

Factor Structure, Criterion-Related Validity, and Longitudinal Measurement Invariance of the Regulation of Eating Behavior Scale (REBS): A Bifactor S-1 Exploratory Structural Equation Modeling Approach

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Measurement Instruments for the Social Sciences, 2023, Vol. 5, Article e11187, <https://doi.org/10.5964/miss.11187>

Received: 2021-08-13 • Accepted: 2023-05-11 • Published (VoR): 2023-07-06

Handling Editor: Matthias Bluemke, GESIS – Leibniz Institute for the Social Sciences, Mannheim, Germany

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Abstract

The Regulation of Eating Behavior Scale (REBS) is one of the most popular measures to assess why people regulate their eating behaviors. However, few studies have examined its psychometric properties and problems with discriminant validity have been identified in previous research. The present study (re)examined the factor structure and criterion-related validity of the REBS using confirmatory factor analysis (CFA), exploratory structural equation modeling (ESEM), and bifactor (S-1) modeling in a sample of middle-aged women (N = 1447). We also examined longitudinal measurement invariance in a subsample of participants (n = 803) who responded to the survey 5 years later. The bifactor S-1 ESEM provided an excellent fit to the data and the factor loading pattern showed a well-defined global self-determination factor anchored in intrinsic motivation with decreasing contribution from the other items on the continuum. Relations between the global and specific motivation factors, food habits, binge eating, and BMI provided evidence of criterion-related validity. Longitudinal measurement invariance across time was also verified. Our results support the idea that the global factor represent a general quantity of self-determination rather than relative self-determination.

Keywords

bifactor modeling, eating behavior, exploratory structural equation modeling, factor structure, measurement equivalence, motivation



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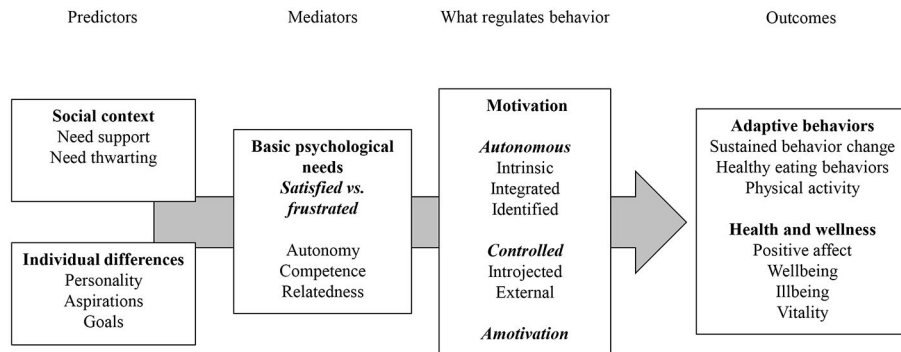
Understanding peoples underlying motivation to regulate their eating behaviors can greatly advance our understanding of why some people are successful at regulating their eating behaviors and others struggle. Self-determination theory (SDT; Ryan & Deci, 2017) conceptualizes motivation along a continuum of behavioral regulatory styles that varies according to their degree of internalization and self-determination. The most self-determined type is intrinsic motivation, which is defined as engaging in an activity or behavior for the inherent satisfaction, interest, and enjoyment of the activity or behavior. At the opposite end of the continuum lies amotivation, which is characterized by an absence of motivation and not valuing the activity or outcomes associated with it. In between these two extremes are four types of extrinsic motivation. External regulation is the least self-determined type and is defined by engagement in an activity or behavior for instrumental reasons where no internalization has occurred. Introjected regulation is characterized by partial internalization of the activity or behavior, however, it is not accepted as one's own and is characterized by internal pressures to avoid shame and guilt or enhance ego and self-worth. Identified regulation is largely internalized and is present when the person values the outcomes of the activity or behavior as personally important. The most self-determined of the extrinsic regulations is integrated regulation, which is present when the activity or behavior is in line with the persons' values and sense of self.

The different types of motivation described in the previous paragraph are key elements of the SDT process model of motivation, which is focused on motivational factors influencing peoples' health and behavior (see Figure 1). In brief, this motivational model highlights predictor variables in the social context and individual difference variables that affect individuals' basic psychological needs for autonomy, competence, and relatedness. Satisfaction or frustration of the basic psychological needs, in turn, influences motivation, which is a key predictor of health behaviors, maintained behavior change, and wellbeing (see e.g., Ntoumanis et al., 2021, for a meta-analysis on the effects of SDT-informed interventions on motivation, health behaviors, and health).

Previous research shows that regulating ones behavior for more autonomous reasons, such as out of pleasure, interest, or that the behavior is congruent with one's own goals and values, is related to adaptive outcomes, such as lower BMI, healthier eating habits, higher self-efficacy for healthy eating, and less body size dissatisfaction (Guertin et al., 2015; Leong et al., 2012; Mask & Blanchard, 2011; Pelletier et al., 2004; Teixeira et al., 2011). Regulating ones eating behavior for more controlled reasons, for example to satisfy or abide to some external standard (e.g., to avoid punishment or gain a reward) or to avoid feelings of guilt, have generally been associated with maladaptive outcomes, such as unhealthy eating habits, negative affect, and bulimic symptoms (Carraça et al., 2019; Otis & Pelletier, 2008; Pelletier et al., 2004; Verstuyf et al., 2012).

Figure 1

The Process Model of Motivation Based on Self-Determination Theory



Regulation of Eating Behavior Scale (REBS)

The primary measure to assess eating behavior regulatory styles based on SDT is the Regulation of Eating Behavior Scale (REBS; Pelletier et al., 2004). However, there has been a lack of studies examining psychometric properties (e.g., factor structure) of the REBS. Three previous studies have been published that examined the factor structure and reliability of the REBS, which included Canadian (Pelletier et al., 2004) and US (Hamilton et al., 2018) student samples with a mean age of 22.5 years or younger and an adult Portuguese sample with a mean age of 30.5 years (Teixeira et al., 2021); how generalizable these findings are to other populations (e.g., older participants, other cultures) is unknown. Furthermore, these previous studies examined the factor structure of the REBS using independent clusters model confirmatory factor analysis (ICM-CFA). Solely relying on ICM-CFA is considered a suboptimal approach for examining the factor structure of multidimensional instruments such as the REBS because of the constraints placed on the ICM-CFA model (e.g., zero cross-loadings; Marsh et al., 2014). These constraints often result in inflated factor correlations and poor discriminant validity among the latent factors (Marsh et al., 2014). Previous studies with the REBS have found latent factor correlations stronger than 0.70 (Hamilton et al., 2018) and some as strong as 0.93 (Teixeira et al., 2021), which indicates poor discriminant validity.

The Present Study

Although these previous studies have made important contributions to the measurement of eating behavioral regulations from an SDT perspective, recent developments in the psychometric and motivational literature (cf. Howard, Gagné, Van den Broeck, et al., 2020) calls for additional psychometric scrutiny of the REBS. The purpose of the present study was thus to (re)examine the factor structure of the REBS to advance our knowledge

of REBS structural validity. More specifically, the current study makes six contributions to the psychometric literature on the REBS. First, we used exploratory structural equation modeling (ESEM) to overcome problems with inflated latent factor correlations and poor discriminant validity (Marsh et al., 2014). Second, bifactor modeling was used to simultaneously conceptualize the behavioral regulations as unidimensional (quantity of self-determination) and multidimensional (motivation quality), which is in line with contemporary views of motivation grounded in SDT (e.g., Gunnell & Gaudreau, 2015; Howard, Gagné, & Morin, 2020; Howard et al., 2018; Stenling et al., 2018). Although most previous applications of bifactor models on SDT-based measures of motivation have used a symmetrical bifactor ESEM (i.e., one specific factor per subscale), there are several unresolved issues related to the symmetrical bifactor ESEM (Bureau et al., 2023). The global factor in the symmetrical bifactor ESEM represents what is common among the items, whereas the specific factors represent what is uniquely common to a group of items (Howard et al., 2018). This separation of what is common and specific, however, does not clarify what conceptual information will be assigned to the global and specific factors. Hence, the interpretation of the global and specific factors may differ between studies depending on for example the measures used, and the types of motivation assessed. Additional concerns have been raised related to the meaning of the specific factors, particularly in cases where they display low validity (e.g., factor loadings close to zero), and the conceptualization of the specific factor of intrinsic motivation and the global factor of self-determination when they are orthogonal (i.e., assumed to measure distinct properties; Bureau et al., 2023). Given that intrinsic motivation is considered a prototypical illustration of self-determination (Ryan & Deci, 2017), estimating intrinsic motivation as orthogonal from self-determination results in uncertainty regarding the conceptualization of either factor (Bureau et al., 2023).

