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A Latent Factor Approach to The Saving Inventory – Revised: Congeneric Evaluation of Construct and Content Validity

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Abstract

Inconsistencies have been identified in the three-factor structure and item loadings of the most commonly used self-report hoarding screening tool, the Saving Inventory – Revised (SI-R), which assesses difficulty discarding, clutter and acquisition. The current study aimed to confirm the factor structure of the SI-R using congeneric modelling, and evaluate the construct and content validity of this measure. 139 participants with self-identified hoarding completed the SI-R. Congeneric structural equation modelling was then performed to validate the SI-R factor structure. The three-factor structure of the SI-R was confirmed as a valid, reliable and good fitting model. However, the difficulty discarding and clutter subscales were required to covary. The SI-R was confirmed as an appropriate screening tool for hoarding severity; however, revision of item wording may improve content validity. Future research could consider exploring the relationships between a range of hoarding-related constructs and the differential endorsement of SI-R subscales.

Highlights:

- The three-factor structure of the SI-R was confirmed as a valid, reliable, and good fitting model.
- Structural equation modelling indicated the difficulty discarding and clutter subscales should covary, suggesting these factors may be particularly central to hoarding phenomenology.
- Revision of item wording may improve content validity of the SI-R.

Introduction

Hoarding disorder (HD) is characterised by three overarching behavioural features: difficulty discarding possessions and debilitating clutter (American Psychiatric Association, 2013), with excessive acquiring also a common feature (Chou et al., 2018; Timpano et al., 2020). These three dimensions are reflected in the most commonly used self-report measure of hoarding severity, the Saving Inventory – Revised (SI-R; Frost et al., 2004). Despite its demonstrated utility (Melli et al., 2003; Tortella-Feliu et al., 2006), several factor analyses have indicated inconsistencies in factor structure and item loadings, suggesting the construct and content validity of the SI-R could be further improved (Coles et al., 2003; Lee et al., 2016; Raines et al., 2015). To optimise the accuracy of hoarding assessment and subsequent treatment, it may be useful to employ novel statistical methods of validating the dimensions of hoarding measured by the SI-R.

The SI-R (Frost et al., 2004) comprises three sub-factors measuring difficulty discarding, excessive acquisition and clutter. Several studies have confirmed this three-factor structure, but have often noted inconsistencies in construct validity. Table 1 details the findings of previous confirmatory factor analyses (CFA) conducted on the SI-R. Kalogeraki et al. (2020) found a three-factor solution with high internal consistency (α = .92) in their exploratory factor analysis (EFA) and CFA amongst a general population sample (N = 554, randomly divided into halves for each analysis); however, item 3 from the clutter subscale loaded similarly to the difficulty discarding factor, while acquisition item 19 loaded substantially higher to the clutter factor. Difficulty discarding items 16 and 17 also loaded strongly to the acquisition factor. Similarly, while Melli et al. (2013) also confirmed a three-factor structure in a general population sample (N = 473), acquisition item 22 loaded similarly to the clutter factor. Lee et al.'s (2016) CFA in a sample of 500 Chinese psychiatric outpatients with a mixed range of psychopathologies reduced the SI-R to 21-items. A first-order model with items loaded to Frost et al.'s three proposed intercorrelated factors produced the best fit; however, it was still considered poor fitting despite removing weakly loaded items. These results suggest that some SI-R items measure different aspects of hoarding across certain contexts.

With respect to content validity, Raines and colleagues' (2015) CFA yielded an alternative model, indicating a general hoarding construct comprising four orthogonal factors; clutter, difficulty discarding, and distress- and urge-related acquisition. Raines et al. concluded this model provided significant improvement over Frost et al.'s (2004) original model. In a subsequent systematic evaluation of self-report hoarding measures, Ong et al. (2021) concluded the SI-R was a valid measure of hoarding severity; however, it was identified that inconsistencies in structural validity may impede reliable representation of theoretical understandings of HD. Taking together the inconsistencies across previous analyses, it seems reasonable to suggest the construct and content validity of the SI-R may be further improved through more comprehensive statistical evaluation.

