# Package 'multid'

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Author Ville-Juhani Ilmarinen [aut, o <a href="https://orcid.org/0000-0">https://orcid.org/0000-0</a>	
<b>Maintainer</b> Ville-Juhani Ilmarinen <	vj.ilmarinen@gmail.com>
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### **Description**

Calculates three different indices for variation between two or more variance estimates. VR = Variance ratio between the largest and the smallest variance. CVV = Coefficient of variance variation (Box, 1954). SVH = Standardized variance heterogeneity (Ruscio & Roche, 2012).

### Usage

cvv(data)

### Arguments

data

Data frame of two or more columns or list of two or more variables.

### Value

A vector including VR, CVV, and SVH.

#### References

Box, G. E. P. (1954). Some Theorems on Quadratic Forms Applied in the Study of Analysis of Variance Problems, I. Effect of Inequality of Variance in the One-Way Classification. The Annals of Mathematical Statistics, 25(2), 290–302.

Ruscio, J., & Roche, B. (2012). Variance Heterogeneity in Published Psychological Research: A Review and a New Index. Methodology, 8(1), 1–11. https://doi.org/10.1027/1614-2241/a000034

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#### **Examples**

```
d <- list(
   X1 = rnorm(10, sd = 10),
   X2 = rnorm(100, sd = 7.34),
   X3 = rnorm(1000, sd = 6.02),
   X4 = rnorm(100, sd = 5.17),
   X5 = rnorm(10, sd = 4.56)
)
cvv(d)</pre>
```

cvv\_manual

Coefficient of variance variation from manual input sample sizes and variance estimates

#### **Description**

Calculates three different indices for variation between two or more variance estimates. VR = Variance ratio between the largest and the smallest variance. CVV = Coefficient of variance variation (Box, 1954). SVH = Standardized variance heterogeneity (Ruscio & Roche, 2012).

### Usage

```
cvv_manual(sample_sizes, variances)
```

#### **Arguments**

sample\_sizes Numeric vector of length > 1. Sample sizes used for each variance estimate.

variances Numeric vector of length > 1. Variance estimates.

#### Value

A vector including VR, CVV, and SVH.

#### References

Box, G. E. P. (1954). Some Theorems on Quadratic Forms Applied in the Study of Analysis of Variance Problems, I. Effect of Inequality of Variance in the One-Way Classification. The Annals of Mathematical Statistics, 25(2), 290–302.

Ruscio, J., & Roche, B. (2012). Variance Heterogeneity in Published Psychological Research: A Review and a New Index. Methodology, 8(1), 1–11. https://doi.org/10.1027/1614-2241/a000034

```
cvv_manual(sample_sizes=c(10,100,1000,75,3),
variances=c(1.5,2,2.5,3,3.5))
```

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ddsc\_ml

Deconstructing difference score correlation with multi-level modeling

### **Description**

Deconstructs a bivariate association between x and a difference score y1-y2 with multi-level modeling approach. Within each upper-level unit (lvl2\_unit) there can be multiple observations of y1 and y2. Can be used for either pre-fitted lmer-models or to long format data. A difference score correlation is indicative that slopes for y1 as function of x and y2 as function of x are non-parallel. Deconstructing the bivariate association to these slopes allows for understanding the pattern and magnitude of this non-parallelism.

### Usage

```
ddsc_ml(
 model = NULL,
  data = NULL,
 predictor,
 moderator,
 moderator_values,
 DV = NULL,
  lv12\_unit = NULL,
  re_cov_test = FALSE,
  var_boot_test = FALSE,
  boot_slopes = FALSE,
  nsim = NULL,
  level = 0.95,
  seed = NULL,
  covariates = NULL,
  scaling_sd = "observed"
)
```

### **Arguments**

model Multilevel model fitted with lmerTest.

data Data frame.

predictor Character string. Variable name of independent variable predicting difference

score (i.e., x).

moderator Character string. Variable name indicative of difference score components (w).

moderator\_values

Vector. Values of the component score groups in moderator (i.e., y1 and y2).

