

**Physical Exercise Participation:
A continuous or categorical phenomenon?**

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Abstract

Objective. Measures of exercise participation are usually one-dimensional continuous variables (e.g., participation frequency). However, there is evidence that projecting exercise participation onto only one dimension cannot adequately reflect the complex multi-dimensional nature of this behaviour. The present study served to identify distinct patterns of exercise participation, to introduce a normative system that allows individual classification of these participation patterns, and to test whether the prediction of exercise participation through psychological variables benefits when one chooses a categorical (multi-dimensional) instead of a continuous operationalisation of the behaviour.

Method. Exercise participation of $N=174$ customers of a fitness centre was recorded electronically for 32 weeks. Subjects completed a questionnaire including the psychological variables self-efficacy, outcome expectations, strength and self-concordance of goal intention which are known to be relevant predictors of exercise participation.

Results. Four different participation patterns were identified by cluster analysis: maintenance, fluctuation, late dropout and early dropout. Based on these findings a normative classification system (NOCLEP) was developed to allow for a sample-independent assignment of individuals to these four participation patterns (categorical measure of exercise participation). For some psychological variables the prediction of exercise behaviour improved markedly when this categorical measure instead a continuous measure was used. This improvement only occurred when the psychological predictors exhibited a non-linear relation to the continuous exercise measure.

Conclusion. Analyses with categorical criterion measures may allow a deeper understanding of the role of specific psychological predictors in exercise participation. Furthermore, NOCLEP might be used as a diagnostic tool in the practice of exercise psychology.

Keywords: exercise participation, classification, behavioral patterns, determinants

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INTRODUCTION

Different psychological theories have been applied to predict physical exercise participation. The most widely used approaches are the theory of planned behavior (Ajzen, 1991), the social cognitive theory (Bandura, 2004), the self determination theory (Deci & Ryan, 2002), the transtheoretical model (Prochaska & Marcus, 1994), and the health action process approach (Schwarzer, 2008). A review by Biddle and Mutrie (2008) concluded that the predictive power of these explanation theories is still modest, reaching 30-40 % of explained inter-individual variance in physical exercise at best. One major reason for this unsatisfactory outcome may be the way in which the criterion variable “physical exercise participation” has been conceptualised (Biddle & Fuchs, 2009). In most cases exercise participation has been operationalised as a continuous variable using one-dimensional measures like participation frequency (times per week), duration of participation (minutes per week), or energy expenditure (kcal per week) (Cox, Burke, Gorely, Beilin, & Puddey, 2003; Fuchs, Göhner, & Seelig, in press; Rhodes, Warburton, & Murray, 2009). However, a closer look at the phenomenon reveals that there may be distinct patterns of exercise participation (e.g., early dropout, late dropout, fluctuation, maintenance) that cannot be adequately projected onto only one dimension. In the present study we compare a continuous (one-dimensional) and a categorical (multi-dimensional) conceptualisation of exercise participation. In particular, we ask whether a categorical assessment of the criterion variable “exercise participation” provides better predictions through psychological variables than a continuous assessment.

To illustrate the difference between a continuous and a categorical conceptualisation of exercise participation, consider the following example: In the course of one year person A exercises every second week, whereas person B exercises every week in the first half year and does not exercise in the second. For both persons we would yield the same annual participation frequency (26 times per year), although they do not show the same participation pattern (maintenance vs. dropout). Thus, applying participation frequency as the criterion measure would conceal the different underlying behavioural patterns. These patterns only become evident when two aspects are taken into account at the same time: frequency of participation and temporal distribution of participation. Considering both aspects

(dimensions) simultaneously implies the use of a categorical variable instead of a continuous variable to describe exercise participation.

In the literature the application of categorical exercise variables is not uncommon. In most studies these variables only represent recodings of originally continuous variables, for example defining a certain amount of energy expenditure to distinguish exercise adherence from non-adherence (e.g., Colley et al., 2008; Pinto, Rabin, & Dunsiger, 2009). Such categorizations are still based on one-dimensional measures of exercise participation. However, there are also studies in which the assessment of exercise participation is based on more than one dimension. By applying the dimensions “frequency of participation” and “temporal distribution of participation,” Annesi (1999) and Stiggelbout, Hopman-Rock, Crone, Lechner, and van Mechelen (2006) differentiate between two distinct participation patterns (“adherence” vs. non-adherence”; or “adherence” vs. dropout”). More than two patterns were specified by Bock, Marcus, Pinto, and Forsyth (2001; four patterns: “stable active,” “progressed,” “regressed,” “stable inactive”); Conroy et al. (2007; four patterns: “no activity,” “occasional with lapses,” “regular with lapses,” “regular without lapses”); Williams et al. (2008; four patterns: “maintain,” “relapse,” “adopt,” “remain inactive”), and Wilbur, Vassalo, Chandler, McDevitt, and Miller (2005; six patterns: “consistent adherence,” “occasional lapse,” “low adherence,” “recycler,” “relapser,” “drop”). In all of these studies the behavioural categories were based on normative definitions (e.g., “relapser” was defined as “3 consecutive weeks with no walks [exercise]”; Wilbur et al., 2005). In contrast to this normative approach, Fuchs, Seelig, and Kilian (2005) chose an explorative research design to identify relevant exercise participation patterns. Cluster analyses with participants in health-related exercise courses revealed four different groups of persons: maintainers, fluctuators, early dropouts, and late dropouts. The result of these cluster analyses is the starting point of our current research.

In the present study (a) we once again use cluster analyses to explore whether different patterns of exercise participation can be identified; however, this time we base these analyses on objective behavioural data (electronic recordings of visits to a fitness centre); (b) we propose a system of rules that serves as a normative algorithm for the classification of distinct participation patterns; and (c) we test whether psychological variables can be used to predict exercise participation better when the target behaviour is operationalised categorically instead of continuously. This would imply that psychological theories could gain additional explanatory power through categorical concepts of physical exercise participation.