Table 1

Fit Indices of Existing CFA Studies of the SI-R

One avenue for improvement may be addressing the methodological weaknesses of prior studies. The majority of validation research on the SI-R has utilised exploratory and confirmatory factor analytic approaches (Kalegoraki et al., 2020; Lee et al., 2016; Melli et al., 2013; Tortella-Feliu et al., 2006); however, these methods are somewhat limited in their ability to deeply explore construct validity. EFA is primarily data driven and does not allow for a priori specification of factor structure, nor does it account for the unique error variance of each item (van Zyl & ten Klooster, 2022). CFA, the measurement component of SEM and exploratory structural equation modelling (ESEM), compensates for these limitations; allowing a more theoretical approach to justifying factor structure (van Zyl & ten Klooster, 2022). However, CFA model fit is often constrained by the assumptions of the measurement model utilised (Widhiarsoa & Kožený, 2013). For example, the parallel measurement model assumes all error variances are equal and each indicator contributes equally to the measurement of a latent construct, while the more common tau-equivalent model assumes equal factor loadings with differing error variances (Widhiarsoa & Kožený, 2013). However, the assumptions of these measurement models are often unrealistic, and may result in overly restrictive and idealised models (van Zyl & ten Klooster, 2022). In addition, the retention of indicators with low communality in estimations of shared variance may lead to poor construct validity (McNeish & Wolf, 2020; Watkins, 2018).

In a congeneric measurement model, factor loadings and error variances are free to vary (Widhiarsoa & Kožený, 2013). Congeneric modelling offers a more theoretical approach to the validation of latent constructs in a manner that is less restrictive than traditional CFA methods applied to the SI-R to date. Congeneric modelling assesses the extent to which several observable indicator variables measure a single latent factor, while allowing for indicators to make different levels of contribution to constructs (Webster & Fisher, 2001). In turn, each item receives a measure of individual error variance; maximising reliability (Graham, 2006; McNeish & Wolf, 2020). The theory-driven orientation of congeneric modelling allows for a greater degree of freedom for researchers to justify covarying or deleting items based on theory, without relying solely on statistical reasoning. It may also be useful for evaluating the conceptualisation of hoarding that underpins the SI-R, and for interrogating the measure's content validity to ensure all domains of the hoarding construct are captured comprehensively yet parsimoniously. As such, the current study aimed to validate the latent three-factor SI-R structure proposed by Frost et al. (2004) using congeneric modelling in a community sample of participants with clinically significant hoarding difficulties. In contrast to traditional CFA approaches, in which predetermined factors established in past studies are entered into the model without prior validation, the current study aimed to validate each individual SI-R construct (i.e., acquiring, difficulty discarding and clutter) in isolation as one-factor congeneric models before being entered into an overall three-factor model for SEM. It was hypothesised that the proposed three-factor model of the SI-R would be upheld, in line with overall findings of past literature; however, potential inconsistences in item loadings were anticipated.

Method

Participants

Participants were recruited using purposive sampling to target social media and community-based support groups attended by individuals experiencing difficulties with hoarding. These included the Anxiety Recovery Centre Victoria (ARCVic), peer-support groups hosted on platforms such as Facebook, and hoarding support communities who had previously consented to receiving invitations for research participation. Participants were required to be aged 18 and over, reside within Australia, and complete the questionnaire in English, but were not required to have received a formal diagnosis of HD. Participants were included in analyses if they surpassed the stipulated cut-off threshold for clinically significant hoarding (≥ 41 on SI-R; Steketee & Frost, 2014). As such, a final sample of 139 participants was obtained after data screening and cleaning, with a mean SI-R score of 52.93 (*SD* = 10.41) indicating mild to moderate hoarding severity, on average (Steketee & Frost, 2014). Participant ages ranged from 20 to 78 years (*M* = 43.58, *SD* = 14.45), and the majority (80.58%) identified as female. Table 2 displays the demographic information of the current sample.