An alternative that could remedy some of the concerns with the symmetrical bifactor ESEM is to specify a bifactor S-1 model (Burns et al., 2020; Eid et al., 2017; Heinrich et al., 2020). The bifactor S-1 model seems particularly suited to situations when items are expected to contribute asymmetrically to the global factor, which is the case for items in SDT-based measures of motivation (ranging from amotivation to intrinsic motivation; Bureau et al., 2023). The S-1 part indicates that one of the specific factors is used as an anchor for the global factor, and that items of that specific factor is only predicted by the global factor and not by a specific factor. Recently, Bureau et al. (2023) proposed that anchoring the global factor of self-determination in intrinsic motivation would be more coherent with SDT than specifying these two factors as orthogonal, given that intrinsic motivation is prototypical of self-determination (Ryan & Deci, 2017). A bifactor S-1 model with the global factor anchored in intrinsic motivation would not have a specific factor for intrinsic motivation items (i.e., intrinsic motivation items are only predicted by the global factor). This, in turn, implies that the global factor conceptually draws its meaning most from the intrinsic motivation items, and in a decreasing fashion

from the other items on the continuum. Hence, this results in a global factor that captures the highest possible amount of self-determination. The specific factors are all orthogonal to the global factor of self-determination and can therefore be interpreted as what is common to their indicators but is unrelated to self-determination (i.e., purely non-self-determined facets of these extrinsic motivations). A bifactor S-1 model can thus overcome shortcomings of the symmetrical bifactor model because it clarifies the meaning of both the global and specific factors and it can also enhance the precision when predicting outcomes (cf. Bureau et al., 2023). Therefore, we focused on the bifactor S-1 model in the current study.

Third, we examined the continuum hypothesis with bifactor modeling by examining the shift in magnitude and sign of the factor loadings on the global factor along the SDT continuum (cf. Chemolli & Gagné, 2014; Howard, Gagné, & Morin, 2020; Howard et al., 2018; Howard, Gagné, Van den Broeck, et al., 2020; Litalien et al., 2017; Stenling et al., 2018). Fourth, we extended the diversity of populations where the psychometric properties of the REBS are evaluated by examining the structural validity in a representative sample of middle-aged women in New Zealand. Fifth, we examined criterion-related validity by examining relations between the global and specific motivation factors, food habits, binge eating, and body mass index (BMI). Based on previous findings (e.g., Leong et al., 2012; Pelletier et al., 2004; Verstuyf et al., 2012), we expected the global factor of self-determination to be related to healthier food habits (more servings of fruits and vegetables, lower intake of high fat and high sugar foods), lower frequency of binge eating, and lower BMI. The more autonomous specific motivation factors were expected to be related to healthier food habits, lower frequency of binge eating, and lower BMI, whereas the more controlled specific motivation factors were expected to be related to less healthy food habits, higher frequency of binge eating, and higher BMI. Finally, we examined longitudinal measurement invariance of the REBS across 5 years to ensure that the same latent construct was measured in the same metric at each time point (Widaman et al., 2010). No previous study has examined longitudinal measurement invariance of the REBS or similar instruments, such as the Motivation for Healthy Eating Scale (Kato et al., 2013; Román et al., 2021).

Method

Study Design and Participants

The present study is based on secondary analysis of data from the longitudinal study ‘Weight Control Practices and Regulation of Eating Behaviours in New Zealand Women’. A description of the population, sampling procedure, mail survey procedures, exclusion criteria, and use of incentives for the study have been described previously (Leong et al., 2012). In brief, a random sample of 2500 women aged 40–50 years were selected from the

nationwide New Zealand General and Māori electoral rolls in May 2009. This age group was chosen for its high risk for weight gain and high prevalence of obesity (Ball et al., 2003). A 66% response rate was achieved with 1601 women returning completed analyzable questionnaire booklets. Women were representative of the New Zealand population in terms of socioeconomic status and percentage identifying as Māori (Leong et al., 2011). Ethical approval for the study was obtained from the University of Otago Human Ethics Committee (reference nr. 08/103) and the project was also approved by The Ngāi Tahu Research Consultation Committee. Participants were informed that by completing and returning the questionnaire they were giving their consent to take part in the study.

In the current study we included those who provided responses to the REBS at Wave 1 in 2009 ($n = 1447$) and 5 years later at Wave 2 in 2014 ($n = 803$; see Table 1). The participants age ranged from 40 to 51 years ($M = 45.4$, $SD = 3.2$) at Wave 1 and 45 to 56 years ($M = 50.5$, $SD = 3.2$) at Wave 2. A majority of the sample was of New Zealand European ethnicity ($\approx 67\%$) and were classified as being of medium socioeconomic status ($\approx 66\%$) according to the New Zealand socioeconomic index 1996 (Statistics New Zealand, 2001).

Table 1

Demographic Characteristics of the Full Sample, Those Responding Only at Wave 1, and Those Responding at Wave 1 and 2

Variable	n (%)		
	Full Sample Wave 1	Wave 1 only	Wave 1 & Wave 2
Primary Ethnicity			
New Zealand European	962 (66.8)	392 (59.7)	570 (71.0)
Other	191 (13.3)	96 (14.6)	95 (11.8)
Maori	163 (11.3)	85 (12.9)	78 (9.7)
Asian	82 (5.7)	46 (7.0)	36 (4.5)
Pacific Island	43 (3.0)	21 (3.2)	22 (2.7)
Total <i>n</i>	1441	640	801
Socioeconomic status^a			
Low (10–29)	211 (14.6)	113 (17.2)	98 (12.2)
Medium (30–59)	957 (66.3)	428 (65.1)	529 (65.9)
High (60–90)	275 (19.1)	100 (15.2)	175 (21.8)
Total <i>n</i>	1443	641	802
BMI category			
Underweight (< 18.5)	25 (1.8)	11 (1.7)	14 (1.7)
Healthy weight (18.5–24.9)	667 (48.5)	285 (43.4)	382 (47.6)
Overweight (25.0–29.9)	402 (29.2)	174 (26.5)	228 (28.4)
Obese (≥ 30.0)	282 (20.5)	125 (19.0)	157 (19.6)
Total <i>n</i>	1376	595	781

Variable	n (%)		
	Full Sample Wave 1	Wave 1 only	Wave 1 & Wave 2
Highest level of education attained			
Primary and/or some secondary school	445 (30.9)	219 (33.3)	226 (28.1)
Completed secondary school	138 (9.6)	67 (10.2)	71 (8.8)
Technical/trade school/polytechnic	398 (27.7)	169 (25.7)	229 (28.5)
University	458 (31.8)	183 (27.9)	275 (34.2)
Total n	1439	638	801

Note. BMI = body mass index.

^aSocioeconomic status was based on the New Zealand Socioeconomic Index 1996, with 10 representing the lowest and 90 representing the highest socioeconomic groups. This is based on a standard New Zealand classification of occupations (Statistics New Zealand, 2001).

Measures

Regulation of Eating Behavior Scale

Regulation of eating behaviors was assessed using the 24-item Regulation of Eating Behavior Scale (REBS; Pelletier et al., 2004). The scale consists of six 4-item subscales (see Table S1 in the [Supplementary Materials](#)) that measure the behavioral regulations as proposed by SDT: amotivation, external regulation, introjected regulation, identified regulation, integrated regulation, and intrinsic motivation. Items were prefaced by the stem “I eat the way I do” and rated on a seven-point Likert scale, ranging from 1 (*does not correspond at all*) to 7 (*corresponds exactly*).