METHOD

Participants and Procedure

The study sample was recruited from members of a health-oriented fitness centre that had opened only recently, i.e. the sample consisted of customers who had just entered into a new contract. Membership fees varied between 45 € and 55 € per month depending on contract durations (24 or 12 months).

Questionnaires measuring socio-demographic and psychological variables were distributed to customers during the first six weeks after the opening of the centre. After the customers had returned the completed questionnaire, their visits to the centre were registered electronically for a period of 32 weeks (observation period). A total of 300 questionnaires were handed out personally by project staff; 187 questionnaires had been completed and returned by the end of the six week period. 13 questionnaires had to be excluded due to incompleteness (response rate: 58.0 %). The final study sample encompassed $N = 174$ participants, 64.4% of whom were female. The mean age was $M = 36.9$ years ($SD = 12.1$ years), and the average body mass index (BMI) was $M = 23.6$ ($SD = 4.4$). The majority of the participants (51.4%) worked full time, 24.3 % worked part time, and 24.3 % were currently unemployed. Furthermore, 41.4 % of the participants indicated that they had been engaged in physical exercise in the weeks and months prior to joining the studio.

Behavioural Measures

When entering or leaving the fitness centre, all customers were obliged to register via magnetic customer cards. This allowed visits to the centre to be recorded electronically over the observation period of 32 weeks. Individual exercise participation was described by the following variables: Participation frequency was operationalised by the number of visits per week (*weekly participation frequency*) and the number of visits over the total observation period (*total participation frequency*). The binary-coded variable *weekly attendance* measured whether or not a subject visited the centre in a given week (0 = no visit; 1 = one or more visits). *Total attendance* was defined as the sum of weekly attendance scores over the total observation period (range: 1 - 32). The variable *attendance rate* was calculated as the sum of weekly attendance scores over k weeks divided by k (weeks of observation); it captures the individual average weekly attendance for those k weeks (range: 0.00 - 1.00 or 0% - 100% in percentages).

Psychological Measures

The questionnaire included measures of selected psychological variables (self-efficacy, outcome expectations, strength and self-concordance of goal intentions) that are well-established predictors of exercise participation (Biddle & Mutrie, 2008; Smith, Ntoumanis, & Duda, 2007):

Self-efficacy refers to people's belief in their capability to perform a given behaviour successfully (Bandura, 2004). The belief of being able to maintain regular activity over an extended time period was measured with one item ("How difficult or easy will it be for you to exercise regularly in this fitness centre in the coming months?"). The response format was a 10-point Likert scale ranging from 1 = "very difficult" to 10 = "very easy." The descriptive statistics for the variable "self-efficacy" were: $M = 6.94$; $SE = 0.18$; $SD = 2.4$; median = 8; skewness = -0.68; excess = -0.47; range = 1 to 10.

Outcome expectations refer to the anticipated consequences of the given behaviour (Bandura, 2004). We assessed eight positive and eight negative outcome expectations (o.e.) regarding physical exercise. All items were launched with "If I exercise on a regular basis ..." and followed by statements like "I would feel better" (positive o.e.) or "I could hurt myself" (negative o.e.). The response format was a 4-point Likert scale ranging from 1 = "not true at all" to 4 = "very true." The positive and negative o.e. were summarized in separated subindices. In order to create a global index "outcome expectations" reflecting the balance of positive and negative expectations, we subtracted the subindex of negative outcome expectations from that of positive outcome expectations. The descriptive statistics for the index "outcome expectations" were: $M = 1.64$; $SE = 0.04$; $SD = 0.55$; median = 1.75; skewness = -0.25; excess = -0.01; range = 0.13 to 3.00.

Strength of goal intention was assessed with one item: "How strong is your intention to exercise regularly in this fitness centre in the coming weeks and months?" (cf., Ajzen, 1991). The response format was a 10-point Likert scale ranging from 1 ("I don't have this intention at all") to 10 ("I have a strong intention to do so"). The descriptive statistics for the variable "strength of goal intention" were: $M = 9.02$; $SE = 0.09$; $SD = 1.19$; median = 9; skewness = -1.16; excess = 1.26; range = 4 to 10.

Self-concordance of the goal intention was measured by the SSK scale, a German-language 12-item instrument that has proven to be a reliable and valid measure of exercise-related goal self-concordance (Seelig & Fuchs, 2006). In line with the self-concordance model by Sheldon and Elliot (1999), the SSK scale consists of four subscales that measure

intrinsic, identified, introjected, or extrinsic motivation to exercise regularly. Each subscale was formed by three items. The items were launched with “I intend to exercise regularly in this fitness centre in the coming weeks and months because ...” and were followed by statements like “... it’s just fun for me” (intrinsic), “... I have good reasons to be active” (identified), “... otherwise I would feel guilty” (introjected), and “... others tell me to become physically active” (extrinsic). The participants were asked to respond on a 6-point Likert scale ranging from 1 (“not true”) to 6 (“true”). Cronbach’s alpha for the subscales was: .62 (intrinsic), .67 (identified), .76 (introjected), and .68 (extrinsic)]. A general index “self-concordance” was calculated by subtracting the values for the introjected and extrinsic subscales from the sum of the values for the identified and intrinsic subscales (cf., Sheldon & Elliot, 1999). The descriptive statistics for the index “self-concordance” were: $M = 4.70$; $SE = 0.16$; $SD = 2.08$; median = 4.67; skewness = -0.08; excess = -0.21; range = -0.67 to 10.00.

RESULTS

1. Exercise participation as continuous variable

Figure 1 displays exercise participation within the observation period of 32 weeks on the basis of the two variables “weekly participation frequency” (left ordinate) and “weekly attendance” (right ordinate). The two variables show the same decreasing trend: In the study sample ($N = 174$) the means of weekly participation frequency decreased from $M = 1.75$ ($SD = 0.89$) visits in week 1 to $M = 0.83$ ($SD = 1.12$) visits in week 32, and the means of weekly attendance diminished from 1.00 in week 1 to 0.47 in week 32. Figure 1 shows a steady decline on both variables from week 1 to about week 19; afterwards, the levels of weekly participation frequency and weekly attendance remained relatively stable. The mean total participation frequency (number of visits over the 32 weeks) was $M = 35.2$ visits ($SD = 21.2$; range: 1 - 100). The mean total attendance (sum of weekly attendance scores over the 32 weeks) was $M = 18.55$ ($SD = 8.34$).