Table 2

Participant Demographic Information (N = 139)

Materials and Procedure

The study protocol was approved by the human research ethics committee at the host institution. Participants were invited to complete a 30-minute online survey hosted on Qualtrics, and compensated for their participation with a digital gift-card to the value of $15 (AUD). The survey featured nine measures as part of a larger research project; however, for the purposes of the current study only the relevant measures are described. Upon providing informed consent to participate in the study, participants provided general demographic information, including biological sex, age, relationship status, highest level of education, current work status and country of birth. Hoarding severity was measured using the SI-R (Frost et al., 2004). The SI-R comprises 23 items scored on a Likert scale ranging from 0 (‘not at all’) to 4 (‘very much so’), with higher scores reflecting greater endorsement of each statement (see Appendix A). The SI-R assesses three core features of hoarding disorder: acquisition, clutter and difficulty discarding. Several studies have reported excellent internal consistency for the SI-R (α = .96, Ayers et al., 2017; α = .92, Frost et al., 2004; α = .93, Kellman-McFarlane et al., 2019). Convergent validity was also found to be consistently good, with high correlations reported with several established hoarding measures including the Saving Cognitions Inventory (SCI; Steketee et al., 2003), Hoarding Rating Scale (Tolin et al., 2010), and Clutter Image Rating (CIR; Frost et al., 2008).

Statistical Analyses

Analyses were carried out using The Statistical Package for Social Sciences (SPSS, Version 27.0; IBM, 2020) and Analysis of Moment Structures (AMOS, Version 26.0; Arbuckle, 2019). Cases with missing values were removed to ensure the viability of the data for structural equation modelling (SEM). All assumptions were checked, including removal of multivariate outliers. Regarding sample size, a sample of 200 participants has been identified as optimal for SEM (Boomsma, 1982; Marsh et al., 1999). However, several studies suggest 100 participants may be sufficient as a minimum to secure unbiased estimates (Boomsma, 1982; Brown, 1989). Marsh et al. (1999) suggest a small sample size could be compensated by a higher number of indicators, with four items considered sufficient for 100 participants. The number of items for each SI-R subscale range from seven to nine. Regarding the ratio of cases to items, Bentler and Chou (1987) argue five participants per indicator to be sufficient, particularly if the number of indicators is high. As such, the current sample size (N = 139) was considered sufficient. Separate reliability analyses were conducted for each individual subscale of the SI-R in accordance with Frost et al.'s (2004) proposed factor structure; difficulty discarding (7 items), acquisition (7 items) and clutter (9 items). Low inter-item correlations (below 0.3) were then deleted per subscale, including the removal of one difficulty discarding item (item 17: 'How much control do you have over your urges to save possessions?') and one acquisition item (item 22: 'To what extent has your saving or compulsive buying resulted in financial difficulties for you?'). Each factor was then entered individually into AMOS for congeneric modelling to assess the extent to which each construct behind the SI-R subscales could be measured by the corresponding factor items. The standardised regression weights for each item within the three factors were used to calculate the construct reliability of each individual subscale and overall SI-R using coefficient H – a measure of maximal reliability which allows for differential item contributions to the reliability of the overall scale (McNeish, 2018). Coefficient H provides an accurate estimation of reliability of multidimensional measures, while Cronbach's α requires all error terms to be uncorrelated and scale indicators to be tau-equivalent, potentially over- or under-estimating the reliability of measures which violate these assumptions (Brunner & Süß, 2005). Given the nature of congeneric modelling, which allows for differential contribution of items, as well as the potential for error term covariance, utilising Coefficient H was considered appropriate. Coefficient H is considered to indicate adequate reliability when it exceeds 0.70 (Hancock & Mueller, 2001). To ensure high individual item reliabilities when interpreting the results of congeneric modelling, all squared multiple correlations were required to surpass the 0.5 threshold. Finally, all three factors were entered into AMOS for SEM to validate the proposed three-factor structure. Data was then transferred to SPSS to calculate the internal consistency reliability for the overall SI-R.