Food Habits

Participants used a five-point scale ranging from 1 (*I don't eat fruit*) to 5 (*three or more servings*) to indicate the number of servings of fruits they usually consumed each day, and a six-point scale ranging from 1 (*I don't eat vegetables*) to 6 (*four or more servings*) to indicate the number of servings of vegetables they usually consumed each day. They also reported the usual frequency of intake of several high fat and/or high sugar foods including chocolate coated and/or cream filled biscuits; potato crisps, corn snacks or corn chips; cakes or scones or muffins or sweet buns; meat pie or sausage roll; and burgers. Respondents used an eight-point scale, ranging from 1 (*never*) to 8 (*two or more times a day*), to estimate how often they usually consumed these foods. These questions were adapted from the 1997 National Nutrition Survey (Russell et al., 1999). In the present study, two composite scores were generated: a fruits and vegetables score (recoded into servings per day), and a high fat and/or high sugar foods score (recoded into servings per month). The recoded fruit and vegetable score had a possible range of zero (*zero servings of fruits or vegetables per day*) to seven (*seven or more servings of fruits and vegetables per day*). The recoded high fat and/or high sugar foods score had a possible range of 0 (*zero*

servings of high fat and/or high sugar foods per month) to 300 (*300 servings of high fat and/or high sugar foods per month*).

Binge Eating

A question regarding binge eating, adapted from Hay et al. (2008), was used to measure how frequently participants had engaged in binge eating over the last 12 months. Binge eating was defined as ‘*eating an unusually large amount of food in one go and at the time feeling that your eating was out of control, that is not being able to prevent from overeating, or that you could not stop eating once you had started*’. Participants used a four-point scale defined as 1 (*not at all*), 2 (*less than weekly*), 3 (*once a week*), and 4 (*two or more times a week*) to indicate the answer that best described them.

Body Mass Index (BMI)

Self-reported current weight and height was collected and used to calculate the body mass index (i.e., kg/m²) of the participants.

Statistical Analysis

We used Mplus Version 8.6 (Muthén & Muthén, 1998–2017) and the robust full information maximum likelihood (FIML) estimator (MLR in Mplus) to estimate the models. FIML (Enders, 2010) was used to account for item-level missing data (range 0% to 1.04%). In the ICM-CFA model, six first-order factors were specified, and items loaded only onto their target factor. The bifactor S-1 (Eid et al., 2017) ICM-CFA was specified with a general self-determination factor anchored in intrinsic motivation alongside five specific factors representing the remaining behavioral regulations. No cross-loadings were specified in the ICM-CFA or the bifactor S-1 ICM-CFA.

We used target rotation (Browne, 2001) in the ESEM that allows for the specification of factor loadings on target and non-target latent factors in a confirmatory manner (Asparouhov & Muthén, 2009). All cross-loadings were specified to be close to zero but not exactly zero, whereas the main factor loadings were freely estimated (Morin et al., 2016). The bifactor S-1 ESEM was specified with a general self-determination factor anchored in intrinsic motivation alongside five specific factors representing the remaining behavioral regulations (Bureau et al., 2023). To ensure interpretability and adhering to bifactor assumptions the specific and general factors were specified as orthogonal (Morin et al., 2020; Reise, 2012). For illustrative purposes, we also estimated symmetrical bifactor ESEM and the results are presented in the [Supplementary Materials](#). Another option is to specify Set-ESEM models, where cross-loadings are permissible within a subset of factors but constrained to zero for factors in different sets (Marsh et al., 2020). Set-ESEM is considered as a parsimonious alternative to Full-ESEM, particularly if there are constructs in the model that should be kept separate. However, we consider the Full-ESEM to be more appropriate than Set-ESEM for SDT-based measures of motivation

due to the additional information provided by the pattern of cross-loadings across the entire motivation continuum (cf. Guay et al., 2015). Thus, we specified Full-ESEM in the current study. The ICM-CFA, ESEM, and bifactor models are shown in Figure 2 and Figure 3. Mplus syntax for all models are provided in the Supplementary Materials.

Model fit was evaluated with fit indices such as the comparative fit index (CFI), the Tucker-Lewis index (TLI), the standardized root mean square residual (SRMR), and the root mean square error of approximation (RMSEA). CFI and TLI values around 0.90 and SRMR and RMSEA values around 0.08 indicated acceptable model fit (Marsh, 2007). Comparisons between the ICM-CFA and ESEM were based on Δ CFI, Δ TLI, and Δ RMSEA (Chen, 2007). A difference in CFI and TLI of .01 or larger and RMSEA of .015 or larger indicates a substantial difference in model fit and favor the model with higher CFI and TLI and lower RMSEA (Maïano et al., 2021). We also carefully inspected the parameter estimates (i.e., factor loadings, cross-loadings, latent factor correlations, omega coefficients) in the model selection process (Morin et al., 2016).

Figure 2

Graphical Representation of the ICM-CFA (Left) and Bifactor S-1 ICM-CFA (Right)

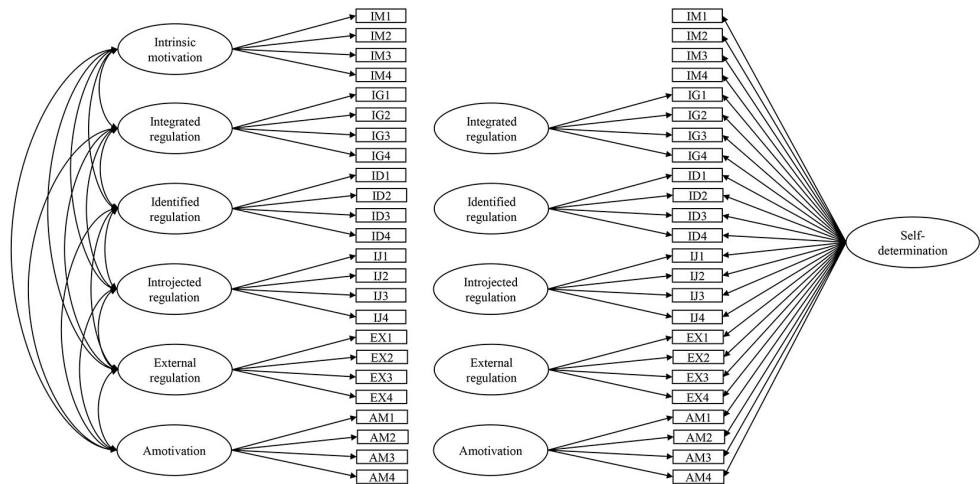
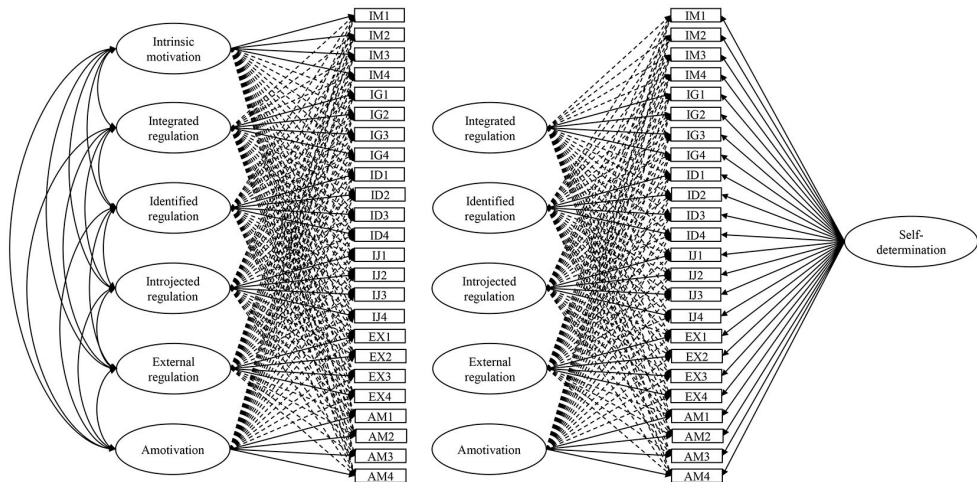


Figure 3

Graphical Representation of the ESEM (Left) and Bifactor S-1 ESEM (Right)



Note. Dashed arrows represent cross-loading.

Following recommendations in the literature (Marsh et al., 2014; Morin et al., 2016) we first compared the first-order ICM-CFA to the first-order ESEM. Reduced factor correlations and relatively well-defined factors would support the ESEM over the ICM-CFA. The retained model is then contrasted to its bifactor counterpart. The orthogonality of the factors in the bifactor model provides a clean partitioning of the variance that is explained by the global factor, which absorbs the covariance shared among all items, and the specific factors that represents the covariance shared among a subset of items that is not shared with the other subsets (Morin et al., 2020). In the bifactor S-1 model the global self-determination factor was anchored in intrinsic motivation and thus represents the highest possible amount of self-determination, whereas the orthogonal specific factors can be interpreted as non-self-determined facets of these extrinsic motivations.

