**Does the premise of deep and surface approaches to learning still hold? A
re-evaluation of the approaches to learning questionnaire**

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Abstract

Scores obtained from the Revised Two Factor Study Process Questionnaire (R-SPQ-2F) are regularly used in Higher Education to profile students as being *Deep* or *Surface* learners. Despite its utility, concerns about its validity have been mounting. Possible factor models have been tested—guided by the original theorising—yet consensus has not been achieved over what is a permissible representation. This study builds on this by seeking to answer a single research question of identifying the best factor model for the R-SPQ-2F. Using data collected from a final sample of 1,158 students, three models were tested using both Exploratory Structural Equation Modelling and Confirmatory Factor Analysis. Findings supported the original decomposition into four factors; however, this came at a cost of distorting factor definitions. A discussion of where these distortions arose and how they can be addressed is offered.

Keywords: Approaches to Learning, R-SPQ-2F, Factor Analysis

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Introduction

Education research regularly uses the Revised Two Factor Study Process Questionnaire (R-SPQ-2F; Biggs et al., 2001) to measure student attitudes towards study strategies and motivations. Examples include Ginns and Ellis (2007), who created learning profiles based on R-SPQ-2F scores, Bliuc et al. (2010), who explored the relationship between R-SPQ-2F scores and final grades, and Gašević et al. (2017) who explored the relationship between R-SPQ-2F scores and learning strategies obtained with analysis of digital trace data. The problem, however, is the growing number of studies raising concerns about the factor structure of the R-SPQ-2F (Justicia et al., 2008; Socha & Sigler, 2014). This paper seeks to address such concerns by exploring various model representations offered in the literature.

Approaches to Learning

Biggs (1987) proposed the 3P (Presage, Process, Product) model of student learning that sought to capture the interplay of personal and situational factors in learning processes. Central to the 3P model is the learning process complex, which Biggs viewed as embodying the students' motives and strategies (Biggs, 1987). A motive is the reason the student approaches the task (e.g., to get a good grade). Strategy is the way the student approaches the task (e.g., making notes, reading widely, or rote learning).

Biggs posited that together, motives and strategies define three approaches to learning: *Achieving*, *Deep*, and *Surface*. *Achieving Approaches* are when students view learning as a competition, wherein the goal is to attain the highest grade. *Deep Approaches* are when students want to be competent in a subject because of an intrinsic interest in the topic. Whereas, *Surface Approaches* are when students are reluctant to understand the topic deeply; rather, there is a preference to do the minimum expected without failing.

Together, these three approaches (*Achieving*, *Deep*, and *Surface*) and Motive-Strategy decomposition provides a 3x2 model of learning approaches.

To measure the constructs of the 3x2 model (i.e., *Deep-Motive*, *Surface-Strategy*, *Achieving-Strategy*), Biggs developed and validated the SPQ (Study Process Questionnaire; Biggs, 1987). With his colleagues, he later revised this to become the R-SPQ-2F (Biggs et al., 2001). What differentiates the R-SPQ-2F from the SPQ, apart from the reduction in item numbers, is the removal of the *Achieving* Approach constructs. This was on account of the ambiguity of measuring Achieving Approaches to monitor learning environments compared to either the *Deep* and *Surface* factors (Biggs et al., 2001). The development of the R-SPQ-2F was therefore about measuring a 2x2 model: *Deep-Motive*, *Deep-Strategy*, *Surface-Motive*, and *Surface-Strategy*.

Proposed Models of Learning Approaches

In the original work of Biggs et al. (2001), they tested two models using R-SPQ-2F data (Figure 1 and 2). The Comparative Fit Index (CFI) and Standardized Root Mean Square Residual (SRMR) were used to evaluate each model. On face value, the fits of the presented models were satisfactory. Although Model B (two higher-order factors each measure by two first-order factors; Figure 2) appeared favourable, it should be viewed with caution as item parcelling may have masked model misspecifications (e.g., cross-loadings; Marsh et al., 2013). The work of Fryer et al. (2012) illustrates this as well. For these authors, an item-based four-factor model was far from perfect (CFI = .78, TLI (Tucker-Lewis Index) = .73, RMSEA (Root Mean Square Error of Approximation) = .063). Upon aggregation at a sub-scale (i.e., *Deep-Strategy*) level, the model fit improved (CFI = 1, TLI = 1, RMSEA = 0). Although preferential from a model fit perspective, it precludes an exploration of item misspecification (e.g., problematic factor loadings). For this reason, the present focus is on item-based representations of the R-SPQ-2F factor structure.

[Figure 1 Here]

[Figure 2 Here]

Subsequent item-based investigations into the factor structure of the R-SPQ-2F have resulted in findings that are contradictory to those reported by Biggs et al. (2001) (Table 1). The work of Justicia et al. (2008) is one such example. Through the evaluation of four model representations, Justicia et al. found the best fitting model to include two factors representing *Deep* and *Surface Approaches* (Table 1). The authors found no evidence to support the decomposition of *Deep* and *Surface* factors into respective *Motive* and *Strategy* factors. Xie (2014) drew similar conclusions and found a better model fit for a two-factor (*Deep* and *Surface Approaches*) model over a four-factor model (*Deep-Strategy*, *Deep-Motive*, *Surface-Strategy*, and *Surface-Motive*; Table 1). However, Johnson et al. (2021) found this two-factor model fit to be far from good.

Immekus and Imbrie (2010) evaluated the suitability of a four first-order factor model. The model deviated from Biggs et al. (2001) as all factors were free to correlate. Biggs et al. (2001) only specified factor-correlations between *Deep-Strategy* and *Deep-Motive*, *Surface-Strategy* and *Surface-Motive*, and *Deep-Motive* and *Surface-Motive*. Immekus and Imbrie did not provide overwhelming support—based on CFI, RMSEA, and SRMR—for a four-factor model (Table 1). High inter-factor correlations (*Deep-Strategy* and *Deep-Motive* = .96; *Surface-Strategy* and *Surface-Motive* = .90) also highlighted issues of discriminant validity. Thus, a four-factor model appeared as an over-extraction. Immekus and Imbrie additionally evaluated a two-factor model (*Deep* and *Surface Approach* factors). Contrary to what Justicia et al. (2008) reported, Immekus and Imbrie did not find support for a two-factor model (Table 1). The model eventually accepted by Immekus and Imbrie—reassessed using exploratory factor analysis—was a four-factor model with five items being dropped (Table 1).