– Figure 1 –

2. Exercise participation as categorical variable: Exploratory classification

We hypothesised that exercise participation should be assessed by a categorical variable in order to capture the underlying discrete participation patterns which are not adequately described by the frequency measures used in the preceding section (Figure 1). To investigate the existence of such discrete participation patterns, we conducted an exploratory cluster analysis (Ward method, squared Euclidean distances) based on the binary-coded

variable “weekly attendance.” Before entering into the cluster analysis, we transformed the individual weekly attendance scores into *moving averages (mA)* by averaging weekly attendance scores in “sliding windows” of six successive weeks each (cf., Weiss, 2005). The purpose of this transformation was to account for the temporal alignment of individual attendance scores (otherwise the cluster analysis would only be based on quantities of weekly attendance). The 32 weekly attendance scores yielded 27 moving averages which incorporated temporal trends in attendance.

From the cluster analysis based on moving averages we chose a 4-cluster solution using the “elbow criteria” (Milligan & Cooper, 1985). This common procedure for determining the number of clusters is seen as a pragmatic approximation. The 4-cluster solution was inspected via discriminant analysis and double cross-validation (Breckenridge, 1989). The discriminant analysis revealed three significant functions which correctly classified 97.3 % of the subjects with respect to their cluster membership (Wilks’ $\lambda = .02$; $p < .001$). Results from the double cross-validation (Cohen’s $\kappa = .83$) also supported the 4-cluster solution. Based on this solution each subject was assigned to a cluster. Table 1a shows the means of attendance rate and total participation frequency per cluster.

– Table 1 a+b–

Figure 2a displays the mean weekly attendance over the 32 weeks of observation for each cluster (a score of 1.00 also means all participants of a cluster visited the centre in this week). The graphs in Figure 2a revealed four distinct participation patterns which were identical to the patterns identified in an earlier study (Fuchs et al., 2005): Cluster 1 encompassed a group of participants (called *maintainers*) that exercised almost every week during the observation period. This group showed a mean attendance rate of 87% (k=32 weeks). Participants of cluster 2 were called *fluctuators*; this group maintained its participation until the end of the observation period, but on an irregular basis with a mean attendance rate (k=32 weeks) of only 68%. The remaining two clusters referred to dropouts. During the first 13 weeks, cluster 3 showed similar weekly attendance scores as the fluctuators (mean attendance rate for k=13 weeks: 73%); however, weekly attendance decreased dramatically thereafter. In weeks 14 to 32, the mean attendance rate of this cluster was at 20%, indicating that some subjects still visited the fitness centre irregularly. Given this participation pattern, we characterised persons from cluster 3 as *late dropouts*. In contrast, cluster 4 represents persons that we named *early dropouts*. During the first weeks

the mean attendance rate of this cluster steadily declined to less than 25% by week 6; in weeks 7 to 32 the rate remained at the low level of 10% (k=26 weeks).

– Figure 2a+b –

3. Exercise participation as categorical variable: sample-independent classification

In cluster analyses such as those conducted in the preceding paragraph, the assignment of participants to specific clusters depends on the characteristics of the given sample; thus, cluster membership cannot be determined independently of a reference sample. For some purposes (e.g., prediction, diagnostics), however, we would prefer a sample-independent procedure for classifying exercise participation. In the following, we therefore propose a normative system of rules for a sample-independent assignment of individuals to the four participation patterns identified above (maintenance, fluctuation, late dropout, and early dropout). This system is abbreviated to NOCLEP (Normative Classification of Exercise Participation).

3.1 Classification rules. The formalised classification rules shown in Table 2a are based on four parameters (AR_O , S_O , $S_{0.25 O}$, $S_{0.75 O}$) that can be derived from binary-coded weekly attendance data (0 = no attendance in week i or 1 = attendance in week i). The index O denotes the length of the observation period (in weeks) for which weekly attendance data are available. In our study, weekly attendance data were available for an observation period of 32 weeks ($O=32$). The four parameters are (1) AR_O : individual attendance rate in observation period O ; (2) S_O : sum of positive substantial relative differences ($psrD$) in observation period O ; (3) $S_{0.25 O}$: sum of positive substantial relative differences in the first quarter of observation period O ; and (4) $S_{0.75 O}$: sum of positive substantial relative differences in the first three quarters of observation period O . A detailed explanation of the parameters is provided below.

– Table 2 a+b –

Table 2a shows that persons with $S_O = 0$ (sum of positive substantial relative differences in the observation period) are classified as *maintainers* if their attendance rate in the observation period (AR_O) is not less than 80 %. *Fluctuators* are either individuals with $S_O = 0$ and an attendance rate (AR_O) below 80 % or individuals with $S_O > 0$ and a sum of positive substantial relative differences in the first three quarters of the observation period ($S_{0.75 O}$) which is below 75 % of S_O . Persons with $S_O > 0$ are *early dropouts* if at least 75 % of the total sum of positive substantial relative differences (S_O) is located in the first quarter of

the observation period. If S_0 is greater than zero and 75 % of S_0 is located outside of the first quarter but within the first three quarters of the observation period, the persons are identified as *late dropouts*. The four parameters were calculated according to the equations shown in Table 2b.

3.2 Example of classification. The classification procedure is illustrated with the following example. Table 3 contains the fictitious attendance data of person A. The observation period is 12 weeks ($O = 12$); the binary-coded attendance data can be used to extract whether person A was present ($A_t = 1$) or absent ($A_t = 0$) in week t . After calculating the classification parameters and applying the classification rules (see Table 2a+b), we identified person A as a late dropout, because: $S_0 = 6.9 (> 0) \wedge S_{0.25O} = 2.76 (< 0.75 \cdot 6.9) \wedge S_{0.75O} = 5.52 (\geq 0.75 \cdot 6.9)$.