Results

SI-R Excessive Acquisition Factor

The congeneric model comprising items 5, 8, 9, 10, 15 and 19 suggested poor fit, χ^2 = 26.635, with 9 *df* (*p* = .002), RMSEA = .119, AGFI = .846, GFI = .934, CFI = .867, IFI = .872, NFI = .819. Modification indices (M.I.) suggested the error for items 5 (‘How distressed or uncomfortable would you feel if you could not acquire something you wanted?’) and 10 (‘How much control do you have over your urges to acquire possessions?’) be covaried (M.I. = 9.806, Par Change = .172). The subsequent model suggested better fit, χ^2 = 14.399 with 8 *df* (*p* = .072). RMSEA = .076, AGFI = .913, GFI = .967, CFI = .952, IFI = .954, NFI = .902. However, M.I. suggested the error for items 10 (‘How much control do you have over your urges to acquire possessions?’) and 19 (‘How upset or distressed do you feel about your acquiring habits?’) should covary (M.I. = 7.173, Par Change = .174). The following model suggested good fit, χ^2 = 6.828, with 7 *df* (*p* =.447), RMSEA < .001, AGFI = .951, GFI = .984, CFI = 1.000, IFI = 1.001, NFI = .954. M.I. did not suggest any further errors be covaried. As congeneric modelling is relatively intolerant of double covariance, item 10 was removed, given its covariance with items 5 and 19. The final model suggested good fit, χ^2 = 6.164, with 5 *df* (*p* =.291), RMSEA < .041, AGFI = .947, GFI = .982, CFI = .988, IFI = .988, NFI = .941. Figure 1 represents the final structure of the acquisition subscale, with the column of values on the far left reflecting the standardised regression weights for each indicator, and the values above each item representing the squared multiple correlations (item reliabilities) for each item.

Figure 1

Final Congeneric Model: Acquisition

Regression weights for all indicators were significant (p < .001); however, only item 15 produced squared multiple correlations above the 0.5 threshold. Coefficient *H* for the final acquisition model was .727, suggesting the latent construct of acquisition was good fitting, reliable and valid.

SI-R Difficulty Discarding Factor

The initial difficulty discarding model, comprising items 1, 2, 4, 11, 16 and 23, suggested poor fit, χ^2 = 27.399, with 9 *df* (p = .001), RMSEA = .122, AGFI = .856, GFI = .938, CFI = .882, IFI = .887, NFI = .840. M.I. suggested the errors of items 11 ('How often do you decide to keep things you do not need and have little space for?') and 16 ('How strong is your urge to save something you know you may never use?') should covary (M.I. = 9.171, Par Change = .175). The subsequent model indicated poor fit, χ^2 = 16.950 with 8 *df* (p =.031). RMSEA = .090, AGFI = .901, GFI = .962, CFI = .943, IFI = .945, NF I= .901. M.I. did not suggest any further errors needed to be covaried. As such, the least reliable item was removed – item 11 ('How often do you decide to keep things you do not need and have little space for?'). The following model indicated better fit, χ^2 = 11.143 with 5 *df* (p = .049). RMSEA = .094, AGFI = .909, GFI = .970, CFI = .951, IFI = .953, NFI = .917. M.I. suggested the error for items 2 ('How distressing do you find the task of throwing things away?') and 16 ('How strong is your urge to save something you know you may never use?') be covaried (M.I. = 5.572, Par Change = .160). The final congeneric model suggested good fit, χ^2 = 4.989 with 4 *df* (p = .288). RMSEA = .042, AGFI = .945, GFI = .985, CFI = .992, IFI = .992, NFI = .963. Figure 2 represents the final structure of the model.

Figure 2

Final Congeneric Model: Difficulty Discarding

While regression weights for all indicators were significant ($p < .001$), squared multiple correlations indicated only item 1 ('To what extent do you have difficulty throwing things away?') surpassed the 0.5 threshold. Coefficient *H* for the overall difficulty discarding subscale was .895, suggesting the model for the latent construct of difficulty discarding was good fitting, reliable and valid.