DV Character string. Name of the dependent variable (if model is not supplied as

input).

1v12\_unit Character string. Name of the level-2 clustering variable (if model is not sup-

plied as input).

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Logical. Significance test for random effect covariation? (Default FALSE) re\_cov\_test Logical. Compare variance by lower-level groups at the upper-level in a reduced var\_boot\_test model with bootstrap? (Default FALSE) Logical. Are bootstrap estimates and percentile confidence intervals obtained boot\_slopes for the estimates presented in results? (Default FALSE) Numeric. Number of bootstrap simulations. nsim Numeric. The confidence level required for the var\_boot\_test output (Default level .95) Numeric. Seed number for bootstrap simulations. seed covariates Character string or vector. Variable names of covariates (Default NULL). scaling\_sd Character string (either default "observed" or "model"). Are the simple slopes scaled with observed or model-based SDs?

#### Value

results Summary of key results.

descriptives Means, standard deviations, and intercorrelations at level 2.

vpc\_at\_moderator\_values

Variance partition coefficients for moderator values in the model without the

predictor and interactions.

model Fitted Imer object.

reduced\_model Fitted lmer object without the predictor.

lvl2\_data Data summarized at level 2.

ddsc\_sem\_fit ddsc\_sem object fitted to level 2 data.

re\_cov\_test Likelihood ratio significance test for random effect covariation.

boot\_var\_diffs List of different variance bootstrap tests.

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ddsc\_sem

Deconstructing difference score correlation with structural equation modeling

### Description

Deconstructs a bivariate association between x and a difference score y1-y2 with SEM. A difference score correlation is indicative that slopes for y1 as function of x and y2 as function of x are non-parallel. Deconstructing the bivariate association to these slopes allows for understanding the pattern and magnitude of this non-parallelism.

### Usage

```
ddsc_sem(
  data,
  х,
 y1,
 y2,
  center_yvars = FALSE,
  covariates = NULL,
  estimator = "ML",
  level = 0.95,
  sampling.weights = NULL,
  q_sesoi = 0,
 min_cross_over_point_location = 0,
 boot_ci = FALSE,
 boot_n = 5000,
  boot_ci_type = "perc"
)
```

#### **Arguments**

data A data frame.

x Character string. Variable name of independent variable.

y1 Character string. Variable name of first component score of difference score.

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y2 Character string. Variable name of second component score of difference score. center\_yvars Logical. Should y1 and y2 be centered around their grand mean? (Default

FALSE)

covariates Character string or vector. Variable names of covariates (Default NULL).

estimator Character string. Estimator used in SEM (Default "ML").

level Numeric. The confidence level required for the result output (Default .95)

sampling.weights

Character string. Name of sampling weights variable.

q\_sesoi Numeric. The smallest effect size of interest for Cohen's q estimates (Default 0;

See Lakens et al. 2018).

min\_cross\_over\_point\_location

Numeric. Z-score for the minimal slope cross-over point of interest (Default 0).

boot\_ci Logical. Calculate confidence intervals based on bootstrap (Default FALSE).

boot\_n Numeric. How many bootstrap redraws (Default 5000).

boot\_ci\_type If bootstrapping was used, the type of interval required. The value should be

one of "norm", "basic", "perc" (default), or "bca.simple".

#### Value

descriptives Means, standard deviations, and intercorrelations.

parameter\_estimates

Parameter estimates from the structural equation model.

data Data frame with original and scaled variables used in SEM.

results Summary of key results.

### References

Edwards, J. R. (1995). Alternatives to Difference Scores as Dependent Variables in the Study of Congruence in Organizational Research. Organizational Behavior and Human Decision Processes, 64(3), 307–324.