Socha and Sigler (2014) tested a series of different model representations (first-order, hierarchical, and bi-factor) based on the work of Biggs et al. (2001), Justicia et al. (2008), and Immekus and Imbrie (2010). Models proposed by Biggs et al. were non-admissible.

The 15-item, four-factor model offered by Immekus and Imbrie met the commonly used Hu and Bentler (1999) criteria ($CFI = .95$, $TLI = .95$, $RMSEA = .06$, $SRMR = .08$; Table 1). However, item loadings distorted factor definitions. Socha and Sigler settled on a two-factor model (Deep and Surface Approaches) with two items being omitted. López-Aguado and Gutiérrez-Provecho (2018) also found support for this model (Table 1). Shahrazad et al. (2013) found support for a two-factor (*Deep* and *Surface*) model, with six items being dropped based on modification indices and factor loadings (Table 1). A limitation here is the use of modification indices that may reflect sampling fluctuations. Finally, Zakariya et al. (2020) offer an alternate two-factor (*Deep* and *Surface* Approaches) model, with one item removed based on having a nominal target factor loading.

Previous research has also explored a hierarchical model proposed by Biggs et al. (2001), whereby two factors of *Deep* and *Surface* are each measured by two first-order factors (*Motive* and *Strategy*). Justicia et al. (2008) found the fit to meet what could be considered acceptable (Table 1). Socha and Sigler (2014), on the other hand, found this model to not converge. Zakariya et al. (2020) found the hierarchical model to converge, but the fit was inadequate (Table 1). A hierarchical model requires, at a minimum, three first-order factors loading to be identified (Kline, 2015). Therefore, it is preferable to keep focus on first-order factor models (i.e., *Deep-Motive*) in lieu of a higher-order representation (i.e., *Deep* and *Surface Approaches*).

[Table 1 Here]

Research Aim

The aim of this work is to review the initially proposed R-SPQ-2F factor structure (Biggs et al., 2001). Although similar undertakings have been carried out by others (Immekus & Imbrie, 2010; Justicia et al., 2008; López-Aguado & Gutiérrez-Provecho, 2018; Shahrazad et al., 2013; Socha & Sigler, 2014; Xie, 2014; Zakariya et al., 2020), this has resulted in a mixture of model representations. With little consensus as to what factor

structure to agree upon, this may have deleterious down-stream effects. That is, research findings could be based on variation of items from the R-SPQ-2F, which is wholly dependent on which paper is initially selected. Thus, we pose the following research question:

- What factor model is the best representation for items of the R-SPQ-2F? (Research Question 1; RQ1)

By answering this question, the paper attempts to identify a preferential factor model for the R-SPQ-2F. We discuss any problematic items identified through such analysis. This remains a constructive venture to support practitioners and researchers intending to use the instrument. Thus, the focus is on identifying areas of improvement (e.g., item re-writes), as opposed to model critiques.

Method

Sample

A total of 1,636 student (Undergraduate and Postgraduate) responses were initially collected using opportunity sampling from an Australian University. Of the 1636 responses, 456 (27.873%) contained missing values for all 20 items and 4 (.244%) responses contained missing student identification details. The 456 missing responses were omitted, in addition to those with 4 instances of missing personal details. Having personal details was a necessity for the analysis to determine how representative the sample was of the student population; thus, they were omitted. Eighteen (1.100%) responses were identified as being duplicates on the basis of the student identification information; all responses given by these students (original and duplicate) were dropped.

One-thousand and fifty eight (1,158) complete responses were retained for the analyses that followed. The gender breakdown for the sample was as follows: 737 (63.60%) Female, 419 (36.20%) Male, and 2 (.173%) Indeterminate/Intersex/Unspecified. To

evaluate the sample characteristics, they can be compared to the student population from which they were sampled. Across the University, the gender counts and percentages are as follows: 47,629 (56.60%) Female, 36,410 (43.30%) Male, and 44 (.052%)

Indeterminate/Intersex/Unspecified students. Ages of the respondents in the sample ranged from 17 to 53 ($M = 21.60$, $SD = 4.74$, $Skewness = 3.25$). For the student population, age ranged from 15 to 87 ($M = 23.30$, $SD = 6.56$, $Skewness = 2.77$; sample and population age distributions are presented in Appendix A. The number of Undergraduate students totalled 905 (78.20%), whilst 253 (21.80%) were Postgraduate students. The University population values for course levels were as follows: 4812 (5.72%, Higher Degree Research), 24,495 (29.10%, Postgraduate), 54,351 (64.60%, Undergraduate), and 425 (.505%, Non-Award). Of the 10 academic disciplines at the university, all but one (Pharmacy and Pharmaceutical Sciences) was represented (Table 2).

[Table 2 Here]

Comparing the sample to the 2019 Academic Discipline enrolment data (Table 2), it was clear that the student population was not well represented. In certain cases, Academic Disciplines were under-represented: *Art, Design, and Architecture*, *Arts, Education, Law, Medicine, Nursing, and Health Sciences*, and *Pharmacy and Pharmaceutical Sciences*.

Whereas, the Academic Disciplines of *Business and Economics*, *Engineering*, *Information Technology*, and *Science* were over-represented in the sample.

Instrument

Data was collected using the 20-item R-SPQ-2F (Appendix B; Biggs et al., 2001). Slight amendments were made to the item wordings to align with the institutional context. In the original item wordings Biggs et al. referred to **course** (e.g., *My aim is to pass the course while doing as little work as possible*); for the context of this study, **unit** was a more appropriate wording choice (e.g., *My aim is to pass the unit while doing as little work*

as possible). Each of the 20-items were answered on a 5-point Likert scale ranging from *This is never or only rarely true of me* (1) to *This is always or almost always true of me* (5).