SI-R Clutter Factor

The initial congeneric model, comprising items 3, 6, 7, 12, 13, 14, 18, 20 and 21, suggested poor fit, χ^2 = 61.173 with 27 *df* ($p < .001$), RMSEA = .096, AGFI = .857, GFI = .914, CFI = .886, IFI = .889, NFI = .818. M.I. recommended errors for items 18 ('How much of your home is difficult to walk through because of clutter?') and 20 ('To what extent does the clutter in your home prevent you from using parts of your home for their intended purpose?') should covary (M.I. = 7.426, Par Change = .188). The model still indicated poor fit, χ^2 = 53.304 with 26 *df* ($p = .001$), RMSEA = .087, AGFI = .872, GFI = .926, CFI = .909, IFI = .912, NFI = .841. M.I. suggested errors for items 3 ('To what extent do you have so many things that your room(s) are cluttered?') and 18 ('How much of your home is difficult to walk through because of clutter?') should covary (M.I. = 4.088, Par Change = .130). The subsequent model indicated poor fit, χ^2 = 48.947 with 25 *df* ($p = .003$), RMSEA = .083, AGFI = .873, GFI = .929, CFI = .920, IFI = .923, NFI = .854. M.I. suggested errors for items 3 ('To what extent do you have so many things that your room(s) are cluttered?') and 21 ('To what extent do you feel unable to control the clutter in your home?') be covaried (M.I. = 4.796, Par Change = .122). The subsequent model indicated poor fit, χ^2 = 42.854 with 24 *df* ($p = .010$), RMSEA = .075, AGFI = .885, GFI = .938, CFI = .937, IFI = .940, NFI = .872. M.I. indicated the errors for items 13 ('To what extent does the clutter in your home cause you distress?')

and 21 (‘To what extent do you feel unable to control the clutter in your home?’) be covaried (M.I. = 4.192, Par Change = .112). The following model indicated poor fit, $\chi^2 = 38.102$ with 23 *df* ($p = .025$), RMSEA = .069, AGFI = .891, GFI = .944, CFI = .950, IFI = .952, NFI = .887. As such, items 18 (‘How much of your home is difficult to walk through because of clutter?’) and 21 (‘To what extent do you feel unable to control the clutter in your home?’) were removed from analyses to avoid double covariance. The following model was good fitting, $\chi^2 = 23.124$ with 14 *df* ($p = .058$), RMSEA = .069, AGFI = .912, GFI = .956, CFI = .954, IFI = .955, NFI = .894. However, M.I. indicated the errors of items 3 (‘To what extent do you have so many things that your room(s) are cluttered?’) and 20 (‘To what extent does the clutter in your home prevent you from using parts of your home for their intended purpose?’) should covary (M.I. = 4.185, Par Change = .132). The final congeneric clutter model demonstrated good fit, $\chi^2 = 18.374$ with 13 *df* ($p = .144$), RMSEA = .055, AGFI = .923, GFI = .964, CFI = .973, IFI = .974, NFI = .915. M.I. suggested no further covariances. Figure 3 displays the factor structure of the final clutter model.

Figure 3

Final Congeneric Model: Clutter

Regression weights for all indicators were significant ($p < .001$). No squared multiple correlations surpassed the 0.5 threshold. However, coefficient *H* for the overall clutter scale was .789, indicating the latent clutter construct was a good fitting, reliable and valid model. Table 3 contains the final items and reliability coefficients for each SI-R factor, while Table 4 displays the bivariate correlations between all SI-R items.

Table 3

Acquisition, Difficulty Discarding and Clutter: Item Structures and Factor Reliabilities

Table 4

Bivariate Correlations Between SI-R Items

SI-R as a three-factor model

To determine the validity of the SI-R with the addition of the re-confirmed factors, all three subscales were entered into AMOS concurrently for SEM to assess the viability of a three-factor solution. The initial model indicated poor fit, $\chi^2 = 7.251$ with 2 *df* ($p = .027$), RMSEA = .138, AGFI = .893, GFI = .964, CFI = .830, IFI = .835, NFI = .786. M.I. suggested that errors of the difficulty discarding and clutter factors should covary (M.I. = 5.506, Par Change = .090). The subsequent model indicated good fit, $\chi^2 = .120$ with 1 *df* ($p = .729$), RMSEA = < .001, AGFI = .997, GFI = .999, CFI = 1.000, IFI = 1.027, NFI = .996. M.I. suggested no further items be covaried. Figure 4 displays the factor structure of the final SI-R model.