Lakens, D., Scheel, A. M., & Isager, P. M. (2018). Equivalence Testing for Psychological Research: A Tutorial. Advances in Methods and Practices in Psychological Science, 1(2), 259–269. https://doi.org/10.1177/2515245918770963

```
## Not run:
set.seed(342356)
d <- data.frame(
    y1 = rnorm(50),
    y2 = rnorm(50),
    x = rnorm(50)
)
ddsc_sem(
    data = d, y1 = "y1", y2 = "y2",</pre>
```

diff\_two\_dep\_cors

```
x = "x",
q_sesoi = 0.20,
min_cross_over_point_location = 1
)$results
## End(Not run)
```

diff\_two\_dep\_cors

Difference between two dependent Pearson's correlations (with common index)

### Description

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Calculates Cohen's q effect size statistic for difference between two correlations,  $r_yx1$  and  $r_yx2$ . Tests if Cohen's q is different from zero while accounting for dependency between the two correlations.

### Usage

```
diff_two_dep_cors(data, y, x1, x2, level = 0.95, missing = "default")
```

### Arguments

data	Data frame.
у	Character. Variable name of the common index variable.
x1	Character. Variable name.
x2	Character. Variable name.
level	Numeric. The confidence level required for the result output (Default .95)
missing	Character. Treatment of missing values (e.g., "ML", default = listwise deletion)

#### Value

Parameter estimates from the fitted structural path model.

```
set.seed(3864)
d<-data.frame(y=rnorm(100),x=rnorm(100))
d$x1<-d$x+rnorm(100)
d$x2<-d$x+rnorm(100)
diff_two_dep_cors(data=d,y="y",x1="x1",x2="x2")</pre>
```

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d_pooled_sd	Standardized mean difference with pooled standard deviation

### Description

Standardized mean difference with pooled standard deviation

### Usage

```
d_pooled_sd(
  data,
  var,
  group.var,
  group.values,
  rename.output = TRUE,
  infer = FALSE
)
```

### Arguments

data	A data frame.
var	A continuous variable for which difference is estimated.
group.var	The name of the group variable.
group.values	Vector of length 2, group values (e.g. c("male", "female) or c(0,1)).
rename.output	Logical. Should the output values be renamed according to the group.values? Default TRUE.
infer	Logical. Statistical inference with Welch test? (default FALSE)

### Value

Descriptive statistics and mean differences

```
d_pooled_sd(iris[iris$Species == "setosa" | iris$Species == "versicolor", ],
  var = "Petal.Length", group.var = "Species",
  group.values = c("setosa", "versicolor"), infer = TRUE
)
```

D\_regularized

D_regularized Multivariate group difference estimation with regularized binomial regression	D_regularized	Multivariate group difference estimation with regularized binomial regression
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### Description

Multivariate group difference estimation with regularized binomial regression

### Usage

```
D_regularized(
 data,
 mv.vars,
 group.var,
 group.values,
 alpha = 0.5,
 nfolds = 10,
  s = "lambda.min",
  type.measure = "deviance",
  rename.output = TRUE,
 out = FALSE,
  size = NULL,
  fold = FALSE,
  fold.var = NULL,
 pcc = FALSE,
 auc = FALSE,
 pred.prob = FALSE,
 prob.cutoffs = seq(0, 1, 0.2),
  append.data = FALSE
)
```

data	A data frame or list containing two data frames (regularization and estimation data, in that order).
mv.vars	Character vector. Variable names in the multivariate variable set.
group.var	The name of the group variable.
group.values	Vector of length 2, group values (e.g. $c("male", "female)$ or $c(0,1)$ ).
alpha	Alpha-value for penalizing function ranging from 0 to 1: $0 = \text{ridge regression}$ , $1 = \text{lasso}$ , $0.5 = \text{elastic net (default)}$ .
nfolds	Number of folds used for obtaining lambda (range from 3 to n-1, default 10).
S	Which lambda value is used for predicted values? Either "lambda.min" (default) or "lambda.1se".
type.measure	Which measure is used during cross-validation. Default "deviance".