Procedure

Survey links for the R-SPQ-2F Biggs et al., 2001 were distributed to students (Undergraduates and Postgraduates) through direct emails. To receive the email, the student had to be enrolled within a course using live-streaming services. The R-SPQ-2F was used as a set of introductory items before a series of items designed to measure live streaming attitudes; results of the latter are not applicable to the current work. Completion of the survey was voluntary; respondents to the survey were eligible to participate in a voluntary prize-draw to win one of five \$20 gift cards. Respondents were only able to access the survey by using their university credentials, which were logged and used to connect survey responses to demographic and educational information. An explanatory statement form was given to students before completing the survey detailing how their university credentials would be collected and used to connect responses to university records; consent was obtained from all respondents. Institutional ethical approval was obtained for all of this work.

Analysis

To answer RQ1, we tested three models (Figure 3) using Confirmatory Factor Analysis (CFA) and Exploratory Structural Equation Modelling (ESEM; Figure 3). Response distributions for the 20 items (Appendix B) showed non-normality, a commonality with ordinal level data. Thus, we used the weighted least square mean and variance adjusted (WLSMV) estimator with delta scaling. All analyses used Mplus 8.3 (Muthén & Muthén, 2017).

Both the original work of Biggs et al. (2001) and work that followed (Fryer et al., 2012; Immekus & Imbrie, 2010; Justicia et al., 2008; López-Aguado & Gutiérrez-Provecho, 2018; Socha & Sigler, 2014; Xie, 2014) informed the models tested. Figure 3a (Model 1) is

the item-level model proposed by Biggs et al. For this model, five items measure each of the four factors: Deep-Motive, Deep-Strategy, Surface-Motive, and Surface-Strategy. The model specifies factor correlations between Motive and Strategy within the same approach (*Surface-Motive* and *Surface-Strategy*), and limits across approach correlations to the *Deep-Motive* and *Surface-Motive* factors. Figure 3b (Model 2) deviates from Model 1 by allowing all factors to freely correlate. This model is a reasonable adjustment to Figure 3a (Model 1), as the inclination of a student using a *Surface-Strategy* toward using a strategy focused on obtaining a deep understanding of the subject (*Deep-Strategy*) would be lower. The findings of Justicia et al. (2008) informed Figure 3c (Model 3). Specifically, the finding that a two-factor (Deep and Surface) representation offers a better fit to the data over a four-factor model. It also accounts for the high correlation between *Motive* and *Strategy* factors that are reported (Immekus & Imbrie, 2010). Table 3 presents the indicator to factor specification for each model.

[Figure 3 Here]

[Table 3 Here]

Figure 3 presents confirmatory factor models with the assumptions of no cross-loading factors and no correlated errors. As discussed by Marsh et al. (2014), the restriction of zero cross-loadings is too restrictive because of indicator fallibility. Marsh et al. instead advocate the use of ESEM, wherein the analyst can specify items to load onto multiple factors. This may be a suitable reflection of reality as items may have nominal loadings onto non-target factors; without specification, the latter may result in sources of ill-fit. The recommendation outlined by Marsh et al. (2014) was therefore followed: a confirmatory factor model was first tested, followed by an ESEM. ESEM was applied to all but Model 3a as a target oblique rotation procedure was used, wherein all factor correlations are freely estimated. For the target rotation, the only factor loadings specified ($= 0$) were those items—based on the work of Biggs et al. (2001) and Justicia et al.

(2008)—not loading onto the target factors. We made no specifications for indicators with target factors (Table 3).

How the ESEM models differed from those presented in Figure 3 was the permittance of cross-loadings; no ESEM model specified correlated errors. We compared models (CFA and ESEM) using general fit measures (χ^2 , CFI, TLI, RMSEA, and SRMR), local fit (residuals), and measurement quality (factor loadings). Model evaluation made use of the regularly cited cut-offs for fit indices (CFI = .95, TLI = .95, RMSEA = .06, SRMR = .08; Hu and Bentler, 1999). As a narrow range of models informed these cut-off values, they may not reflect those models tested (Marsh et al., 2004). Global fit indices only served as one element in the model evaluation. We, therefore, supplemented global fit interpretation with an assessment of how well indicators measure the construct of interest and an exploration of potential sources of misfit. Two approaches were used to identify sources of localised strain in the models: residual correlations, using $\geq .10$ as a guideline Kline, 2015, and modification index (MI) and standardised/expected parameter change (S/EPC) values (Sarlis et al., 2009). This model evaluation helped determine a suitable candidate factor model (Model 1-3; RQ1).

With 20 indicators, the number of observations totalled 270 (190 polychoric correlations and 80 thresholds). For Model 1, the confirmatory factor model required 103 parameters to be estimated (16 factor loadings, 80 thresholds, 3 factor covariances, and 4 factor variances), equating to 167 degrees of freedom (df). For Model 2, the confirmatory factor model estimated 106 parameters (16 factor loadings, 80 thresholds, 6 factor covariances, and 4 factor variances; $df = 164$). The ESEM model required 154 parameters to be estimated (74 factor loadings and 80 thresholds; $df = 116$). Model 3 required 101 parameters to be freely estimated for the CFA (18 factor loadings, 80 thresholds, 1 factor covariance, and 2 factor variances; $df = 169$) and 119 for the ESEM (39 factor loading and 80 thresholds; $df = 151$). In all instances, the models were overidentified.

Results

Model 1

The first confirmatory factor model (Model 1; Figure 3a) resulted in a latent variable covariance matrix that was not positive definite. A detailed inspection of the output showed estimated correlations between latent variables to exceed the value of one (*Deep-Motive* and *Deep-Strategy* = 1.008; *Surface-Motive* and *Surface-Strategy* = 1.032).

Model 2

CFA Model. When all inter-factor correlations are specified (Model 2; Figure 3b) in the confirmatory factor model, the results were again not positive definite. This was attributed to the correlations between the constructs of a particular approach exceeding 1 (*Deep-Motive* and *Deep-Strategy* = 1.008; *Surface-Motive* and *Surface-Strategy* = 1.030).