Figure 4

Path Diagram: Three-Factor SI-R Model

While the squared multiple correlations for the final model all fell below the 0.5 threshold, the 17-item SI-R displayed good internal consistency reliability ($\alpha = .822$). While this falls below reliability values reported for the full scale in previous studies (e.g., Ayers et al., 2017; Frost et al., 2004; Kellman-McFarlane et al., 2019), this may be attributable to the reduced number of questionnaire items.

Discussion

The current study aimed to validate the latent three-factor SI-R structure proposed by Frost et al. (2004) using congeneric modelling in a community sample of participants with clinically significant hoarding difficulties. To the best of our knowledge, this is the first study to utilise congeneric modelling to evaluate the construct and content validity of this measure. Overall, results provided support for the three-factor structure of the SI-R. However, taking these results together with previous findings, some revision of individual items may be warranted.

The final compulsive acquisition subscale in the current study consisted of five items after removing items 10 ('How much control do you have over your urges to acquire possessions?') for double covariance and 22 ('To what extent has your saving or compulsive buying resulted in financial difficulties for you?') for low inter-item correlations. This is consistent with previous studies, for example, Melli et al. (2013) also found item 22 to be problematic, concurrently loading to the clutter subscale in their sub-clinical sample of 473 participants. Similarly in line with past research, the weakest loading acquisition item in the current study was item 19 ('How upset or distressed do you feel about your acquiring habits?'). Kalogeraki et al. (2020) also found that item 19 loaded unexpectedly to the clutter factor in their sub-clinical sample. This may provide support for Coles et al.'s (2003) proposed interference/distress factor, considering the emergent themes of financial impairment (item 22) and acquiring-related distress (item 19) amongst these deleted and weakly loaded items in the current analyses.

In contrast, the three highest loading acquisition items in the current study refer to the urge to acquire and acting upon these urges – item 15 ('How often do you actually buy (or acquire for free) things for which you have no immediate use or need?'); item 8 ('How often do you feel compelled to acquire something you see (e.g., when shopping or offered free things)?'); item 9 ('How strong is your urge to buy or acquire free things for which you have no immediate use?'). This echoes Tortella-Feliu et al.'s findings (2006), who also reported these three items as most strongly loaded. The consistent high endorsement of urge-related items across the current and previous studies may support Raines et al.'s (2015) proposed urge-specific acquisition factor, potentially indicating the role of impulsivity in acquiring behaviours (e.g., Frost et al., 2011; Timpano et al., 2013). Overall, the construct of compulsive acquisition was validated in the current study, displaying acceptable construct reliability. The current findings are consistent with previous literature regarding the identification of loading issues with item 22 (‘To what extent has your saving or compulsive buying resulted in financial difficulties for you?’), potentially due to the subclinical status of both the present and past samples (e.g., Melli et al., 2013).

The final structure of the difficulty discarding subscale was similarly reduced to five items after the deletion of item 17 (‘How much control do you have over your urges to save possessions?’) for low inter-item correlations and item 11 (‘How often do you decide to keep things you do not need and have little space for?’) for low reliability. The errors of items 2 (‘How distressing do you find the task of throwing things away?’) and 16 (‘How strong is your urge to save something you know you may never use?’) should be covaried as the desire to save and distress when discarding seem conceptually similar and therefore likely to covary theoretically (Timpano et al., 2011). Item 16 also produced the weakest loading and lowest reliability in the current study. This is consistent with the findings of past studies; Kalogeraki et al. (2020) reported that item 16 loaded onto the acquisition subscale as opposed to difficulty discarding. In light of these findings, it is possible that the use of the term “urge” in item 16 relates more strongly to the compulsion to acquire than the reluctance to discard or the desire to save possessions. This association is further evidenced by the strong endorsement of urge-related acquisition items 15, 8, and 9. In addition, when the poor loading of saving-related item 16 is considered in conjunction with the deletion of the control-related item 17 (‘How much control do you have over your urges to save possessions?’) for low inter-item correlations, this may indicate the existence of an underlying construct potentially related to the strength of one’s desire to save and a need for control over one’s possessions or environment. This may reflect Raines et al.’s (2014) findings that low perceived control over environmental threats was significantly associated with greater difficulty discarding, supporting existing theories that diminished control over aversive events may contribute to the development and maintenance of saving behaviours in particular. Overall, the construct of difficulty discarding demonstrated strong construct reliability; however, the poor loading of item 16 and deletion of item 17 may indicate a need to replace the term “urge” in relation to saving behaviours.