– Table 3 –

3.3 Rationale of NOCLEP. To classify a person's exercise participation, we focus on the individual attendance rate (AR_0). This rate can be interpreted as the expected probability of attendance in any week of the observation period. The expected attendance at time point t (AR_0) can be compared to the actual attendance (A_t) at t . The difference of the two values is then divided by the individual attendance rate [$rD_t = (A_t - AR_0) / AR_0$]. The resulting index rD_t (called *relative difference*) reflects the deviation of actual attendance from expected attendance at time t .

This “relative difference” requires a first constriction: Our classification system only considers the *positive relative differences* ($rD_t > 0$). The reason for this is that – arithmetically speaking – all “relative differences” add up to zero. This means that if a positive relative difference (prD_t) occurs at time point t_i , there has to be at least one negative relative difference at another time point t_j . If exercise participation takes place on a regular basis, positive and negative relative differences should be evenly distributed. Dropout can be detected from the fact that positive relative differences accumulate up to a certain time point, after which predominantly negative relative differences occur.

Additionally, there is a second constriction of the “relative difference”: Minor fluctuations in attendance should not be considered. Therefore, the values of a positive relative difference prD_t must exceed a given minimum (*Min*) to be considered “substantial” for the classification of attendance patterns. This leads us to the index *positive substantial relative difference* ($psrD_t$). The positive substantial relative differences within certain time

intervals (S_I) and within the total observation period (S_O) are summed up. To capture the temporal distribution of weekly attendance these sums (S_I ; S_O) are related to each other (see Table 2).

Our classification system requires four specifications. *First specification:* The definition of “maintenance” is based on an individual attendance rate of at least 80% ($AR_O \geq 0.8$; see Table 2). This specification was derived from our exploratory cluster analysis and from definitions used in other normative classification systems, for example that proposed by Wilbur et al. (2005). *Second specification:* The value 1 is chosen for the index Minimum (Min). This index is crucial for the identification of *positive substantial relative differences* and therefore regulates the “sensitivity” of our classification system. The smaller the value of Min , the smaller are the deviations from the attendance rate that are taken into account to classify participation patterns. Choosing $Min = 1$ implies that a positive substantial relative difference is detected if the difference between actual weekly attendance at time t and the attendance rate is not less than the attendance rate itself. Note: The identification of positive substantial relative differences is related indirectly to attendance rates, because the minimum Min and the attendance rate AR_O are arithmetically associated in the following way: $Min = (1 - AR_O) / AR_O$. Thus, $Min = 1$ implies that positive substantial relative differences can only occur if the attendance rate does not exceed 50%. *Third specification:* We propose inspecting the first ($I = \frac{1}{4} O$) and the first three quarters ($I = \frac{3}{4} O$) of observation period O in order to classify attendance patterns. Quarters as subdivision of O were chosen for pragmatic reasons: They provide meaningful “time slots” for detecting substantial changes in exercise behaviour an. *Fourth specification:* Finally, for the classification we need to specify limiting values for the ratios of interval sums and the total sum (S_I / S_O). To clearly identify dropout we want the ratios to be greater than 0.75, which in other words means that 75% of all positive substantial relative differences have to emerge in either interval.

4. Application of the normative classification system

The classification system NOCLEP presented in the preceding paragraph was applied to our study with $N=174$ visitors of a newly opened fitness centre. In this study, the observation period was 32 weeks ($O = 32$). The parameter minimum was set to one ($Min = 1$). The classification grouped the sample into $n = 43$ maintainers, $n = 62$ fluctuators, $n = 46$ late dropouts, and $n = 23$ early dropouts. The graphs in Figure 2b show mean weekly attendance for each group. As intended they resemble those in Figure 2a. However, the graphs in Figure 2b are now based on sample-independent normative rules instead of sample-

dependent explorative cluster analyses. Table 1b shows group means and standard deviations of the attendance rates and participation frequencies. Analyses of variance yielded significant group differences for attendance rate ($F_{3, 170} = 448.2$) and participation frequency ($F_{3, 170} = 171.5$) (with all pairwise comparisons [Scheffé test]: $p < .001$).

5. Comparing continuous and categorical operationalisations of exercise participation

Our hypothesis was that the usage of categorical operationalisations of exercise participation would lead to a better prediction of behaviour through psychological variables than the typically applied continuous operationalisations. We can now test this assumption by comparing the predictability of our continuous criterion measures (participation frequency, attendance rate) to our categorical criterion measure (based on NOCLEP).

5.1 Comparison of means. Figure 3 depicts how the four participation groups (maintainers, fluctuators, late dropouts, and early dropouts) identified by NOCLEP differed with respect to the selected psychological variables. Note that the means of self-efficacy and strength of goal intention steadily decreased in the following order: maintainers > fluctuators > late dropouts > early dropouts. This corresponded to the descending means of participation frequency and attendance rate in these four groups (Table 1b) and indicated *linear* relationships between each of the psychological variables and the continuous measures of exercise participation. The ranking for *self-concordance* and outcome expectations was different in that late dropouts showed markedly lower means than early dropouts. Accordingly, the relationship between the two psychological variables and the means of our continuous measures in the four groups was *non-linear*. The findings of Figure 3 demonstrate that the usage of categorical criterion measures allows one to identify non-linear relationships between cognitive predictors and exercise participation.

– Figure 3 –

5.2 Predicting exercise participation through psychological variables. Finally, we examined whether the prediction of exercise participation through psychological measures differed for continuous or categorical operationalisations of exercise participation by comparing effect sizes taken from two different statistical procedures. While the prediction of continuous criterion variables (such as “total participation frequency” or “attendance rate”) is usually based on *linear multiple regression analysis*, the prediction of categorical variables typically requires methods like *discriminant analysis*. As effect sizes we receive the multiple correlation coefficient R^2 (regression analysis) or the Wilks’ lambda (discriminant analysis),

which can be transformed into η^2 values following a proposal by Olejnik and Algina (2000). Both parameters – R^2 and η^2 – can be interpreted as “proportions of explained variance.” However, since the measures are based on different theoretical and mathematical models it is recommended not to compare their values – at least not when predicting a categorical variable which contains more than two categories (groups) by discriminant analysis (Backhaus, Erichson, Plinke, & Weiber et al., 2006, p. 177).