ESEM Model. The ESEM version of Model 2 converged; $\chi^2(116) = 695.729$, $p < .001$, CFI = .948, TLI = .915, RMSEA = .066 (90% CI = .061—.070), SRMR = .026. Inter-factor correlations were small (Table 4). A low to moderate amount of the underlying continuous latent response variables was accounted for by the factors ($R^2 = .309$ —.636). Nine instances of residual variances being $> 50\%$ were identified (Table 5).

[Table 4 Here]

Factor loadings are presented in Table 5, showing the following absolute value ranges:

- .021—.589 ($M = .276$; *Deep-Motive*);
- .082—.670 ($M = .282$; *Deep-Strategy*);
- .005—.670 ($M = .274$; *Surface-Motive*); and
- .013—.706 ($M = .216$; *Surface-Strategy*).

Focusing on target factor loadings only, $|\lambda|$ values ranged from:

- .172—.589 ($M = .453$; *Deep-Motive*);
- .082—.670 ($M = .404$; *Deep-Strategy*);
- .202—.670 ($M = .524$; *Surface-Motive*); and
- .240—.706 ($M = .385$; *Surface-Strategy*).

[Table 5 Here]

An inspection of the residual correlation matrix (Appendix C) showed three locations with absolute values $\geq .10$. The areas of localised strain are presented in Appendix C, along with MI and S/EPC values.

Model 3

CFA Model. Model 3 (Figure 3c), as a confirmatory factor model, successfully converged and was positive definite. The obtained fit was as follows: $\chi^2(169) = 1844.252$, $p < .001$, CFI = .851, TLI = .832, RMSEA = .093 (90% CI = .089—.096), and SRMR = .066. Both unstandardised and standardised factor loadings for the model are presented in Table 6. Standardised loadings ranged from:

- .513—.769 ($M = .662$; *Deep Approach*); and
- .513—.733 ($M = .618$; *Surface Approach*).

The two factors of *Deep Approach* and *Surface Approach* were not strongly correlated ($r = -.107$). A low to moderate amount of the variance in the latent continuous response variables is accounted for by the factors ($R^2 = .263—.592$). Residual variances for 15 of the 20 indicators showed the factors to account for less than 50% of the latent response variable (Table 6).

Residual correlations for the CFA model are presented in Appendix D, wherein 41 sources of ill-fit can be identified using $\geq .10$ as a cut-off. Table D presents the residual correlations that were $\geq .10$, along with MI, EPC, and SEPC values.

[Table 6 Here]

ESEM Model. The ESEM version of Model 3 converged and achieved a slightly improved global fit over the confirmatory factor model, $\chi^2(151) = 1607.452$, $p < .001$, CFI = .870, TLI = .837, RMSEA = .091 (90% CI = .087—.095), and SRMR = .043. The inter-factor correlation was found to be low (-.090). Loadings are presented in Table 7, with $|\lambda|$ values ranging from:

- .020—.771 ($M = .383$; *Deep Approach*); and
- .000—.708 ($M = .337$; *Surface Approach*).

For target factor loadings, the $|\lambda|$ values ranged from:

- .527—.771 ($M = .662$; *Deep Approach*); and
- .486—.708 ($M = .618$; *Surface Approach*).

A low to moderate amount of the underlying continuous latent response variable was accounted for by the factors (R^2 range = .252—.591). There were 15 instances of residual variance values being $> 50\%$ (Table 7).

[Table 7 Here]

The residual correlation matrix (Appendix D) showed nine locations where absolute values $\geq .10$. Appendix D presents the locations at which this localised strain within the model occurs, along with MI, EPC, and SEPC values.

Discussion

Results show the four-factor model (the adapted Biggs et al. (2001) model; Figure 3b) to be the best representation when analysing items of the R-SPQ-2F (RQ1), contrary to prior works (Justicia et al., 2008; Xie, 2014). This is both informed by global fit and local fit measures. There are two caveats, however. First, this only applies to the use of ESEM, not CFA. Second, this came at the expense of clear factor definitions. What follows is a discussion of these problematic items in Model 2 (ESEM).

Distorted Factor Definitions

Model 2 (ESEM) factor loadings showed eight items (2, 4, 6, 9, 10, 12, 16, and 20) that resulted in distorted factor definitions. Simply put, items loaded onto factors that were contrary to those previously hypothesised (Biggs et al., 2001).

Item 2's (*I find that I have to do enough work on a topic so that I can form my own conclusions before I am satisfied*) hypothesised target factor is *Deep-Strategy*. The results here show a target factor (*Deep-Strategy*) loading of .082, with a moderate loading onto *Deep-Motive* ($\lambda = .574$). Item 2 is asking about satisfaction, similar to Item 1 (*I find that at times studying gives me a feeling of deep personal satisfaction*). Therefore, it is possible that there is a wording effect because of the items being framed around the feeling of satisfaction that arises from studying. Item 2 is also asking why the student approaches the task (i.e., to form conclusions), which maps more with a motivation than a strategy.

Item 4 (*I only study seriously what's given out in class or in the unit guide*) had a higher factor loading for *Surface-Motive* ($\lambda = .334$) than its target factor of *Surface-Strategy* ($\lambda = .240$). Based on these loadings, Item 4 is an imperfect measure of either the *Surface-Strategy* or *Surface-Motive* factors. From an item wording perspective, there are additional complexities. The item is asking if the student studies seriously, which does not convey explicit details on the strategy or the motive. A further issue of the item is its context dependency (Johnson et al., 2021). For some classes, the requirement may

simply equate to having a thorough understanding of the material.

Proposed as an indicator of *Deep-Strategy*, Item 6 (*I find most new topics interesting and often spend extra time trying to obtain more information about them*) showed similar issues of moderate loadings on the target factor ($\lambda = .558$) and a non-target factor (*Deep-Motive*; $\lambda = .445$). As Item 6 asks students about their interest in a topic, this clearly taps into the *Motive* facet as it is asking why the student is approaching the task. The latter half of the item explores the *Strategy* factor by asking how they approach the task, specifically by allocating more time. Thus, the item problems are from it being ‘double-barrelled’, resulting in students answering either the *Motive* or *Strategy* aspect of the item Bandalos, 2018. This is the reason that Item 6 does not function well as a measure of a single factor (*Deep-Strategy*).