Lastly, the clutter subscale in the current study was reduced to seven items, following the removal of items 18 (‘How much of your home is difficult to walk through because of clutter?’) and 21 (‘To what extent do you feel unable to control the clutter in your home?’) for double covariance. Errors for items 3 (‘To what extent do you have so many things that your room(s) are cluttered?’) and 20 (‘To what extent does the clutter in your home prevent you from using parts of your home for their intended purpose?’) were covaried. This covariance may reflect a relationship between the extent of one’s clutter and the resultant functional impairment, that is, one can no longer use rooms for their intended purpose. These results complement Kalogeraki et al.’s (2020) findings that item 3 was the weakest loading clutter item, and loaded more strongly to the difficulty discarding subscale. While the weakest loaded clutter item in the current study was item 20, the covariance between this item and item 3 may support Coles et al.’s (2003) proposed interference/distress subscale, which includes the functional impairment associated with one’s hoarding behaviours. Overall, the final clutter subscale was validated, displaying acceptable construct reliability.

When reflecting on the items removed across all three subscales, item 10 from acquisition, 17 from difficulty discarding, and 21 from the clutter subscale all reference feelings of control. Using bivariate correlations, these items were found to be uncorrelated ($p > .05$) and indicated divergent validity. However, in Lee et al.’s (2016) validation of the SI-R amongst Chinese psychiatric outpatients, the control-related items 10 and 17 were also removed. While this was attributed to the differential emphasis of self-control in collectivist cultures, it may indicate a pattern of insubstantial measurement of control as a construct of relevance to hoarding phenomenology, likely due to the inclusion of only one control-related item per subscale. If assessment of control is to remain in the SI-R, the exploration of its relationship to each subscale and contribution to HD symptom maintenance is recommended.

In line with findings of past literature (Kalogeraki et al., 2020; Melli et al., 2013; Tortella-Feliu et al., 2006), the three-factor solution of the SI-R, proposed by Frost et al. (2004), was confirmed in the current study. The RMSEA and CFI indices in particular indicated improved fit when compared with previous SI-R validation studies (see Table 1). While the acquisition factor was upheld independently, the difficulty discarding and clutter factors were covaried. This aligns partially with past research that found all three SI-R subscales to be moderately to highly correlated (Frost et al., 2004; Kalogeraki et al., 2020; Lee et al., 2016; Melli et al., 2013). More importantly, these results mirror Timpano et al.'s (2020) findings that difficulty discarding and clutter may be more central to HD, potentially validating the DSM-5 classification of acquiring as a specifier, rather than a core symptom. The relationship between difficulty discarding and clutter may suggest these symptoms are indicative of a key process of hoarding behaviours, in that the more difficulty discarding one experiences, the more clutter is likely to accumulate. Despite the retention of clutter as the strongest loaded factor, it was still less reliable than acquisition, which contained fewer items. This may suggest that the clutter factor's poor item reliabilities and content validity was only compensated for by its greater number of items and subsequent higher loading. This reiterates the need for a more accurate and parsimonious representation of hoarding phenomenology in the SI-R. In addition, future amendments to the wording of items may be beneficial to reduce redundance or repetition and comprehensively measure the relationship between control and hoarding.

Despite Ong et al.'s (2021) conclusions that research has demonstrated sufficient construct validity of the SI-R, the current findings suggest this measure may lack adequate content validity. When aspects of a latent construct are unassessed, or irrelevant items are included, a scale's content validity is threatened. This could potentially explain the poor individual items reliabilities identified, the covariance between multiple items and deletion of all discriminant control-related items. This may suggest the need for future refinement of item phrasing to adequately capture the complexity of hoarding phenomenology. Future research could consider exploring related psychological constructs that may facilitate accurate conceptualisation and screening of hoarding severity, such as the role of insight as a HD specifier, or key associated cognitions, for example, as measured by the SCI (Slyne & Tolin, 2014; Steketee et al., 2003). The validation of acquisition as a stand-alone factor, with strongly endorsed urge-related items, may reflect research linking hoarding-related acquiring with impulse-control disorders (Frost et al., 2011; Timpano et al., 2013). In light of this, and given each subscale carries a unique cut-off score (Steketee & Frost, 2014), SI-R subscale scores should likely be interpreted alongside the total SI-R score. Further exploration of associated constructs and their relationship to hoarding severity may provide clinicians with guidance regarding potential predisposing or perpetuating factors underlying differences in subscale endorsement.