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rename.output Logical. Should the output values be renamed according to the group.values? Default TRUE. out Logical. Should results and predictions be calculated on out-of-bag data set? (Default FALSE) Integer. Number of cases in regularization data per each group. Default 1/4 of size cases. fold. Logical. Is regularization applied across sample folds with separate predictions for each fold? (Default FALSE, see details) fold.var Character string. Name of the fold variable. (default NULL) Logical. Include probabilities of correct classification? Default FALSE. рсс Logical. Include area under the receiver operating characteristics? Default auc FALSE. pred.prob Logical. Include table of predicted probabilities? Default FALSE. prob.cutoffs Vector. Cutoffs for table of predicted probabilities. Default seq(0,1,0.20).

### **Details**

append.data

fold = TRUE will apply manually defined data folds (supplied with fold.var) for regularization and obtain estimates for each separately. This can be a good solution, for example, when the data are clustered within countries. In such case, the cross-validation procedure is applied across countries.

Logical. If TRUE, the data is appended to the predicted variables.

out = TRUE will use separate data partition for regularization and estimation. That is, the first cross-validation procedure is applied within the regularization set and the weights obtained are then used in the estimation data partition. The size of regularization set is defined with size. When used with fold = TRUE, size means size within a fold."

For more details on these options, please refer to the vignette and README of the multid package.

#### Value

D Multivariate descriptive statistics and differences.

pred.dat A data.frame with predicted values.

cv.mod Regularized regression model from cv.glmnet.P.table Table of predicted probabilities by cutoffs.

#### References

Lönnqvist, J. E., & Ilmarinen, V. J. (2021). Using a continuous measure of genderedness to assess sex differences in the attitudes of the political elite. Political Behavior, 43, 1779–1800. doi:10.1007/s11109021096812

Ilmarinen, V. J., Vainikainen, M. P., & Lönnqvist, J. E. (2023). Is there a g-factor of genderedness? Using a continuous measure of genderedness to assess sex differences in personality, values, cognitive ability, school grades, and educational track. European Journal of Personality, 37, 313-337. doi:10.1177/08902070221088155

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#### See Also

```
cv.glmnet
```

```
D_regularized(
  data = iris[iris$Species == "setosa" | iris$Species == "versicolor", ],
  mv.vars = c("Sepal.Length", "Sepal.Width", "Petal.Length", "Petal.Width"),
  group.var = "Species", group.values = c("setosa", "versicolor")
)$D
# out-of-bag predictions
D_regularized(
  data = iris[iris$Species == "setosa" | iris$Species == "versicolor", ],
  mv.vars = c("Sepal.Length", "Sepal.Width", "Petal.Length", "Petal.Width"),
  group.var = "Species", group.values = c("setosa", "versicolor"),
  out = TRUE, size = 15, pcc = TRUE, auc = TRUE
)$D
# separate sample folds
# generate data for 10 groups
set.seed(34246)
n1 <- 100
n2 <- 10
d <-
 data.frame(
   sex = sample(c("male", "female"), n1 * n2, replace = TRUE),
    fold = sample(x = LETTERS[1:n2], size = n1 * n2, replace = TRUE),
   x1 = rnorm(n1 * n2),
   x2 = rnorm(n1 * n2),
   x3 = rnorm(n1 * n2)
# Fit and predict with same data
D_regularized(
  data = d,
 mv.vars = c("x1", "x2", "x3"),
  group.var = "sex",
  group.values = c("female", "male"),
  fold.var = "fold",
  fold = TRUE,
  rename.output = TRUE
)$D
# Out-of-bag data for each fold
D_regularized(
  data = d,
  mv.vars = c("x1", "x2", "x3"),
  group.var = "sex",
  group.values = c("female", "male"),
  fold.var = "fold",
  size = 17,
```

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```
out = TRUE,
fold = TRUE,
rename.output = TRUE
)$D
```

 $ml_dadas$ 

Predicting algebraic difference scores in multilevel model

### Description

Decomposes difference score predictions to predictions of difference score components by probing simple effects at the levels of the binary moderator.

### Usage