Item 9 (*I find that studying academic topics can at times be as exciting as a good novel or movie*) cross-loaded on both *Deep-Strategy* ($\lambda = .422$) and *Deep-Motive* ($\lambda = .451$). While this item appears to touch upon motivations for the approach, specifically the excitement students experience whilst studying, it is not explicit in asking whether this is the underlying reason. There is good reason to view this item as measuring *Deep-Strategy* too, as it seeks to evaluate the strategy used. Put differently, students are being asked if they find the act of studying to be exciting. This is a different perspective than a question asking if a student studies because of the satisfaction that arises.

Item 10 (*I test myself on important topics until I understand them completely*) had two problems. One, it had a low target factor loading ($\lambda_{\text{Deep-Strategy}} = .253$). Two, it had low to moderate non-target factor loadings ($\lambda_{\text{Deep-Motive}} = .403$; $\lambda_{\text{Surface-Strategy}} = .315$). These issues may stem from the wording itself. It reads as a *Surface-Strategy* item by asking if the student repeats a behaviour (testing) until they understand the topic. A repetitive behaviour such as this is reminiscent of rote learning, depending on the interpretation of *test*. Item 10 also reads as a *Deep-Motive* item by asking if the strategy is about wanting a complete understanding of the topic. Thus, the item explores the

reasoning behind the adopted approach (i.e., to improve topic understanding), in addition to the strategy adopted. In sum, Item 10 bears semblance to an array of factors that it was not intended to measure.

Factor loading values for Item 12 (*I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra*) raise questions as to what is being measured. The highest factor loading was for a non-target factor ($\lambda_{Surface-Motive} = .410$), although the target factor loading value was moderate ($\lambda_{Surface-Strategy} = .371$). Wording of this item is problematic as it encompasses two themes: *Motive* and *Strategy*. The first part of the statement asks about how the student approaches their studying, i.e. restricting the amount studied. The second half, however, asks about the underlying motivation for the approach adopted (the student sees any additional work as unnecessary). There are two things essentially being asked of students with Item 12, what is their approach (*Strategy*) and why adopt this approach (*Motive*).

With Item 16 (*I believe that lecturers shouldn't expect students to spend significant amounts of time studying material*), loadings are higher for non-target factors ($\lambda_{Deep-Motive} = .297$; $\lambda_{Surface-Motive} = .465$) than the target factor ($\lambda_{Surface-Strategy} = .270$). A moderate loading on the *Surface-Motive* factor is understandable as the item asks students about their motivations for adopting a particular approach (the belief that lecturers should not expect such workload levels from students). For the *Deep-Motive* factor, item 16's loading is not straightforward. Being negatively phrased, there is a possibility that this presents a difficult item for students to respond to. For example, a student who agrees with the statement has to respond with '*This is never or only rarely true of me*'. It may be necessary for work to explore interpretations of this item by respondents to explore if there are any associated difficulties.

Finally, Item 20 (*I find the best way to pass examinations is to try to remember answers to likely questions*) had low loadings on its target factor (*Surface-Strategy*; $\lambda = .339$), which were comparable to the non-target factor loading on *Surface-Motive* ($\lambda =$

.324). This is another instance where an item taps into two constructs. There is an element of *Motive* by framing the statement around passing an exam, and an element of *Strategy* in trying to remember answers to likely questions.

Conclusion

Validity concerns with the R-SPQ-2F are not exclusive to this work (Johnson et al., 2021). The study results reiterate the need for an item re-write. A plethora of models and item combinations is not helpful for researchers intending on using the measure when item wordings remain an issue. Thus, insisting on dropping items is unlikely to correct the underlying problem. Researchers need to work on bringing clarity to the 20 R-SPQ-2F items, be that through removing ambiguous terminology or by removing compound sentences. Without doing so, we may wrongly conclude that four-factors are being measured, despite distorted factor definitions. The R-SPQ-2F can continue to be a helpful tool for education research, but only if more work is done to correct the identified problematic areas.

Those intent on using the R-SPQ-2F should be mindful of the validity concerns raised here. At face-value, four-factors appear reasonable. It is only upon closer inspection we identify misspecifications. Thus, with each usage of the R-SPQ-2F researchers and practitioners should evaluate the construct validity using exploratory factor analysis and report problematic items. Without these necessary steps, this could have deleterious downstream effects on educational research, as we may not be measuring what we intend to be measuring.

Limitations

Data was obtained through the use of opportunity sampling, as opposed to the use of stratified or random sampling approaches. Based on the sample and population demographic breakdowns, it was clear that the sample was not representative. Follow-up

work should seek to obtain a more representative sample of the student population, which is also large enough to conduct measurement invariance tests across various sub-groups.

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Table 1

Alternative Model Representations of the R-SPQ-2F Factor Structure Evaluated by Other Researchers

Authors	Model Tested	χ^2	df	P-Value	CFI	TLI	RMSEA	SRMR
Justicia et al. (2008)	Four-factor model	667.83	168	< .001	.92	–	.07	.12
	Two-factor model	645.77	169	< .001	.92	–	.07	.09
	Hierarchical model	623.19	165	< .001	.93	–	.07	.09
Immekus and Imbrie (2010)	Four-factor model	598.60	79	< .01	.87	–	.06	.06
	Two-factor model	607.94	79	< .01	.86	–	.10	.06
	Four-factor model ^a	160.78	49	< .01	.96	–	.05	.04
Shahrazad et al. (2013)	Two-factor model ^b	111.48	73	< .05	.94	.93	.04	–
Socha and Sigler (2014)	Four-factor model ^a	282.336	84	< .001	.95	–	.05	.045
	Two-factor model ^c	504.826	134	< .001	.95	–	.06	.051
Xie (2014)	Four-factor model	463.64	164	< .001	.92	–	.065	–
	Two-factor model	489.40	169	< .001	.92	–	.067	–
López-Aguado and Gutiérrez-Provecho (2018)	Two-factor model ^c	226.53	134	< .001	.914	.900	.050	.052
	Two-factor model	522.179	169	< .001	.769	.740	.091	.081
Zakariya et al. (2020)	Two-factor model ^d	377.676	151	< .001	.844	.824	.077	.072
	Hierarchical model	521.114	168	< .001	.769	.739	.091	.081
Johnson et al. (2021)	Two-factor model	634.366	169	< .001	.558	.503	.085	.102

^aRemoval of five items: 1, 3, 7, 13, and 15. ^bRemoval of six items: 4, 5, 11, 12, 15, and 17. ^cRemoval of two items: 7 and 8. ^dRemoval of one item: 8.