As an alternative, we chose *categorical regression analyses*. This statistical method provides the possibility to integrate variables with different scaling properties in a single analysis. Categorical regression uses a so-called “optimal scaling procedure” which quantifies categorical variables and then treats them as numerical variables (Meulman, 2003). Interval-scaled variables remain unchanged. Analogous to the linear regression model, a multiple correlation coefficient R^2 (effect size) can be calculated no matter what kind of scaling properties the predictor or criterion variables have. R^2 can be interpreted as the percentage of explained variance.

All effect sizes R^2 shown in Table 4 resulted from categorical regression analyses performed using the CATREG procedure in SPSS (Meulman, Heiser, & SPSS Inc., 2005). Table 4 depicts the results of different prediction models. The four *one-predictor models* provided the following result: For self concordance and outcome expectations the predictive power was higher with the categorical criterion variable ($R^2=9.8\%$ or 6.1%) than with the continuous criterion variables ($R^2=2.1/2.5\%$ or $4.2/4.2\%$). For self-efficacy and strength of goal intention, on the other hand, similar effect-sizes were obtained with the two types of criterion variables. The *four-predictor model*, in which all psychological measures were considered simultaneously, also yielded only small differences in R^2 between the analyses with the categorical and continuous criterion variables.

Additionally, we tested two different *two-predictor models* (Table 4). Predicting categorical or continuous measures of exercise participation through self-efficacy and strength of goal intention simultaneously (two-predictor model 1) resulted in only minor differences in R^2 . However, if self-concordance and outcome expectations are used as predictors simultaneously (two-predictor model 2), the predictive power is markedly lower for the continuous criterion variables (4.1 % and 4.5%) than for the categorical criterion variable (11.4%).

DISCUSSION

In most studies exercise participation is regarded as a continuous (one-dimensional) phenomenon (see review by Rhodes et al., 2009) and is thus usually operationalised as participation frequency (times per week), participation duration (minutes per week), or energy expenditure (kcal per week). However, there is increasing evidence that projecting exercise participation onto only one dimension cannot adequately reflect the complex structure of this behaviour (Bock et al., 2001; Conroy et al., 2007; Fuchs et al., 2005; Stiggelbout et al., 2006; Wilbur et al., 2005; Williams et al., 2008). The present study served (a) to identify distinct patterns of exercise participation on an exploratory basis; (b) to introduce a normative system of rules that allows a sample-independent classification (individual diagnostic) of these participation patterns; and (c) to test whether the prediction of the target behaviour “exercise participation” benefits when one chooses a categorical (multi-dimensional) instead of a continuous (one-dimensional) operationalisation. To our knowledge this is the first study that systematically compares the usage of continuous and categorical operationalisations of exercise participation in psychological prediction models.

(a) Exploratory identification of exercise participation patterns. A cluster analysis based on objective attendance data (electronically registered visits to a fitness centre) yielded four different participation patterns which already had been identified in an earlier study (Fuchs et al., 2005): maintenance, fluctuation, late dropout and early dropout. The results of this analysis were exploratory because the assignment of participants to the four clusters (exercise patterns) as well as the definition of each cluster itself depended on the specific characteristics of the sample. Thus, changes in the composition of the sample would result in changes in cluster assignments and cluster definitions.

(b) Normative classification system. To allow for a sample-independent assignment of an individual’s exercise participation, we developed the normative classification system NOCLEP. Using NOCLEP it is possible to classify an individual’s exercise participation into one of the following participation patterns: maintenance, fluctuation, late dropout, and early dropout. The normative definitions of these four patterns were derived from the results of our exploratory cluster analysis (see previous paragraph), from criteria used in other studies (Wilbur et al., 2005; Williams et al., 2008), and from pragmatic considerations (e.g., subdividing the observation period into quarters, which provides a mid-level preciseness (between too specific and too general). NOCLEP applies a two-dimensional description of exercise participation by simultaneously considering (a) the frequency of exercise

participation and (b) the temporal distribution of this participation during a given observation period. Four parameters are used to describe a given participation pattern: (1) AR_O : individual attendance rate in observation period O; (2) S_O : sum of positive substantial relative differences in observation period O; (3) $S_{0.25 O}$: sum of positive substantial relative differences in the first quarter of observation period O; (4) $S_{0.75 O}$: sum of positive substantial relative differences in the first three quarters of observation period O.

The classification system described in this paper should be seen as a proposal which will need to demonstrate its utility in subsequent empirical applications. The parameters of the system allow adaptations to specific situations. For instance, the index O (length of observation period) is based on an observation period subdivided into weekly intervals, corresponding to the fact that physical exercise is typically performed in a weekly rhythm. However, our classification rules also allow for alternatives, for example daily intervals ($O=224$ [days] instead of $O=32$ [weeks]).

NOCLEP is based on simplifying approximations. It certainly would be possible to achieve a more accurate classification of an individual's exercise behaviour by applying more complex statistical methods (e.g., latent growth curve models; see Wang & Bodner, 2007). However, this would severely constrain intuitive plausibility and practical manageability in research and practice. The classification system suggested here may thus be viewed as a compromise between accurateness and practicability.