```
ml_dadas(
   model,
   predictor,
   diff_var,
   diff_var_values,
   scaled_estimates = FALSE,
   re_cov_test = FALSE,
   var_boot_test = FALSE,
   nsim = NULL,
   level = 0.95,
   seed = NULL,
   abs_diff_test = 0
)
```

model	Multilevel model fitted with lmerTest.		
predictor	Character string. Variable name of independent variable predicting difference score.		
diff_var	Character string. A variable indicative of difference score components (two groups).		
diff_var_values			
	Vector. Values of the component score groups in diff_var.		
scaled_estimates			
	Logical. Are scaled estimates obtained? Does fit a reduced model for correct standard deviations. (Default FALSE)		
re_cov_test	Logical. Significance test for random effect covariation? Does fit a reduced model without the correlation. (Default FALSE)		
var_boot_test	Logical. Compare variance by lower-level groups at the upper-level in a reduced model with bootstrap? (Default FALSE)		

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nsim Numeric. Number of bootstrap simulations.

level Numeric. The confidence level required for the var\_boot\_test output (Default

.95)

seed Numeric. Seed number for bootstrap simulations.

abs\_diff\_test Numeric. A value against which absolute difference between component score

predictions is tested (Default 0).

#### Value

dadas A data frame including main effect, interaction, regression coefficients for com-

ponent scores, dadas, and comparison between interaction and main effect.

scaled\_estimates

Scaled regression coefficients for difference score components and difference

score

vpc\_at\_reduced Variance partition coefficients in the model without the predictor and interac-

tions.

re\_cov\_test Likelihood ratio significance test for random effect covariation.

boot\_var\_diffs List of different variance bootstrap tests.

```
## Not run:
set.seed(95332)
n1 <- 10 # groups
n2 <- 10 # observations per group
dat <- data.frame(</pre>
  group = rep(c(LETTERS[1:n1]), each = n2),
  w = sample(c(-0.5, 0.5), n1 * n2, replace = TRUE),
  x = rep(sample(1:5, n1, replace = TRUE), each = n2),
  y = sample(1:5, n1 * n2, replace = TRUE)
library(lmerTest)
fit <- lmerTest::lmer(y \sim x * w + (w | group),
  data = dat
)
round(ml_dadas(fit,
  predictor = "x",
  diff_var = "w",
  diff_var_values = c(0.5, -0.5)
)$dadas, 3)
## End(Not run)
```

pcc 15

рсс

Returns probabilities of correct classification for both groups in independent data partition.

### Description

Returns probabilities of correct classification for both groups in independent data partition.

### Usage

```
pcc(data, pred.var, group.var, group.values)
```

### **Arguments**

data	Data frame including predicted values (e.g., pred.dat from D_regularized_out).
pred.var	Character string. Variable name for predicted values.
group.var	The name of the group variable.
group.values	Vector of length 2, group values (e.g. c("male", "female) or c(0,1)).

### Value

Vector of length 2. Probabilities of correct classification.

```
D_out <- D_regularized(
  data = iris[iris$Species == "versicolor" | iris$Species == "virginica", ],
  mv.vars = c("Sepal.Length", "Sepal.Width", "Petal.Length", "Petal.Width"),
  group.var = "Species", group.values = c("versicolor", "virginica"),
  out = TRUE,
  size = 15
)

pcc(
  data = D_out$pred.dat,
  pred.var = "pred",
  group.var = "group",
  group.values = c("versicolor", "virginica")
)</pre>
```

plot\_ddsc

plot\_ddsc

Plot deconstructed difference score correlation

### **Description**

Plots the slopes for y1 and y2 by x, and a slope for y1-y2 by x for comparison.

### Usage