Criterion-related validity was examined by integrating the food and eating habit variables into the final retained measurement model. More specifically, we regressed food habits, binge eating, and BMI on the global and specific factors. Standardized regression coefficients and percentage of explained variance (R^2) in food habits, binge eating, and BMI were examined.

The final model at Wave 1 was subjected to longitudinal measurement invariance testing using nested model comparisons for continuous variables (Little, 2013). We examined three types of longitudinal invariance: (i) configural invariance; (ii) metric/weak invariance (invariance of factor loadings); (iii) scalar/strong invariance (invariance of factor loadings and intercepts). We performed nested model comparisons using the Δ CFI,

Δ TLI, and Δ RMSEA (Chen, 2007; Morin et al., 2020). A difference in CFI and TLI of .01 or larger and RMSEA of .015 or larger would indicate measurement noninvariance. Note that we also report the chi-square values and the chi-square difference tests for reasons of transparency, however, we do not include these in the interpretation of the models or model comparisons due to their sample size dependency and oversensitivity to minor and substantively unimportant misspecifications (Marsh et al., 2005).

Following current recommendations in the literature regarding reliability estimation in ESEM and bifactor ESEM (Morin et al., 2020), we computed omega reliability coefficients according to McDonald (1970) $\omega = (\sum|\lambda_i|)^2 / ([\sum|\lambda_i|^2] + \sum\delta_{ii})$ using standardized parameters where λ_i are the factor loadings and δ_{ii} are the error variances. Cross-loadings were ignored in the calculation of ω because they do not reflect properties of scores on the construct, nor do they reflect random measurement error. They are merely incorporated into the ESEM to control for the fallible nature of indicators (Morin et al., 2020).

Results

Factor Structure of the REBS

The ESEM displayed an excellent model fit at Wave 1, and the model fit comparison indicated a superior model fit (Δ CFI = 0.101, Δ TLI = 0.095, Δ RMSEA = 0.030) of the ESEM compared to the ICM-CFA (Table 2). The bifactor S-1 ESEM showed an excellent fit to the data, whereas the bifactor S-1 ICM-CFA had poor model fit (Δ CFI = 0.137, Δ TLI = 0.141, Δ RMSEA = 0.040).

The standardized factor loadings in the ICM-CFA ranged from 0.421 to 0.922 ($M = 0.750$). In the ESEM model the standardized factor loadings ranged from 0.115 to 1.017 ($M = 0.643$; see Table 3), however, the ESEM also revealed one out-of-bound factor loading (> 1.0). Omega coefficients ranged from 0.707 to 0.861 ($M = 0.778$) in the ICM-CFA and ranged from 0.709 to 0.856 ($M = 0.772$) in the ESEM across the six factors. Omega coefficients for all subdimensions in the ICM-CFA and ESEM are reported in Table 3.

Table 2
Model Fit Indices of the Measurement Models, Structural Model, and Longitudinal Measurement Invariance Models

Model	χ^2	df	p	CFI	TLI	RMSEA	90% CI	SRMR	Δ Model	Δ CFI	Δ TLI	Δ RMSEA	$\Delta\chi^2$	p
Wave 1 (N = 1447)														
1a. ICM-CFA	2275.121	237	< .001	.868	.846	.077	[.074, .080]	.077						
2a. ESEM	632.129	147	< .001	.969	.941	.047	[.044, .052]	.018	1a vs. 2a	.101	.095	.030	1629.914	< .001
3a. Bifactor S-1 ICM-CFA	2817.670	232	< .001	.832	.801	.088	[.085, .091]	.126						
4a. Bifactor S-1 ESEM	632.129	147	< .001	.969	.941	.048	[.044, .052]	.018	3a vs. 4a	.137	.141	.040	2175.671	< .001
7. Structural model	797.633	219	< .001	.966	.941	.043	[.040, .046]	.018						
Wave 2 (n = 803)														
1b. ICM-CFA	1457.204	237	< .001	.864	.841	.080	[.076, .084]	.081						
2b. Full ESEM	536.659	147	< .001	.956	.918	.057	[.052, .063]	.020	1b vs. 2b	.092	.077	.023	867.889	< .001
3b. Bifactor S-1 ICM-CFA	1911.213	232	< .001	.812	.777	.095	[.091, .099]	.131						
4b. Bifactor S-1 ESEM	536.659	147	< .001	.956	.918	.057	[.052, .063]	.020	4b vs. 5b	.144	.141	.038	1258.146	< .001
Longitudinal invariance (n = 803)														
Bifactor S-1 ESEM														
5. Configural	1573.792	810	< .001	.964	.950	.034	[.032, .037]	.023						
6. Metric	1644.812	918	< .001	.966	.958	.031	[.029, .034]	.026	5 vs. 6	.002	.008	.003	89.436	.902
7. Scalar	1681.247	936	< .001	.965	.958	.031	[.029, .034]	.026	6 vs. 7	.001	.000	.000	37.168	.005

Table 3
Factor Loadings, Uniquenesses, and Omega Reliability of the CFA and ESEM Models at Wave 1 (N = 1447)

Item	CFA								ESEM							
	AM	EX	IJ	ID	IG	IM	δ	AM	EX	IJ	ID	IG	IM	δ		
AM1	0.666						0.556	0.623	0.023	0.028	-0.003	-0.090	0.084	0.567		
AM2	0.807						0.349	0.800	-0.008	0.026	-0.038	0.012	0.027	0.365		
AM3	0.770						0.408	0.738	0.066	0.011	0.043	0.000	0.009	0.401		
AM4	0.777						0.397	0.814	0.017	0.030	-0.012	0.145	-0.032	0.362		
EX1		0.421					0.823	-0.029	0.418	0.051	0.040	-0.011	0.176	0.749		
EX2		0.814					0.338	0.088	0.632	0.156	-0.066	-0.046	-0.018	0.402		
EX3		0.706					0.501	-0.087	0.799	0.024	0.006	-0.041	-0.037	0.420		
EX4		0.693					0.520	0.164	0.653	-0.092	-0.019	-0.020	-0.047	0.481		
IJ1			0.716				0.488	0.108	0.733	-0.030	-0.068	0.032	-0.035	0.470		
IJ2			0.769				0.409	-0.042	0.973	0.006	-0.138	-0.138	-0.007	0.213		
IJ3			0.615				0.622	-0.078	0.381	0.118	0.097	0.097	0.031	0.591		
IJ4			0.578				0.666	0.173	0.280	0.113	-0.029	-0.023	-0.023	0.644		
ID1				0.831			0.310	-0.170	0.072	0.055	0.115	0.465	0.263	0.290		
ID2				0.617			0.619	-0.086	0.031	0.191	0.172	0.341	0.049	0.618		
ID3				0.726			0.473	-0.013	0.025	0.025	0.824	-0.013	0.030	0.277		
ID4				0.791			0.374	0.013	-0.057	0.058	0.853	0.029	0.057	0.157		
IG1					0.830		0.312	-0.087	-0.029	0.029	-0.076	0.731	0.186	0.248		
IG2					0.922		0.151	-0.070	-0.014	0.015	0.144	0.698	0.126	0.157		
IG3					0.759		0.424	0.021	-0.043	0.046	0.221	0.562	0.049	0.424		
IG4					0.887		0.213	-0.010	-0.014	-0.025	0.263	0.638	0.081	0.225		
IM1						0.845	0.286	0.034	-0.011	-0.018	-0.134	0.185	0.814	0.254		
IM2						0.845	0.286	-0.003	0.009	0.019	-0.058	-0.148	1.017	0.195		
IM3						0.747	0.442	-0.033	0.033	0.043	0.204	0.398	0.285	0.353		
IM4						0.878	0.229	0.032	-0.007	-0.027	0.186	-0.137	0.885	0.204		
Reliability (ω)	0.779	0.707	0.710	0.770	0.861	0.842		0.778	0.709	0.712	0.745	0.833	0.856			

Note. AM = amotivation; EX = external regulation; IJ = introjected regulation; ID = identified regulation; IG = integrated regulation; IM = intrinsic motivation; δ = uniquenesses; ω = omega reliability. Bold values represent target factor loadings.