(c) Continuous vs. categorical participation behaviour. In the present study we compared the predictability of a categorically operationalised participation behaviour („participation patterns“) and a continuously operationalised participation behaviour („participation frequency“, „attendance rate“) on the basis of selected psychological predictors (self-efficacy, outcome expectations, strength of goal intention, and self-concordance). When all four predictors were taken into account simultaneously (four-predictor model) the amount of explained variance was 1.3 to 2.1% higher for the categorical criterion variable than for the continuous criterion variables (see Table 4). This difference is not large enough to conclude that a categorical operationalisation of participation behaviour had led to substantial improvements in predictions. However, the results also indicate that on the level of specific predictors the usage of a continuous or categorical criterion variable makes a difference. With the predictors *self-concordance* and *outcome expectations* a categorical exercise measure leads to predictions that are twice as high as a continuous exercise measure (explained variance in the two-predictor model: 4.1/4.5% vs. 11.4%; see

Table 4). In turn, the usage of the categorical behavioural measure neither improved nor diminished the explained variance with the two predictors *self-efficacy* and *strength of goal intention*.

These results suggest that a categorical criterion variable does not automatically result in better predictions of exercise behaviour. Rather, this is presumably only the case when the predictor exhibits a non-linear relation to the continuous exercise measure. Figure 3 provides a graphical illustration of this non-linearity for the predictors *self-concordance* and *outcome expectations*. The mean values of these two predictors did not decrease steadily along the line maintenance ($M=61.2$) > fluctuation ($M=38.9$) > late dropout ($M=19.7$) > early dropout ($M=8.0$) (in brackets: means of total participation frequency; Table 1b). Rather, the values of early dropouts were very similar to those of the maintainers and fluctuators. The psychological significance of this finding has already been discussed elsewhere (Fuchs et al., 2005).

IMPLICATIONS

Our results suggest that a multi-dimensional conceptualisation of exercise participation does not automatically improve the predictive power of psychological models, such as the theory of planned behavior by Ajzen (1991), the social cognitive theory by Bandura (2004) or the health action process approach by Schwarzer (2008). For specific psychological predictors it may be useful to conduct analyses with categorical criterion measures to achieve a better understanding of the role of these variables in the process of exercise participation. However, for other psychological predictors the use of categorical criterion measures might not lead to deeper insight.

Our classification system (NOCLEP) may also prove useful in exercise psychology practice. It allows individual diagnostics of participation behaviour and can thus be used to develop personally tailored interventions to help people make physical exercise an integral part of their daily lives (Brehm, 2004). NOCLEP only appears to be complicated at first sight. Once one becomes familiar with its logic, it is relatively easy to classify single persons or groups. Standardisations and technical aids (templates, electronic aids) in which (weekly) attendance can be entered will make classification immediately apparent.

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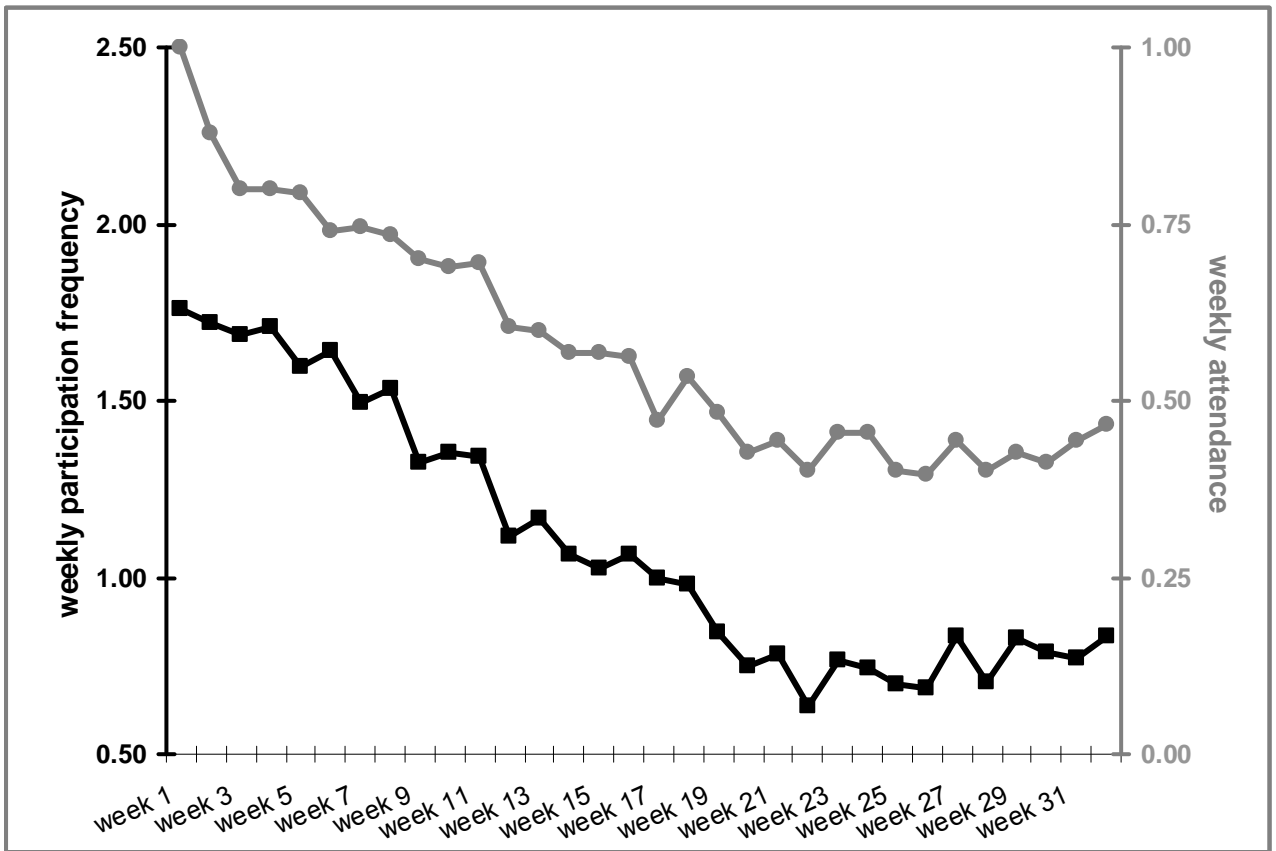


Figure 1. Means of weekly participation frequency (black line; left ordinate) and weekly attendance (grey line; right ordinate) over the observation period of 32 weeks; $N = 174$.