```
plot_ddsc(
   ddsc_object,
   diff_color = "black",
   y1_color = "turquoise",
   y2_color = "orange",
   x_label = NULL,
   y_labels = NULL,
   densities = TRUE,
   point_alpha = 0.5,
   dens_alpha = 0.75,
   col_widths = c(3, 1),
   row_heights = c(2, 1, 0.5),
   coef_locations = c(0/3, 1/3, 2/3),
   coef_names = c("b_11", "b_21", "r_x_y1-y2")
)
```

ddsc_object	An object produced by ddsc_sem function.	
diff_color	Character. Color for difference score (y1-y2). Default "black".	
y1_color	Character. Color for difference score component y1. Default "turquoise".	
y2_color	Character. Color for difference score component y2. Default "orange".	
x_label	Character. Label for variable X. If NULL (default), variable name is used.	
y_labels	Character vector. Labels for variable y1 and y2. If NULL (default), variable names are used.	
densities	Logical. Are y-variable densities plotted? Default TRUE.	
point_alpha	Numeric. Opacity for data points (default 0.50)	
dens_alpha	Numeric. Opacity for density distributions (default 0.75)	
col_widths	Numeric vector. Widths of the plot columns: slope figures and density figures; default $c(3, 1)$ .	
row_heights	Numeric vector. Heights of the plot rows: components, difference score, slope coefs; default $c(2, 1, 0.5)$ .	
coef_locations	Numeric vector. Locations for printed coefficients. Quantiles of the range of x-variable. Default $c(0, 1/3, 2/3)$ .	
coef_names	Character vector. Names of the printed coefficients. Default c("b_11", "b_21", "r_x_y1-y2").	

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### **Examples**

qcc

Quantile correlation coefficient

### Description

For computation of tail dependence as correlations estimated at different variable quantiles (Choi & Shin, 2022; Lee et al., 2022) summarized across two quantile regression models where x and y switch roles as independent/dependent variables.

### Usage

```
qcc(
   x,
   y,
   tau = c(0.1, 0.5, 0.9),
   data,
   method = "br",
   boot_n = NULL,
   ci_level = 0.95
)
```

X	Name of x variable. Character string.
У	Name of y variable. Character string.
tau	The quantile(s) to be estimated. A vector of values between 0 and 1, default $c(.1,.5,.9)$ . @seealso rq
data	Data frame.
method	The algorithmic method used to compute the fit (default "br"). @seealso rq
boot_n	Number of bootstrap redraws (default NULL = no bootstrap inference).
ci_level	Level for percentile bootstrap confidence interval. Numeric values between 0 and 1. Default .95.

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#### Value

```
r Pearson's correlation estimate for comparison.

rho_tau Correlations at different tau values (quantiles).

r_boot_est Pearson's correlation bootstrap estimates.

rho_tau_boot_est
```

Bootstrap estimates for correlations at different tau values (quantiles).

#### References

Choi, J.-E., & Shin, D. W. (2022). Quantile correlation coefficient: A new tail dependence measure. Statistical Papers, 63(4), 1075–1104. https://doi.org/10.1007/s00362-021-01268-7

Lee, J. A., Bardi, A., Gerrans, P., Sneddon, J., van Herk, H., Evers, U., & Schwartz, S. (2022). Are value–behavior relations stronger than previously thought? It depends on value importance. European Journal of Personality, 36(2), 133–148. https://doi.org/10.1177/08902070211002965

### **Examples**

```
set.seed(2321) d <- data.frame(x = rnorm(2000)) d$y <- 0.10 * d$x + (0.20) * d$x^2 + 0.40 * d$x^3 + (-0.20) * d$x^4 + rnorm(2000) qcc_boot <- qcc(x = "x", y = "y", data = d, tau = 1:9 / 10, boot_n = 50) qcc_boot$rho_tau
```

reliability\_dms

Reliability calculation for difference score variable that is a difference between two mean variables calculated over upper-level units (e.g., sex differences across countries)

#### **Description**

Calculates reliability of difference score (Johns, 1981) based on two separate ICC2 values (Bliese, 2000), standard deviations of mean values over upper-level units, and correlations between the mean values across upper-level units.

### Usage

