifiable or non-modifiable. For example, younger age is a predictor for dropout in chronic pain management programmes. This predictor is non-modifiable and may be addressed by modifying the treatment schedule.

Other strategies that have been developed in the mental health literature that may also be applied in interdisciplinary pain management programmes are: to focus on the assessment of patient's expectations and preferences and motivation before treatment onset and during the treatment programme, to provide education to address patient's expectations, preferences and motivation, to monitor the work-alliance between patient and therapist and create the possibility for patients to give feedback to the therapist. Since dropout patients are all different, ideally, prediction of dropout would use prospective cohort designs including session by

session evaluation of progress and define no fixed length of the programme (10–13, 39). This systematic review will challenge clinicians and researchers to pay more attention to dropout and collaborate in developing strategies to overcome dropout in order to generate better outcomes in chronic pain management programmes.

### Conclusion

This systematic review presents an overview of predictors of dropout. The literature with regard to the prediction of dropout has focused mainly on patient characteristics and is still in the stage of model development. Future research might also focus on therapist/therapy-related predictors and the interaction between these predictors. This review suggests future research on this topic, in order to generate better outcomes in interdisciplinary pain management programmes.

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