The latent factor correlations (Table 4) ranged from -0.353 to 0.915 ($M = 0.279$) in the ICM-CFA and several correlations were strong ($r > 0.70$), which indicates a need to account for possible sources of construct-relevant psychometric multidimensionality at the item level via cross-loadings and/or a global factor (Morin et al., 2016). The latent factor correlations were substantially reduced in the ESEM ($M = 0.233$, range -0.368 to 0.692). We also observed overlap between some factors in the ESEM, indicated by weak target factor loadings and substantial cross-loadings (items IJ3, IJ4, ID1, ID2, and IM3). However, most cross-loadings in the ESEM were relatively weak (< 0.30), with the exception of ID1 (0.465), ID2 (0.341), and IM3 (0.398), with cross-loadings onto the integrated regulation factor (see Table 3). These results support the superiority of the ESEM representation of the REBS compared to the ICM-CFA representation. However, the out-of-bound parameter and cross-loadings associated with the ESEM suggests that it might not be optimal and highlights a need to consider alternative models.

Table 4

Latent Factor Correlations From the ICM-CFA and ESEM at Wave 1

Variable	AM	EX	IJ	ID	IG	IM
ICM-CFA						
AM						
EX	0.670					
IJ	0.382	0.627				
ID	-0.251	0.045	0.390			
IG	-0.353	-0.085	0.211	0.915		
IM	-0.210	0.021	0.210	0.807	0.799	
ESEM						
AM						
EX	0.564					
IJ	0.245	0.534				
ID	-0.168	0.147	0.389			
IG	-0.368	0.031	0.228	0.606		
IM	-0.276	0.091	0.221	0.565	0.692	

Note. AM = amotivation; EX = external regulation; IJ = introjected regulation; ID = identified regulation; IG = integrated regulation; IM = intrinsic motivation.

The bifactor S-1 ESEM solution provided an excellent fit to the data (Table 2). Inspection of the factor loadings (see Table 5) of the bifactor S-1 ESEM revealed a relatively well-defined global factor representing self-determination. The factor loadings onto the global factor were strong and positive for intrinsic motivation items ($M = 0.819$, range 0.779 to 0.850), integrated regulation items ($M = 0.768$, range 0.677 to 0.832), identified regulation

items ($M = 0.665$, range 0.544 to 0.803), weaker for introjected regulation items ($M = 0.191$, range 0.085 to 0.361), weak and near-zero for external regulation items ($M = 0.042$, range -0.027 to 0.253), and negative for the amotivation items ($M = -0.207$, range -0.182 to -0.252).

Table 5

Factor Loadings, Uniquenesses, and Omega Reliability of the Bifactor S-1 ESEM Model at Wave 1 ($N = 1447$)

Item	AM	EX	IJ	ID	IG	G	δ
AM1	0.575	0.199	0.117	0.004	-0.101	-0.195	0.567
AM2	0.711	0.216	0.130	-0.012	-0.046	-0.252	0.365
AM3	0.683	0.264	0.138	0.047	-0.041	-0.200	0.401
AM4	0.724	0.241	0.147	0.014	0.040	-0.182	0.362
EX1	0.143	0.381	0.139	0.016	-0.039	0.253	0.749
EX2	0.327	0.626	0.310	-0.012	-0.030	-0.027	0.402
EX3	0.209	0.697	0.218	0.031	-0.012	0.043	0.420
EX4	0.358	0.607	0.110	0.007	-0.015	-0.100	0.481
IJ1	0.205	0.175	0.663	0.017	0.024	0.131	0.470
IJ2	0.098	0.124	0.847	0.081	-0.058	0.186	0.213
IJ3	0.088	0.299	0.406	0.109	0.063	0.361	0.591
IJ4	0.297	0.346	0.358	0.114	-0.011	0.085	0.644
ID1	-0.122	0.028	0.024	0.033	0.217	0.803	0.290
ID2	-0.041	0.048	0.175	0.118	0.194	0.544	0.618
ID3	0.038	0.045	0.118	0.566	0.038	0.619	0.277
ID4	0.039	-0.013	0.131	0.582	0.057	0.694	0.157
IG1	-0.115	-0.056	-0.035	-0.096	0.362	0.771	0.248
IG2	-0.089	-0.036	-0.011	0.065	0.369	0.832	0.157
IG3	-0.007	-0.026	0.041	0.136	0.311	0.677	0.424
IG4	-0.037	-0.026	-0.020	0.153	0.349	0.792	0.225
IM1	0.052	-0.003	-0.099	-0.216	-0.077	0.825	0.254
IM2	0.066	0.024	-0.066	-0.184	-0.295	0.822	0.195
IM3	-0.007	0.031	0.033	0.094	0.174	0.779	0.353
IM4	0.085	0.012	-0.069	0.001	-0.249	0.850	0.204
Reliability (ω)	0.761	0.693	0.703	0.659	0.725	0.668	

Note. AM = amotivation; EX = external regulation; IJ = introjected regulation; ID = identified regulation; IG = integrated regulation; IM = intrinsic motivation; G = global self-determination factor; δ = uniquenesses, ω = omega reliability. Bold values represent target factor loadings.

The specific factors in the bifactor S-1 ESEM also showed factor loadings largely in line with their placement on the continuum. Amotivation, external regulation, and introjected regulation represents no to low levels of self-determination and should therefore contribute less to the global factor and more to their specific factors. The specific

amotivation ($M = 0.673$, range 0.575 to 0.724), external regulation ($M = 0.578$, range 0.381 to 0.697), and introjected regulation ($M = 0.569$, range 0.358 to 0.847) factors remained relatively well-defined with medium to strong and positive factor loadings. Identified and integrated regulation, which are autonomous regulations, should contribute more to the global factor of self-determination and less to their specific factors, which represents the non-self-determined part of these regulations. The specific identified regulation factor had two items with weak factor loadings (ID1 and ID2) and the mean factor loading ($M = 0.325$, range 0.033 to 0.582) was the weakest of the five specific factors. The integrated regulation factor had positive and moderate factor loadings ($M = 0.348$, range 0.311 to 0.369). Omega coefficients from the bifactor S-1 ESEM at Wave 1 ranged from 0.659 to 0.761 ($M = 0.701$). Omega coefficients for all subdimensions in the bifactor S-1 ESEM are reported in Table 5.

Criterion-Related Validity

We assessed criterion-related validity of the global and specific factors based on the final retained bifactor S-1 ESEM solution. Model fit of the structural model is displayed in Table 2 and the results (standardized coefficients and R^2) are presented in Table 6. As expected, the global self-determination factor was positively related to healthy food habits (i.e., servings of fruits and vegetables), and negatively related to unhealthy food habits (i.e., servings of high fat and high sugar foods), binge eating, and BMI.

Table 6

Tests of Criterion-Related Validity of the Global and Specific Factors

Predictor variable	β (SE)			
	Fruit/vegetables	Fat/sugar	Binge eating	BMI
Global self-determination	0.336 (0.025)***	-0.184 (0.029)***	-0.149 (0.030)***	-0.273 (0.026)***
Specific integrated regulation	0.158 (0.031)**	-0.072 (0.029)**	-0.095 (0.032)**	-0.281 (0.027)***
Specific identified regulation	-0.090 (0.032)**	0.061 (0.031)*	0.094 (0.028)***	0.105 (0.030)***
Specific introjected regulation	-0.077 (0.030)**	-0.002 (0.034)	0.188 (0.029)***	-0.003 (0.030)
Specific external regulation	-0.039 (0.037)	0.036 (0.039)	0.161 (0.040)***	0.153 (0.033)***
Specific amotivation	-0.086 (0.032)**	0.049 (0.034)	0.157 (0.035)***	0.109 (0.038)**
R^2	0.161	0.047	0.126	0.200

Note. β = standardized regression coefficient; SE = standard error; R^2 = proportion of explained variance.

* $p < .05$. ** $p < .01$. *** $p < .001$.