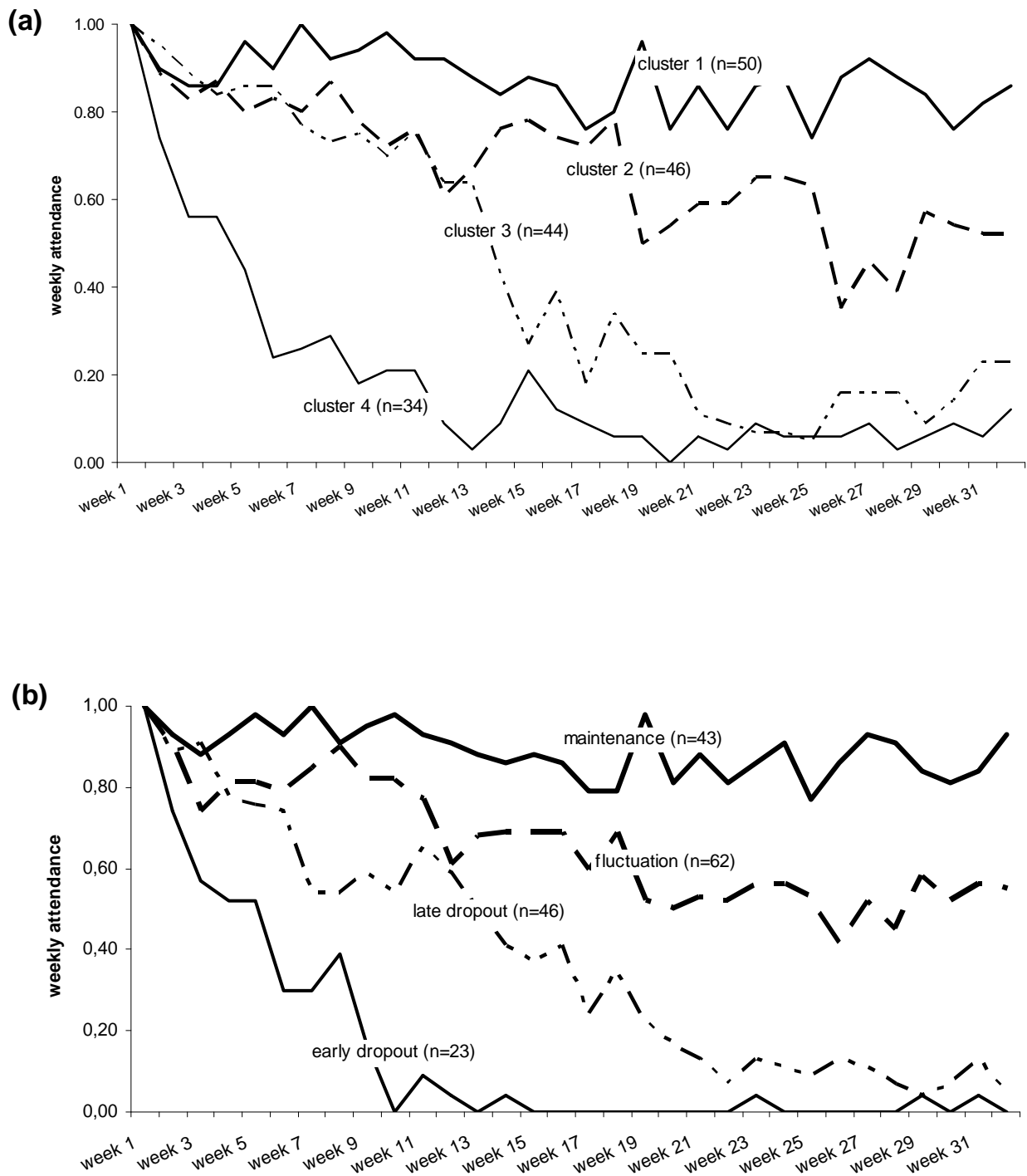


Figure 2a+b. Mean weekly attendance (a) per cluster (explorative cluster analysis) and (b) per group (normative classification).