Table 2*Sample and 2019 Population Academic Discipline Enrolment Counts and Percentages*

Academic Discipline	Sample		Population	
	<i>n</i>	%	<i>n</i>	%
Art, Design, and Architecture	21	1.81	2773	3.30
Arts	90	7.77	7954	9.47
Business and Economics	341	29.40	21007	25.00
Education	87	7.51	7079	8.42
Engineering	179	15.50	9011	10.70
Information Technology	137	11.80	7169	8.53
Law	32	2.76	4095	4.87
Medicine, Nursing, and Health Sciences	127	11.00	15893	18.90
Pharmacy and Pharmaceutical Sciences	–	–	2546	3.03
Science	144	12.40	6500	7.74

Table 3*Indicator to Factor Specification for 3 Tested Models (Item wordings presented in Appendix 1.2)*

Model	Factor	Items
1 & 2	Deep-Motive	1 5 9 13 17
	Deep-Strategy	2 6 10 14 18
	Surface-Motive	3 7 11 15 19
	Surface-Strategy	4 8 12 16 20
3	Deep Approach	1 2 5 6 9 10 13 14 17 18
	Surface Approach	3 4 7 8 11 12 15 16 19 20

Table 4

Factor Correlation Matrix for the ESEM Version of Model 2 (Figure 3b)

	Deep-Motive	Deep-Strategy	Surface-Motive	Surface-Strategy
Deep-Motive	1			
Deep-Strategy	.332	1		
Surface-Motive	-.125	-.200	1	
Surface-Strategy	.103	.127	.386	1

Table 5
ESEM Factor Loadings for Model 2 (Figure 3b)

Items	Deep-Motive		Deep-Strategy		Surface-Motive		Surface-Strategy		δ
	λ	S.E.	λ	S.E.	λ	S.E.	λ	S.E.	
1	.589	.029	.111	.030	-.217	.029	.147	.031	.489
2	.574	.032	.082	.039	-.215	.035	.139	.040	.533
3	-.066	.033	.137	.035	.626	.033	.078	.033	.570
4	.147	.030	-.262	.031	.334	.044	.240	.058	.690
5	.517	.032	.250	.033	.022	.029	-.036	.030	.595
6	.445	.033	.558	.035	.114	.025	-.097	.028	.372
7	-.206	.030	.097	.028	.670	.029	.067	.027	.466
8	-.096	.037	.139	.062	.005	.030	.706	.038	.468
9	.451	.029	.422	.026	-.041	.026	-.013	.029	.481
10	.403	.035	.253	.047	-.248	.028	.315	.030	.509
11	-.198	.037	.221	.060	.202	.042	.648	.036	.378
12	.045	.024	-.103	.027	.410	.035	.371	.040	.561
13	.535	.025	.342	.024	-.166	.022	.033	.024	.400
14	.326	.041	.670	.039	.182	.026	-.141	.030	.364
15	-.094	.029	.186	.028	.600	.030	.208	.029	.493
16	.297	.030	-.360	.035	.465	.048	.270	.072	.443
17	.172	.038	.559	.029	.066	.035	.062	.045	.589
18	.154	.029	.455	.031	-.039	.032	.102	.038	.691
19	.176	.029	-.307	.028	.524	.046	.299	.059	.397
20	-.021	.027	.121	.031	.324	.032	.339	.034	.687

Table 6*Unstandardised and Standardised CFA Factor Loadings for Model 3*

Items	Unstandardised Solution				Standardised Solution				δ
	Deep Approach ^a		Surface Approach ^b		Deep Approach		Surface Approach		
	λ	S.E.	λ	S.E.	λ	S.E.	λ	S.E.	
DA1	1.000	.000	-	-	.661	.019	-	-	.563
DA2	.947	.035	-	-	.626	.020	-	-	.608
DA3	.931	.036	-	-	.615	.020	-	-	.622
DA4	1.160	.037	-	-	.767	.014	-	-	.412
DA5	1.094	.039	-	-	.723	.017	-	-	.477
DA6	.969	.037	-	-	.640	.019	-	-	.590
DA7	1.164	.037	-	-	.769	.015	-	-	.408
DA8	1.101	.039	-	-	.728	.016	-	-	.471
DA9	.871	.039	-	-	.575	.021	-	-	.669
DA10	.776	.040	-	-	.513	.022	-	-	.737
SA1	-	-	1.000	.000	-	-	.606	.023	.633
SA2	-	-	.847	.045	-	-	.513	.024	.737
SA3	-	-	1.086	.049	-	-	.658	.021	.567
SA4	-	-	.851	.047	-	-	.516	.023	.734
SA5	-	-	1.063	.050	-	-	.644	.020	.585
SA6	-	-	1.092	.048	-	-	.662	.018	.562
SA7	-	-	1.101	.049	-	-	.667	.022	.554
SA8	-	-	1.081	.049	-	-	.655	.019	.571
SA9	-	-	1.209	.052	-	-	.733	.016	.463
SA10	-	-	.860	.048	-	-	.521	.023	.728

^aDA (Deep Approach): Items (in order) 1, 2, 5, 6, 9, 10, 13, 14, 17, 18. ^bSA (Surface Approach):

Items (in order) 3, 4, 7, 8, 11, 12, 15, 16, 19, 20.