The specific motivation factors also contributed with explaining unique variance in addition to the global self-determination factor. Integrated regulation was positively related to healthy food habits and negatively related to unhealthy food habits, binge eating, and

BMI. Identified regulation was negatively related to healthy food habits, and positively related to unhealthy food habits, binge eating, and BMI. Introjected regulation was negatively related to healthy food habits and positively related to binge eating. External regulation and amotivation were positively related to binge eating and BMI, and amotivation was also negatively related to healthy food habits. The global self-determination factor and the specific motivation factors explained 4.7% to 20.0% of the variance in the eating-related outcome variables. These relations aligned relatively well with theoretical expectations (except for identified regulation). In particular, the global self-determination factor showed a consistent pattern of relations in line with SDT.

Longitudinal Measurement Invariance

We proceeded with longitudinal measurement invariance testing of the bifactor S-1 ESEM. The goodness-of-fit indices were fully satisfactory at each stage and none of the goodness-of-fit indices indicated a substantial decrease when constraints were placed on the factor loadings or intercepts (Table 2). Thus, longitudinal measurement invariance of the bifactor S-1 ESEM of the REBS was supported (factor loadings from the configural model are displayed in Table S4 in the [Supplementary Materials](#)).

Discussion

In the current study, we examined the psychometric properties of the REBS in a sample of middle-aged women in New Zealand. The bifactor S-1 ESEM solution provided an excellent fit to the data and the global self-determination factor anchored in intrinsic motivation provided a clear meaning of both the global self-determination factor and the specific motivation factors. Whereas the global self-determination factor represents the highest possible amount of self-determination, the orthogonal specific factors can be interpreted as what is common to their indicators but is unrelated to self-determination (i.e., non-self-determined facets of these extrinsic motivations; Bureau et al., 2023). For amotivation, which is not an extrinsic type of motivation, it is the variance attributed to indifference or apathy, which is indicated by negative factor loadings on the global factor.

The bifactor S-1 ESEM resolves many of the concerns highlighted with the symmetrical bifactor ESEM because it provides clearer conceptual boundaries for the global and specific factors and previous studies indicate that the bifactor S-1 ESEM can predict outcomes with better precision (Bureau et al., 2023). The factor loadings on the global factor support the presence of a continuum structure; however, it did not completely conform to a relative self-determination continuum. The factor loadings for introjected regulation and external regulation items were not in agreement with assumptions in previous SDT-based research of what has been described as a relative self-determination continuum

(Chemolli & Gagné, 2014; Grolnick & Ryan, 1987; Howard et al., 2018). Introjected regulation and external regulation items should load negatively onto the continuum factor to support a relative self-determination continuum. In the current study, the introjected regulation items had weak positive loadings and the external regulation items had weak positive and negative factor loadings onto the global factor. However, the factor loadings on the global self-determination factor anchored in intrinsic motivation aligned well with the conceptualization of a global factor representing amount of self-determination. The intrinsic motivation items made the largest contribution to the meaning of the global factor (i.e., they had the strongest factor loadings), with a decreasing contribution from the other items on the continuum in line with their factor loading on the global factor (Bureau et al., 2023). The strongest average factor loading was observed for the intrinsic motivation factor, followed by the other behavioral regulations in decreasing magnitude along the continuum. To summarize, our results align well with the conceptualization of a global factor representing level of self-determination and the bifactor S-1 model is more in line with the idea that the global factor (when anchored in intrinsic motivation) represents general quantity of self-determination rather than relative self-determination (cf. Bureau et al., 2023; Gunnell & Gaudreau, 2015; Howard, Gagné, Van den Broeck, et al., 2020).

We also examined criterion-related validity by regressing measures of food habits, binge eating, and BMI on the global and specific motivation factors. The global self-determination factor showed a consistent pattern of relations in line with SDT, indicating that higher self-determination is related to healthier food habits, lower frequency of binge eating, and lower BMI. This finding is in line with previous studies in other settings (e.g., educational, work) using the bifactor ESEM framework showing that relations between global self-determination and various outcomes often are theoretically consistent and relatively strong (Howard et al., 2018; Litalien et al., 2017; Lohbeck et al., 2022).

When examining the pattern of relations involving the specific factors, we were able to provide a more fine-grained picture of how these specific factors associate with eating-related outcomes. Integrated regulation showed positive relations to healthier food habits, less binge eating, and lower BMI. We also noted different patterns of associations between the controlled types of motivation and these eating-related outcomes. For example, introjected regulation was negatively related to healthy food habits and positively related to frequency of binge eating, whereas external regulation was related to higher frequency of binge eating and higher BMI. Thus, introjected regulation was associated with both food choice and eating behavior, whereas external regulation was related to eating behavior but not to food choice. Our results also showed that introjected regulation, external regulation, and amotivation were positively related to frequency of binge eating, suggesting the controlled types of motivation might be more strongly related to certain types of unhealthy eating behaviors, rather than food choice. Finally,

identified regulation showed negative relations to healthy food habits and positive relations to binge eating and BMI. Unexpected patterns involving identified regulation have been observed in previous studies using the bifactor ESEM framework, for example in work settings showing negative relations to need satisfaction (Howard et al., 2018). These findings indicate that the specific regulations do not necessarily associate with other variables in a manner consistent with their position on the continuum. The specific factors in the bifactor S-1 model represent non-self-determined facets of extrinsic motivation (once global self-determination anchored in intrinsic motivation is taken into account) and may therefore display differential patterns of relations to outcomes.

The current study is also the first study to provide evidence of longitudinal measurement invariance of the REBS, which indicates that the same latent construct was measured in the same metric at each time point (Widaman et al., 2010). These results are encouraging and enable researchers to examine change, interrelations between variables, or make mean comparisons across different time points with a high degree of certainty that observed changes represent true changes in the latent constructs and not measurement bias. If longitudinal measurement invariance is not achieved, observed changes over time may be a consequence of recalibration of the metric or a redefinition or reconceptualization of the latent construct, sometimes referred to as beta and gamma change (Golembiewski et al., 1976; Millsap & Hartog, 1988), respectively. In other words, without satisfying longitudinal measurement invariance constraints, there is a high risk that researchers are comparing apples and oranges across time, instead of true changes in the latent construct. It is therefore encouraging that the accumulating evidence of the psychometric properties of the REBS now also includes a solid base for conducting longitudinal research.

Our findings also extend previous research by showing support for the structural validity of the REBS in a representative sample of middle-aged women. Previous research has provided psychometric evidence of the REBS in Canadian and US student samples (Hamilton et al., 2018; Pelletier et al., 2004) and a relatively young adult Portuguese sample (Teixeira et al., 2021), however, this is the first study providing evidence of structural validity in a middle-aged sample. Given that these previous studies only examined REBS using first-order ICM-CFA models, we cannot compare our results related to the ESEM and bifactor models. However, the magnitude of some factor correlations in these previous studies were around 0.90, which indicates poor discriminant validity among some of the behavioral regulations and signals that ESEM and bifactor models would have been viable options in these previous studies as well.

Limitations and Suggestions for Future Research

First, although the current study included a relatively large and representative sample it only included middle-aged women, hence, we do not know how these results generalize to younger or older people or to men. Second, we examined criterion-related validity in a

rather narrow set of eating-related variables assessing food habits, binge eating, and BMI. Future studies should continue to explore the nomological network (Cronbach & Meehl, 1955) around the global and specific factors to expand our knowledge about the role of quantity and quality of motivation in relation to eating behaviors.

Future research should continue to explore the psychometric properties of the REBS in diverse samples. The psychometric properties of the REBS have to date only been examined in four studies (Hamilton et al., 2018; Pelletier et al., 2004; Teixeira et al., 2021) including the current study, thus more studies are needed to determine the generalizability of the factor structure of the REBS. The results from the current study showed a relatively high overlap between identified regulation, integrated regulation, and intrinsic motivation. Future studies should examine how these factors can be adapted or altered to become more distinct. Additional research is also needed on the application of the bifactor S-1 model to REBS and other SDT-based measures of motivation, however, we agree with Bureau et al. (2023) that it has many advantageous and compelling features for modeling the self-determination continuum.

Conclusions

We found evidence of structural validity, criterion-related validity, longitudinal measurement invariance, and satisfactory reliability estimates of the REBS. The bifactor S-1 ESEM approach used in the current study separates what is common and what is specific across the eating behavioral regulations, provides clear conceptual boundaries for the global and specific factors, and provides increased conceptual accuracy in the estimation of the self-determination continuum (Bureau et al., 2023). However, it is important to highlight that although the evidence is mounting in support of bifactor and ESEM solutions when modeling SDT-based measures of motivation, it may not be suitable for all research questions involving the REBS. Other statistical models (e.g., ICM-CFA, item response theory [IRT] models) might be more appropriate, for example due to various constraints (e.g., small sample size) or because they align better with the research question. We encourage researchers to continue to explore these complex multidimensional models in future studies, and we agree with Howard, Gagné, Van den Broeck, et al. (2020) that they will be necessary for the future theoretical development of SDT.