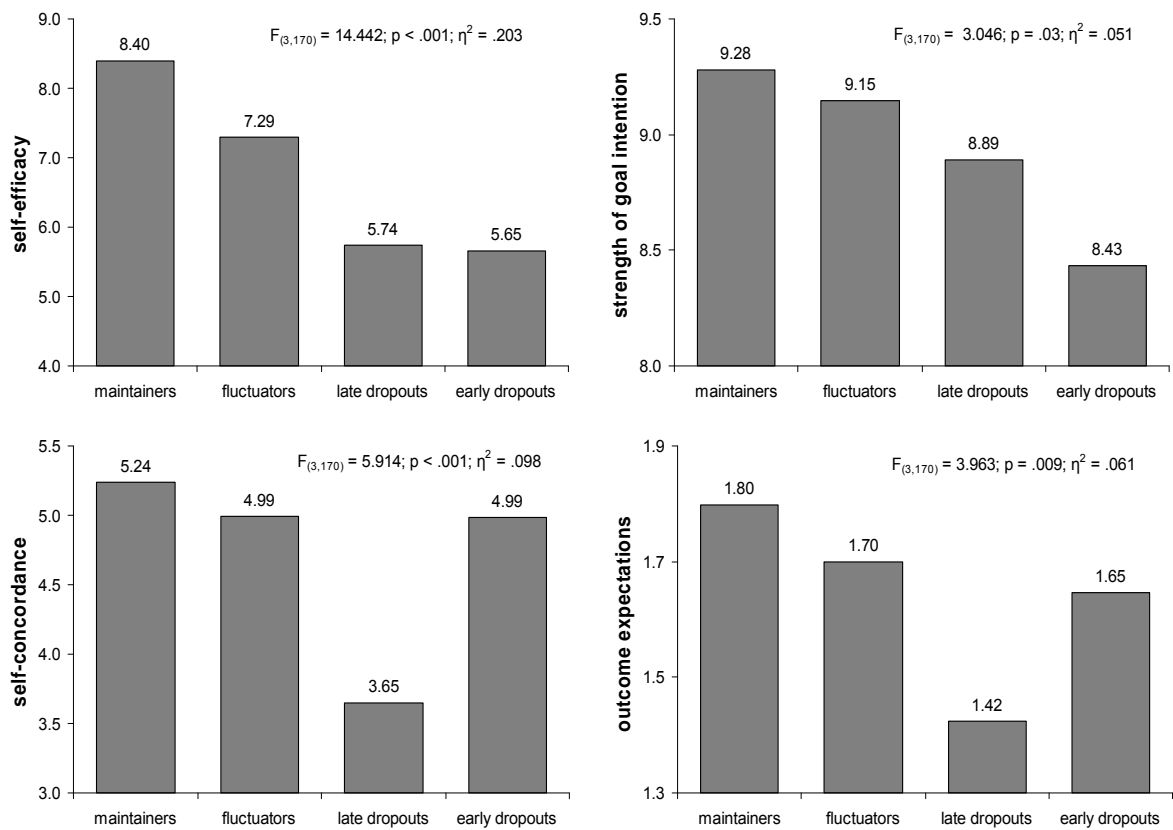


Figure 3. Self-efficacy, strength of goal intention, self-concordance, and outcome expectations in the normatively classified groups.

Table 1 a+b

Attendance rate and total participation frequency (a) per cluster and (b) of normatively classified groups

(a)	attendance rate ^a		total participation frequency ^a	
	(k=32) ^b			
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
cluster 1 (<i>n</i> = 50)	0.87	0.07	59.24	14.60
cluster 2 (<i>n</i> = 46)	0.68	0.07	39.00	10.47
cluster 3 (<i>n</i> = 44)	0.44	0.08	24.23	8.24
cluster 4 (<i>n</i> = 34)	0.19	0.10	9.00	5.16
total (<i>N</i> = 174)	0.58	0.26	35.22	21.15

(b)	attendance rate ^a		total participation frequency ^a	
	(k=32) ^b			
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
maintainers (<i>n</i> = 43)	0.89	0.06	61.21	14.45
fluctuators (<i>n</i> = 62)	0.66	0.11	38.89	11.80
late dropouts (<i>n</i> = 46)	0.38	0.09	19.69	6.80
early dropouts (<i>n</i> = 23)	0.16	0.08	8.00	5.61
total (<i>N</i> = 174)	0.58	0.26	35.22	21.15

Notes:

^a All pairwise comparisons revealed significant differences

^b total observation period (k=32 weeks)

Table 2a+b

(a) System of rules for the classification of exercise participation and (b) calculation of classification parameters

(a)	maintenance:	$S_O = 0 \wedge AR_O \geq 0.8$
	fluctuation:	$(S_O = 0 \wedge AR_O < 0.8) \vee (S_O > 0 \wedge S_{0.75 O} < 0.75 \cdot S_O)$
	late dropout:	$S_O > 0 \wedge S_{0.25 O} < 0.75 \cdot S_O \wedge S_{0.75 O} \geq 0.75 \cdot S_O$
	early dropout:	$S_O > 0 \wedge S_{0.25 O} \geq 0.75 \cdot S_O$
(b)	(1)	$AR_O = \frac{\sum_{t=1}^O A_t}{O}$
	(2)	$psrD_t = \frac{A_t - AR_O}{AR_O} \quad \text{if } \frac{A_t - AR_O}{AR_O} \geq Min$
	(3)	$S_I = \sum_{t=1}^I psrD_t$
	(3a)	$S_O = \sum_{t=1}^O psrD_t$
	(3b)	$S_{\frac{O}{4}} = \sum_{t=1}^{\frac{1}{4} \cdot O} psrD_t$
	(3c)	$S_{\frac{3 \cdot O}{4}} = \sum_{t=1}^{\frac{3}{4} \cdot O} psrD_t$
	with:	
	O	= length of observation period (in weeks)
	A_t	= attendance at time point t
	AR_O	= attendance rate in the observation period
	$psrD_t$	= positive substantial relative difference at time point t
	S_I	= sum of positive substantial relative differences in the interval I
	Min	= Minimum criterion for the determination of substantial relative differences

Table 3

Fictitious example: classification of person A's exercise participation (O = 12 weeks)

	time point t (week)												parameter
	1	2	3	4	5	6	7	8	9	10	11	12	
	quarter 1			quarter 2			quarter 3			quarter 4			
binary-coded attendance A_t	1	1	0	1	1	0	0	0	0	1	0	0	$AR_O = 0.42 = (5/12)$
	0.58	0.58	-	0.58	0.58	-	-	-	-	0.58	-	-	$A_t - AR_O$
	1.38	1.38	-1.00	1.38	1.38	-1.00	-1.00	-1.00	-1.00	1.38	-1.00	-1.00	$(A_t - AR_O) / AR_O$
psrD _t	1.38	1.38		1.38	1.38					1.38			$S_O = 6.9$
psrD _t in first quarter	1.38	1.38											$S_{(0.25\ O)} = 2.76$
psrD _t in first three quarters	1.38	1.38		1.38	1.38								$S_{(0.75\ O)} = 5.52$

Note: Specification $Min = 1$.

Table 4

Multiple correlations for different operationalisations of exercise participation

	continuous operationalisation		categorical operationalisation
	attendance rate (k=32) ^a R^2	total participation frequency R^2	participation patterns R^2
Predictors			
One-predictor models:			
self-efficacy	19.0%	17.2%	20.3%
strength of goal intention	4.6%	6.3%	5.1%
outcome expectations	4.2%	4.2%	6.1%
self-concordance	2.1%	2.5%	9.8%
Two-predictor model 1:			
self-efficacy & strength of goal intention	20.1%	19.2%	20.5%
Two-predictor model 2:			
self-concordance & outcome expectations	4.5%	4.1%	11.4%
Four-predictor model	20.3%	19.5%	21.6%

Note: ^a total observation period (k=32 weeks)