```
reliability_dms(
  model = NULL,
  data = NULL,
  diff_var,
  diff_var_values,
  var,
  group_var
)
```

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### **Arguments**

model Multilevel model fitted with lmer (default NULL)

data Long format data frame (default NULL)

diff\_var Character string. A variable indicative of difference score components (two groups).

diff\_var\_values

Vector. Values of the component score groups in diff\_var.

var Character string. Name of the dependent variable or variable of which mean values are calculated.

group\_var Character string. Upper-level clustering unit.

#### Value

A vector including ICC2s (r11 and r22), SDs (sd1, sd2, and sd\_d12), means (m1, m2, and m\_d12), correlation between means (r12), and reliability of the mean difference variable.

#### References

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K. J. Klein & S. W. J. Kozlowski (Eds.), Multilevel theory, research, and methods in organizations: Foundations, extensions, and new directions (pp. 349–381). Jossey-Bass.

Johns, G. (1981). Difference score measures of organizational behavior variables: A critique. Organizational Behavior and Human Performance, 27(3), 443–463. https://doi.org/10.1016/0030-5073(81)90033-7

```
set.seed(4317)
n2 <- 20
n1 <- 200
ri <- rnorm(n2, m = 0.5, sd = 0.2)
rs < -0.5 * ri + rnorm(n2, m = 0.3, sd = 0.15)
d.list <- list()</pre>
for (i in 1:n2) {
  x \leftarrow rep(c(-0.5, 0.5), each = n1 / 2)
  y < -ri[i] + rs[i] * x + rnorm(n1)
  d.list[[i]] \leftarrow cbind(x, y, i)
d <- data.frame(do.call(rbind, d.list))</pre>
names(d) \leftarrow c("x", "y", "cntry")
reliability_dms(
  data = d, diff_var = "x",
  diff_{var_values} = c(-0.5, 0.5), var = "y", group_var = "cntry"
)
```

20 sem\_dadas

sem_dadas	Predicting algebraic difference scores	in structural equation model
Selii_uauas	Tredicting digeorate difference scores	in structural equation model

### Description

Predicting algebraic difference scores in structural equation model

### Usage

```
sem_dadas(
  data,
  var1,
  var2,
  center = FALSE,
  scale = FALSE,
  predictor,
  covariates = NULL,
  estimator = "MLR",
  level = 0.95,
  sampling.weights = NULL,
  abs_coef_diff_test = 0
)
```

data	A data frame.	
var1	Character string. Variable name of first component score of difference score $(Y_1)$ .	
var2	Character string. Variable name of second component score of difference score $(Y_2)$ .	
center	Logical. Should var1 and var2 be centered around their grand mean? (Default FALSE)	
scale	Logical. Should var1 and var2 be scaled with their pooled sd? (Default FALSE)	
predictor	Character string. Variable name of independent variable predicting difference score.	
covariates	Character string or vector. Variable names of covariates (Default NULL).	
estimator	Character string. Estimator used in SEM (Default "MLR").	
level	Numeric. The confidence level required for the result output (Default .95)	
sampling.weights		
	Character string. Name of sampling weights variable.	
abs_coef_diff_test		
	Numeric. A value against which absolute difference between component score predictions is tested (Default 0).	

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#### Value

#### References

Edwards, J. R. (1995). Alternatives to Difference Scores as Dependent Variables in the Study of Congruence in Organizational Research. Organizational Behavior and Human Decision Processes, 64(3), 307–324.

### **Examples**

```
## Not run:
set.seed(342356)
d <- data.frame(
    var1 = rnorm(50),
    var2 = rnorm(50),
    x = rnorm(50)
)
sem_dadas(
    data = d, var1 = "var1", var2 = "var2",
    predictor = "x", center = TRUE, scale = TRUE,
    abs_coef_diff_test = 0.20
)$results
## End(Not run)</pre>
```

value\_correlation

Testing and quantifying how much ipsatization (profile centering) influence associations between value and a correlate

### **Description**

Testing and quantifying how much ipsatization (profile centering) influence associations between value and a correlate

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### Usage