Funding: This research was funded by Department of Human Nutrition PBRF funding and a University of Otago Research Grant.

Acknowledgments: The authors would like to thank Professor Caroline Horwath for her contributions in the early stages of this study and for valuable input on initial drafts of the manuscript.

Competing Interests: The authors have declared that no competing interests exist.

Ethics Statement: Ethical approval for the study was obtained from the University of Otago Human Ethics Committee. Participants were informed in the cover letter that by completing and returning the questionnaire they were giving their consent to take part in the study.

Author Contributions: AS developed the study concept. All authors contributed to the study design. AS performed the data analysis and drafted the manuscript and HM and EH provided critical revisions. All authors approved the final version of the manuscript for submission.

Data Availability: The data that support the findings of this study are available from the corresponding author upon reasonable request.

Supplementary Materials

The following Supplementary Materials are available (for access see [Index of Supplementary Materials](#) below):

- Modifications and item content of the REBS
- Descriptive statistics of the items of the REBS
- The symmetrical bifactor ESEM
- Factor loadings, uniquenesses, and reliability of the configural model of the bifactor S-1 ESEM
- Mplus syntax

Index of Supplementary Materials

Stenling, A., Martin, H., & Hargreaves, E. (2023). *Supplementary materials to "Factor structure, criterion-related validity, and longitudinal measurement invariance of the Regulation of Eating Behavior Scale (REBS): A bifactor S-1 exploratory structural equation modeling approach"* [Additional materials]. *PsychOpen GOLD*. <https://doi.org/10.23668/psycharchives.12962>

References

Asparouhov, T., & Muthén, B. (2009). Exploratory structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *16*(3), 397–438.
<https://doi.org/10.1080/10705510903008204>

- Ball, K., Crawford, D., Ireland, P., & Hodge, A. (2003). Patterns and demographic predictors of 5-year weight change in a multi-ethnic cohort of men and women in Australia. *Public Health Nutrition*, 6(3), 269–280. <https://doi.org/10.1079/PHN2002431>
- Browne, M. W. (2001). An overview of analytic rotation in exploratory factor analysis. *Multivariate Behavioral Research*, 36(1), 111–150. https://doi.org/10.1207/S15327906MBR3601_05
- Bureau, J. S., Guay, F., Plamondon, A., Ratelle, C. F., Howard, J. L., & Gilbert, W. (2023). Empirical testing of an alternative modeling of the self-determination continuum. *Motivation and Emotion*, 47(1), 46–60. <https://doi.org/10.1007/s11031-022-09976-9>
- Burns, G. L., Geiser, C., Servera, M., Becker, S. P., & Beauchaine, T. P. (2020). Application of the bifactor S – 1 model to multisource ratings of ADHD/ODD symptoms: An appropriate bifactor model for symptom ratings. *Journal of Abnormal Child Psychology*, 48(7), 881–894. <https://doi.org/10.1007/s10802-019-00608-4>
- Carraça, E. V., Leong, S. L., & Horwath, C. C. (2019). Weight-focused physical activity is associated with poorer eating motivation quality and lower intuitive eating in women. *Journal of the Academy of Nutrition and Dietetics*, 119(5), 750–759. <https://doi.org/10.1016/j.jand.2018.09.011>
- Chemolli, E., & Gagné, M. (2014). Evidence against the continuum structure underlying motivation measures derived from self-determination theory. *Psychological Assessment*, 26(2), 575–585. <https://doi.org/10.1037/a0036212>
- Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, 14(3), 464–504. <https://doi.org/10.1080/10705510701301834>
- Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological Bulletin*, 52(4), 281–302. <https://doi.org/10.1037/h0040957>
- Eid, M., Geiser, C., Koch, T., & Heene, M. (2017). Anomalous results in G-factor models: Explanations and alternatives. *Psychological Methods*, 22, 541–562. <https://doi.org/10.1037/met0000083>
- Enders, C. (2010). *Applied missing data analysis*. The Guilford Press.
- Golembiewski, R. T., Billingsley, K., & Yeager, S. (1976). Measuring change and persistence in human affairs: Types of change generated by OD designs. *The Journal of Applied Behavioral Science*, 12(2), 133–157. <https://doi.org/10.1177/002188637601200201>
- Grolnick, W. S., & Ryan, R. M. (1987). Autonomy in children's learning: An experimental and individual difference investigation. *Journal of Personality and Social Psychology*, 52(5), 890–898. <https://doi.org/10.1037/0022-3514.52.5.890>
- Guay, F., Morin, A. J. S., Litalien, D., Valois, P., & Vallerand, R. J. (2015). Application of exploratory structural equation modeling to evaluate the Academic Motivation Scale. *The Journal of Experimental Education*, 83(1), 51–82. <https://doi.org/10.1080/00220973.2013.876231>
- Guertin, C., Rocchi, M., Pelletier, L. G., Émond, C., & Lalande, G. (2015). The role of motivation and the regulation of eating on the physical and psychological health of patients with cardiovascular disease. *Journal of Health Psychology*, 20(5), 543–555. <https://doi.org/10.1177/1359105315573471>

- Gunnell, K. E., & Gaudreau, P. (2015). Testing a bi-factor model to disentangle general and specific factors of motivation in self-determination theory. *Personality and Individual Differences, 81*, 35–40. <https://doi.org/10.1016/j.paid.2014.12.059>
- Hamilton, T., Hoffman, J., Arsiwalla, D., Volpe, R., Schmidt, E., & Gropper, S. (2018). Gender comparisons of young adults' eating behavior regulation: Re-examination of the Regulation of Eating Behavior Scale (REBS). *Appetite, 126*, 80–89. <https://doi.org/10.1016/j.appet.2018.03.014>
- Hay, P. J., Mond, J., Buttner, P., & Darby, A. (2008). Eating disorder behaviors are increasing: Findings from two sequential community surveys in south Australia. *PLOS ONE, 3*(2), Article e1541. <https://doi.org/10.1371/journal.pone.0001541>
- Heinrich, M., Zagorscak, P., Eid, M., & Knaevelsrud, C. (2020). Giving G a meaning: An application of the bifactor-(S-1) approach to realize a more symptom-oriented modeling of the Beck Depression Inventory–II. *Assessment, 27*(7), 1429–1447. <https://doi.org/10.1177/1073191118803738>
- Howard, J. L., Gagné, M., & Morin, A. J. S. (2020). Putting the pieces together: Reviewing the structural conceptualization of motivation within SDT. *Motivation and Emotion, 44*(6), 846–861. <https://doi.org/10.1007/s11031-020-09838-2>
- Howard, J. L., Gagné, M., Morin, A. J. S., & Forest, J. (2018). Using bifactor exploratory structural equation modeling to test for a continuum structure of motivation. *Journal of Management, 44*(7), 2638–2664. <https://doi.org/10.1177/0149206316645653>
- Howard, J. L., Gagné, M., Van den Broeck, A., Guay, F., Chatzisarantis, N., Ntoumanis, N., & Pelletier, L. G. (2020). A review and empirical comparison of motivation scoring methods: An application to self-determination theory. *Motivation and Emotion, 44*(4), 534–548. <https://doi.org/10.1007/s11031-020-09831-9>
- Kato, Y., Iwanaga, M., Roth, R., Hamasaki, T., & Greimel, E. (2013). Psychometric validation of the Motivation for Healthy Eating Scale (MHES). *Psychology, 4*, 136–141. <https://doi.org/10.4236/psych.2013.42020>
- Leong, S. L., Madden, C., Gray, A., & Horwath, C. (2012). Self-determined, autonomous regulation of eating behavior is related to lower body mass index in a nationwide survey of middle-aged women. *Journal of the Academy of Nutrition and Dietetics, 112*(9), 1337–1346. <https://doi.org/10.1016/j.jand.2012.04.018>
- Leong, S. L., Madden, C., Gray, A., Waters, D., & Horwath, C. (2011). Faster self-reported speed of eating is related to higher body mass index in a nationwide survey of middle-aged women. *Journal of the American Dietetic Association, 111*(8), 1192–1197. <https://doi.org/10.1016/j.jada.2011.05.012>
- Litalien, D., Morin, A. J. S., Gagné, M., Vallerand, R. J., Losier, G. F., & Ryan, R. M. (2017). Evidence of a continuum structure of academic self-determination: A two-study test using a bifactor-ESEM representation of academic motivation. *Contemporary Educational Psychology, 51*, 67–82. <https://doi.org/10.1016/j.cedpsych.2017.06.010>
- Little, T. D. (2013). *Longitudinal structural equation modeling*. The Guilford Press.