Table 7*ESEM Factor Loadings for Model 3*

Items	Deep Approach		Surface Approach		δ
	λ	S.E.	λ	S.E.	
1	.648	.020	-.061	.022	.569
2	.612	.020	-.064	.021	.615
3	-.039	.024	.599	.024	.635
4	-.087	.023	.486	.024	.748
5	.610	.020	.000	.021	.628
6	.771	.013	.027	.017	.409
7	-.190	.021	.626	.022	.551
8	.226	.022	.567	.021	.651
9	.714	.017	-.039	.017	.483
10	.655	.018	.043	.019	.574
11	.165	.021	.683	.018	.526
12	-.021	.020	.654	.018	.570
13	.751	.016	-.109	.016	.409
14	.733	.016	.048	.017	.466
15	.020	.021	.677	.021	.543
16	-.062	.021	.636	.019	.585
17	.596	.020	.107	.021	.645
18	.527	.022	.049	.022	.725
19	-.120	.019	.708	.017	.469
20	.116	.023	.549	.022	.696

Figure 1

First-Order Factor Model Tested by Biggs et al. (2001) (DS = Deep-Strategy, DM = Deep-Motive, SS = Surface-Strategy, SM = Surface-Motive; Model A). Freely estimated correlations between: DS and DM, DM and SM, and SS and SM. Model Fit: CFI = .904, SRMR = .058.

Figure 2

Higher-Order Factor Structure Tested by Biggs et al. (2001) using an Item Parcelling Approach (DS = Deep-Strategy, DM = Deep-Motive, SS = Surface-Strategy, SM = Surface-Motive; Model B). Model Fit: CFI = .992, SRMR = .015.

(a) Model proposed by Biggs et al. (2001) (Model 1). Four factors (DS = Deep-Strategy, DM = Deep-Motive, SS = Surface-Strategy, SM = Surface-Motive). Five indicators per factor. Freely estimated correlations between: DS and DM, DM and SM, and SS and SM.

(b) Adaptation of the Biggs et al. (2001) model with four freely correlated factors (Deep-Strategy, Deep-Motive, Surface-Strategy, Surface-Motive), each with five indicators (Model 2).

(c) Two-Factor (Deep and Surface) Model (Model 3). Freely estimated correlation between factors, each of which has 10 indicators.

Figure 3

Three Confirmatory Factor Models Tested in the Current Work

Appendix A**Age Distributions for Student Sample and Population** **Figure A1**

Age Distributions for the Student Sample (Left) and Student Population (Right)

Appendix B

Questionnaire Items and Response Distributions

Biggs et al. (2001) R-SPQ-2F

Item	Wording
1	I find that at times studying gives me a feeling of deep personal satisfaction
2	I find that I have to do enough work on a topic so that I can form my own conclusions before I am satisfied
3	My aim is to pass the unit while doing as little work as possible
4	I only study seriously what's given out in class or in the unit guide
5	I feel that virtually any topic can be highly interesting once I get into it
6	I find most new topics interesting and often spend extra time trying to obtain more information about them
7	I do not find my unit very interesting so I keep my work to the minimum
8	I learn some things by rote, going over and over them until I know them by heart even I do not understand them
9	I find that studying academic topics can at times be as exciting as a good novel or movie
10	I test myself on important topics until I understand them completely
11	I find I can get by in most assessments by memorising key sections rather than trying to understand them
12	I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra
13	I work hard at my studies because I find the material interesting
14	I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes
15	I find it is not helpful to study topics in depth. It confuses and wastes time, when all you need is a passing acquaintance with topics
16	I believe that lecturers shouldn't expect students to spend significant amounts of time studying material everyone knows won't be examined
17	I come to most classes with questions in my mind I want answering
18	I make a point of looking at most of the suggested readings that go with the lectures
19	I see no point in learning material which is not likely to be in the examination
20	I find the best way to pass examinations is to try to remember answers to likely questions

Response Distributions for the R-SPQ-2F Items

Appendix C

Local Fit Measures: Model 2

Residual Correlations for Model 2 (ESEM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	-																			
2	.066	-																		
3	.036	.053	-																	
4	.019	.031	.111	-																
5	.009	.007	.041	.022	-															
6	-.018	-.004	.005	-.025	.078	-														
7	.041	.030	.040	.023	-.024	-.019	-													
8	.015	.008	.022	-.006	.004	.038	-.010	-												
9	.009	-.033	.015	-.002	-.029	-.003	.031	.002	-											
10	-.010	.008	-.043	.009	-.001	-.004	.062	.026	.007	-										
11	-.004	-.014	.002	-.016	.025	.014	-.017	.003	.005	-.012										
12	-.007	-.021	.002	.100	.019	.012	-.007	-.017	.010	-.039	.036	-								
13	-.012	-.059	-.035	.028	-.029	-.036	-.051	-.051	.042	.001	.007	.057	-							
14	-.011	.005	-.015	-.030	-.047	.015	-.011	-.015	.002	-.001	.022	-.023	.024	-						
15	.047	.012	-.009	-.059	-.007	-.015	.025	.024	-.017	-.014	-.014	.006	-.017	.009	-					
16	-.079	-.034	-.062	-.061	-.033	-.024	-.034	.004	.026	.016	-.023	-.030	.058	.014	.013	-				
17	-.005	-.013	-.002	-.007	-.025	-.045	.002	-.023	-.011	.019	-.032	-.007	.016	-.008	.021	.020	-			
18	-.052	.010	-.037	-.029	-.036	-.035	-.031	-.020	-.034	-.001	-.041	-.014	.049	-.020	.005	.036	.103	-		
19	-.028	-.042	-.077	-.058	-.024	-.008	-.028	-.016	-.042	.014	-.007	-.039	-.009	.032	.012	.061	.045	.064	-	
20	-.020	-.006	-.003	-.034	-.011	.021	-.015	-.003	-.003	-.025	.023	-.022	.011	.017	-.037	.012	-.030	.039	.046	-

Areas of Localised Strain for Model 2 (ESEM)

Items	Residual Correlation	MI	EPC	SEPC
3 4	.111	50.903	.162	.258
4 12	.100	64.774	.148	.238
17 18	.103	74.832	.160	.251