```
value_correlation(
  data,
  rv,
  cf,
  correlate,
  scale_by_rv = FALSE,
  standardize_correlate = FALSE,
  estimator = "ML",
  level = 0.95,
  sampling.weights = NULL,
  sesoi = 0
)
```

### **Arguments**

data	A data frame.	
rv	Character string or vector. Variable name(s) of the non-ipsatized value variable(s) (raw value score).	
cf	Character string. Variable name of the common factor that is used for ipsatizing raw value scores.	
correlate	Character string. Name of the variable to which associations with values are examined.	
scale_by_rv	Logical. Is standard deviation of the raw non-ipsatized value score used for scaling the common factor as well? (Default FALSE)	
standardize_correlate		
	Logical. Should the correlate be standardized? (Default FALSE)	
estimator	Character string. Estimator used in SEM (Default "ML").	
level	Numeric. The confidence level required for the result output (Default .95)	
sampling.weights		
	Character string. Name of sampling weights variable.	
sesoi	Numeric. Smallest effect size of interest. Used for equivalence testing differences in ipsatized and non-ipsatized value associations (Default 0).	

### Value

parameter\_estimates

Parameter estimates from the structural equation model.

transformed\_data

Data frame with variables used in SEM (after scaling is applied).

results Summary of key results.

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#### **Examples**

```
## Not run:
set.seed(342356)
d <- data.frame(</pre>
 rv1 = rnorm(50),
 rv2 = rnorm(50),
 rv3 = rnorm(50),
 rv4 = rnorm(50),
 x = rnorm(50)
d$cf<-rowMeans(d[,c("rv1","rv2","rv3","rv4")])</pre>
fit<-value_correlation(</pre>
 data = d, rv = c("rv1", "rv2", "rv4"), cf = "cf",
 correlate = "x",scale_by_rv = TRUE,
 standardize_correlate = TRUE,
 sesoi = 0.10
round(fit$variability_summary,3)
round(fit$association_summary,3)
## End(Not run)
```

vpc\_at

Variance partition coefficient calculated at different level-1 values

### **Description**

Calculates variance estimates (level-2 Intercept variance) and variance partition coefficients (i.e., intra-class correlation) at selected values of predictor values in two-level linear models with random effects (intercept, slope, and their covariation).

### Usage

```
vpc_at(model, lvl1.var, lvl1.values)
```

### **Arguments**

model	Two-level model fitted with lme4. Must include random intercept, slope, and their covariation.
lvl1.var	Character string. Level 1 variable name to which random slope is also estimated.
lvl1.values	Level 1 variable values.

#### Value

Data frame of level 2 variance and std.dev. estimates at level 1 variable values, respective VPCs (ICC1s) and group-mean reliabilities (ICC2s) (Bliese, 2000).

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#### References

Goldstein, H., Browne, W., & Rasbash, J. (2002). Partitioning Variation in Multilevel Models. Understanding Statistics, 1(4), 223–231. https://doi.org/10.1207/S15328031US0104\_02

Bliese, P. D. (2000). Within-group agreement, non-independence, and reliability: Implications for data aggregation and analysis. In K. J. Klein & S. W. J. Kozlowski (Eds.), Multilevel theory, research, and methods in organizations: Foundations, extensions, and new directions (pp. 349–381). Jossey-Bass.

```
fit <- lme4::lmer(Sepal.Length ~ Petal.Length +
    (Petal.Length | Species),
data = iris
)

lvl1.values <-
    c(
    mean(iris$Petal.Length) - stats::sd(iris$Petal.Length),
    mean(iris$Petal.Length),
    mean(iris$Petal.Length) + stats::sd(iris$Petal.Length)
)

vpc_at(
    model = fit,
    lvl1.var = "Petal.Length",
    lvl1.values = lvl1.values
)</pre>
```

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