- Lohbeck, A., Tóth-Király, I., & Morin, A. J. S. (2022). Disentangling the associations of academic motivation with self-concept and academic achievement using the bifactor exploratory structural equation modeling framework. *Contemporary Educational Psychology*, 69, Article 102069. <https://doi.org/10.1016/j.cedpsych.2022.102069>
- Mañano, C., Morin, A. J. S., Aimé, A., Lepage, G., & Bouchard, S. (2021). Psychometric properties of the Body Checking Questionnaire (BCQ) and of the Body Checking Cognitions Scale (BCCS): A bifactor-exploratory structural equation modeling approach. *Assessment*, 28(2), 632–646. <https://doi.org/10.1177/1073191119858411>
- Marsh, H. W. (2007). Application of confirmatory factor analysis and structural equation modeling in sport and exercise psychology. In G. Tenenbaum & R. C. Eklund (Eds.), *Handbook of sport psychology* (3rd ed., pp. 774–798). <https://doi.org/10.1002/9781118270011.ch35>
- Marsh, H. W., Guo, J., Dicke, T., Parker, P. D., & Craven, R. G. (2020). Confirmatory factor analysis (CFA), exploratory structural equation modeling (ESEM), and Set-ESEM: Optimal balance between goodness of fit and parsimony. *Multivariate Behavioral Research*, 55(1), 102–119. <https://doi.org/10.1080/00273171.2019.1602503>
- Marsh, H. W., Hau, K.-T., & Grayson, D. (2005). Goodness of fit in structural equation models. In A. Maydeu-Olivares & J. J. McArdle (Eds.), *Contemporary psychometrics: A festschrift for Roderick P. McDonald*. (pp. 275–340). Lawrence Erlbaum Associates Publishers.
- Marsh, H. W., Morin, A. J. S., Parker, P. D., & Kaur, G. (2014). Exploratory structural equation modeling: An integration of the best features of exploratory and confirmatory factor analysis. *Annual Review of Clinical Psychology*, 10(1), 85–110. <https://doi.org/10.1146/annurev-clinpsy-032813-153700>
- Mask, L., & Blanchard, C. M. (2011). The effects of “thin ideal” media on women's body image concerns and eating-related intentions: The beneficial role of an autonomous regulation of eating behaviors. *Body Image*, 8(4), 357–365. <https://doi.org/10.1016/j.bodyim.2011.06.003>
- McDonald, R. P. (1970). Theoretical foundations of principal factor analysis, canonical factor analysis, and alpha factor analysis. *British Journal of Mathematical and Statistical Psychology*, 23(1), 1–21. <https://doi.org/10.1111/j.2044-8317.1970.tb00432.x>
- Millsap, R. E., & Hartog, S. B. (1988). Alpha, beta, and gamma change in evaluation research: A structural equation approach. *Journal of Applied Psychology*, 73(3), 574–584. <https://doi.org/10.1037/0021-9010.73.3.574>
- Morin, A. J. S., Arens, A. K., & Marsh, H. W. (2016). A bifactor exploratory structural equation modeling framework for the identification of distinct sources of construct-relevant psychometric multidimensionality. *Structural Equation Modeling: A Multidisciplinary Journal*, 23(1), 116–139. <https://doi.org/10.1080/10705511.2014.961800>
- Morin, A. J. S., Myers, N. D., & Lee, S. (2020). Modern factor analytic techniques: Bifactor models, exploratory structural equation modeling (ESEM), and Bifactor-ESEM. In G. Tenenbaum, R. C. Eklund, & N. Boiangin (Eds.), *Handbook of sport psychology: Exercise, methodologies, & special topics* (Vol. 2, 4th ed., pp. 1044–1073). John Wiley & Sons.
- Muthén, L. K., & Muthén, B. (1998–2017). *Mplus user's guide* (8th ed.). Muthén & Muthén.

- Ntoumanis, N., Ng, J. Y. Y., Prestwich, A., Quested, E., Hancox, J. E., Thøgersen-Ntoumani, C., Deci, E. L., Ryan, R. M., Lonsdale, C., & Williams, G. C. (2021). A meta-analysis of self-determination theory-informed intervention studies in the health domain: effects on motivation, health behavior, physical, and psychological health. *Health Psychology Review*, *15*(2), 214–244. <https://doi.org/10.1080/17437199.2020.1718529>
- Otis, N., & Pelletier, L. G. (2008). Women's regulation styles for eating behaviors and outcomes: The mediating role of approach and avoidance food planning. *Motivation and Emotion*, *32*(1), 55–67. <https://doi.org/10.1007/s11031-008-9083-3>
- Pelletier, L. G., Dion, S. C., Slovinec-D'Angelo, M., & Reid, R. (2004). Why do you regulate what you eat? Relationships between forms of regulation, eating behaviors, sustained dietary behavior change, and psychological adjustment. *Motivation and Emotion*, *28*(3), 245–277. <https://doi.org/10.1023/B:MOEM.0000040154.40922.14>
- Reise, S. P. (2012). The rediscovery of bifactor measurement models. *Multivariate Behavioral Research*, *47*(5), 667–696. <https://doi.org/10.1080/00273171.2012.715555>
- Román, N., Rigó, A., Kato, Y., Horváth, Z., & Urbán, R. (2021). Cross-cultural comparison of the motivations for healthy eating: investigating the validity and invariance of the motivation for healthy eating scale. *Psychology & Health*, *36*(3), 367–383. <https://doi.org/10.1080/08870446.2020.1773462>
- Russell, D., Parnell, W., Wilson, N., Faed, J., Ferguson, E., Herbison, P., Horwath, C., Nye, T., Reid, P., & Walker, R. (1999). *NZ food: NZ people. Key results of the 1997 National Nutrition Survey*. Ministry of Health, New Zealand.
- Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: Basic psychological needs in motivation, development, and wellness*. Guilford Press.
- Statistics New Zealand. (2001). *New Zealand standard classifications of occupations, 1999 (NZSCO99)* (Catalogue no. 19.004.0099). Statistics New Zealand.
- Stenling, A., Ivarsson, A., Lindwall, M., & Gucciardi, D. F. (2018). Exploring longitudinal measurement invariance and the continuum hypothesis in the Swedish version of the Behavioral Regulation in Sport Questionnaire (BRSQ): An exploratory structural equation modeling approach. *Psychology of Sport and Exercise*, *36*, 187–196. <https://doi.org/10.1016/j.psychsport.2018.03.002>
- Teixeira, D. S., Pelletier, L., Encantado, J., Marques, M. M., Rodrigues, B., & Carraça, E. V. (2021). Adaptation and validation of the Portuguese version of the regulation of eating behavior scale (REBSp). *Appetite*, *156*, Article 104957. <https://doi.org/10.1016/j.appet.2020.104957>
- Teixeira, P. J., Patrick, H., & Mata, J. (2011). Why we eat what we eat: The role of autonomous motivation in eating behaviour regulation. *Nutrition Bulletin*, *36*(1), 102–107. <https://doi.org/10.1111/j.1467-3010.2010.01876.x>
- Verstuyf, J., Patrick, H., Vansteenkiste, M., & Teixeira, P. J. (2012). Motivational dynamics of eating regulation: A self-determination theory perspective. *International Journal of Behavioral Nutrition and Physical Activity*, *9*(1), Article 21. <https://doi.org/10.1186/1479-5868-9-21>

Widaman, K. F., Ferrer, E., & Conger, R. D. (2010). Factorial invariance within longitudinal structural equation models: Measuring the same construct across time. *Child Development Perspectives*, 4(1), 10–18. <https://doi.org/10.1111/j.1750-8606.2009.00110.x>