Appendix D

Local Fit Measures: Model 3

Residual Correlations for Model 3 (CFA)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	-																			
2	.141	-																		
3	-.064	-.050	-																	
4	.004	.019	.079	-																
5	.030	.028	.036	.013	-															
6	-.063	-.052	.054	-.085	.084	-														
7	-.177	-.184	.108	-.015	-.130	-.081	-													
8	.135	.114	-.045	-.059	.079	.160	-.112	-												
9	-.003	-.047	-.009	-.072	-.029	.002	-.105	.115	-											
10	.036	.051	-.092	-.006	-.007	-.039	-.093	.281	-.001	-										
11	.028	.006	-.028	-.089	.056	.118	-.066	.226	.074	.172	-									
12	-.022	-.038	-.020	.107	.025	.011	-.038	-.005	-.022	-.003	.035	-								
13	.010	-.038	-.129	-.057	-.025	-.055	-.270	.051	.036	.013	.036	-.009	-							
14	-.093	-.081	.071	-.109	-.052	.079	-.024	.111	.014	-.051	.153	-.025	-.005	-						
15	-.025	-.066	.046	-.103	.006	.066	.078	.020	-.011	-.007	.013	-.009	-.081	.129	-					
16	-.048	-.002	-.101	.015	.005	-.057	-.092	-.082	-.022	.027	-.141	-.014	-.005	-.053	-.045	-				
17	-.072	-.084	.082	-.056	-.049	-.009	.011	.184	-.009	.015	.177	.034	-.014	.066	.152	-.026	-			
18	-.097	-.038	-.009	-.090	-.063	-.020	-.072	.164	-.036	.010	.129	-.003	.029	.021	.077	-.030	.160	-		
19	-.065	-.076	-.105	-.003	-.037	-.076	-.062	-.098	-.135	-.016	-.108	-.032	-.133	-.054	-.032	.152	-.005	-.010	-	
20	.010	.017	.000	-.064	.046	.124	-.029	.079	.058	.082	.101	-.021	.036	.135	-.010	-.029	.114	.143	.008	-

Areas of Localised Strain for Model 3 (CFA)

Items	Residual Correlation	MI	EPC	SEPC
1 2	.141	62.226	.191	.326
1 7	-.177	39.251	-.179	-.317
1 8	.135	20.937	.136	.212
2 7	-.184	40.513	-.187	-.318
2 8	.114	15.096	.115	.172

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Items	Residual Correlation	MI	EPC	SEPC
3 7	.108	29.283	.152	.253
3 13	-.129	19.828	-.131	-.257
3 16	-.101	13.462	-.123	-.204
3 19	-.105	17.648	-.136	-.251
4 12	.107	28.080	.141	.220
4 14	-.109	14.859	-.110	-.187
4 15	-.103	14.219	-.123	-.192
5 7	-.130	20.280	-.132	-.222
6 8	.160	32.555	.161	.294
6 11	.118	16.081	.119	.243
6 20	.124	18.070	.125	.229
7 8	-.112	18.053	-.134	-.208
7 9	-.105	13.441	-.107	-.205
7 13	-.270	120.434	-.277	-.575
8 9	.115	16.362	.116	.197
8 10	.281	108.881	.283	.431
8 11	.226	186.216	.322	.492
8 14	.111	15.195	.112	.190
8 17	.184	43.491	.185	.264
8 18	.164	30.085	.164	.224
9 19	-.135	23.851	-.137	-.292
10 11	.172	34.945	.174	.297
11 14	.153	28.953	.155	.296
11 16	-.141	30.964	-.176	-.305

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Items	Residual Correlation	MI	EPC	SEPC
11 17	.177	40.210	.179	.286
11 18	.129	20.284	.130	.198
11 19	-.108	22.388	-.145	-.278
11 20	.101	22.224	.130	.199
13 19	-.133	24.152	-.136	-.313
14 15	.129	20.217	.131	.256
14 20	.135	23.203	.136	.233
15 17	.152	25.987	.154	.253
16 19	.152	137.765	.284	.552
17 18	.160	59.159	.193	.275
17 20	.114	15.203	.114	.164
18 20	.143	22.925	.144	.196

Residual Correlations for Model 3 (ESEM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	-																			
2	.147	-																		
3	-.010	.005	-																	
4	.082	.096	.089	-																
5	.038	.036	.053	.060	-															
6	-.057	-.045	.059	-.040	.087	-														
7	-.025	-.037	.112	-.011	-.023	.037	-													
8	.018	.007	-.053	-.045	-.062	-.033	-.081	-												
9	.003	-.040	.033	.001	-.022	.006	.045	-.029	-											
10	.037	.053	-.099	.024	-.010	-.049	-.004	.107	-.004	-										
11	-.044	-.058	-.034	-.075	-.049	-.034	-.041	.156	-.024	.032	-									
12	.023	.008	-.015	.121	.030	.000	-.028	-.017	.009	-.024	.027	-								
13	.014	-.033	-.043	.053	-.015	-.046	-.069	-.064	.042	.015	-.022	.068	-							
14	-.086	-.073	.063	-.076	-.050	.075	.075	-.084	.018	-.062	-.005	-.049	.005	-						
15	-.005	-.043	.044	-.092	-.013	.024	.087	-.010	-.008	-.055	-.012	-.009	-.031	.074	-					
16	.021	.068	-.093	.029	.034	-.037	-.085	-.081	.037	.032	-.137	-.002	.101	-.047	-.040	-				
17	-.069	-.080	.035	-.062	-.053	-.021	.048	-.011	-.010	-.003	.004	-.029	-.006	.051	.063	-.064	-			
18	-.096	-.036	-.023	-.073	-.066	-.029	-.010	.016	-.038	-.003	.006	-.030	.032	.011	.028	-.035	.144	-		
19	.046	.033	-.098	.008	.027	-.015	-.064	-.086	-.033	.023	-.097	-.021	.023	-.011	-.026	.164	-.018	.011	-	
20	-.037	-.025	-.004	-.053	-.029	.015	-.011	.027	-.009	-.020	.058	-.027	.002	.020	-.028	-.026	-.016	.053	.017	-

Areas of Localised Strain for Model 3 (ESEM)

Items		Residual Correlation	MI	EPC	SEPC
1	2	.147	123.885	.196	.332
3	7	.112	57.996	.156	.263
4	12	.121	65.949	.158	.242
8	10	.107	36.658	.134	.220
8	11	.156	184.341	.249	.425
11	16	-.137	55.602	-.175	-.315
13	16	.101	28.853	.128	.261
16	19	.164	288.489	.296	.566
17	18	.144	90.215	.176	.258