It is important to note that the current data were collected in 2020 during the COVID-19 pandemic, which may have exacerbated or precipitated the onset of hoarding and related acquiring behaviours. David et al. (2021), investigating the relationships between panic buying and hoarding behaviours in an Australian sample, found panic buying was moderately positively related to all three SI-R subscales, with excessive acquisition being uniquely significantly predicted by observing others panic buy at the beginning of the pandemic. This may explain the emergence of acquisition as a strong, stand-alone factor during SEM, as individuals with, or even without, existing hoarding difficulties may have felt compelled to acquire to a greater extent. It was also found that intolerance to uncertainty (IU) – the behavioural avoidance of ambiguous situations that are perceived as threatening – uniquely predicted clutter severity (Carleton et al., 2007; David et al., 2021). Future research could consider the relationships between constructs like IU and hoarding severity during the COVID-19 pandemic.

There are some further limitations to the current study, acknowledged herein. The online survey used in the current study did not contain any checks to ensure participants were paying attention, a limitation that should be addressed in future research. Methodologically, given the SI-R is a self-report tool, the accuracy of hoarding severity is dependent on participants' levels of insight, as this was not assessed in the current study. Future research could consider including a more objective measure of hoarding severity, such as the CIR (Frost et al., 2008) to ensure screening accuracy. Further research should also assess the convergent validity of the 17-item SI-R with putatively similar hoarding measures such as the SCI (Steketee et al., 2003) and Hoarding Rating Scale (Tolin et al., 2010). Similarly, as surveys were completed online and no additional diagnostic information was collected, it could not be verified that participants' symptoms met diagnostic criteria for HD; however, participants were recruited through community-based and online peer-support groups for hoarding difficulties, and only those endorsing clinically significant symptoms were included (Steketee & Frost, 2014). The decision to select cases with a global SI-R score ≥ 41 may have limited the utility of the current findings, given Kellman-McFarlane et al.'s (2019) recommendations of an alternative cut-off score for participants older than 60. While the implication is that some older participants with clinically significant hoarding may have been excluded from this study, pragmatically, this was necessary to avoid sacrificing measure specificity. Future research should consider replicating the current study in an older cohort.

It is also acknowledged that the current sample displayed a relatively high rates of employed persons (76.3%) and people in a relationship (66.9%) compared to typical clinical samples (e.g., Ayers et al., 2018; Grisham et al., 2018). This may indicate a lower level of interpersonal and occupational impairment overall, as would be expected for a sub-clinical sample. Additionally, the majority of participants in the current study identified as female (80.58%), while a previous meta-analysis found an equal prevalence of hoarding behaviours across binary genders (Postlethwaite et al., 2019). Future research should endeavour to replicate these findings in a more gender balanced sample. It is recommended that the utility of the proposed 17-item scale is further validated in more diverse, clinically typical samples, and across both clinical and subclinical populations prior to being applied in standard practice. However, it may still be useful for clinicians to remain mindful of the potential complexities of HD that may not be captured adequately by the 23-item SI-R.

In sum, through the use of congeneric modelling and an exploratory, theory-driven approach, the established three-factor model of the SI-R was confirmed as a valid hoarding severity screening tool. Further amendments to the wording of items may be necessary to improve content validity. The covariance between difficulty discarding and clutter factors supports the categorisation of acquisition as a specifier, as per the DSM-5 conceptualisation of HD, and aligns with the recent findings identified in Timpano et al.'s (2020) network analysis. However, further research is required to explore the relationships between related psychological constructs and the modified SI-R factors supported in the current study to determine their convergent and discriminant validity in more diverse samples.

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Figure 1

Final Congeneric Model: Acquisition

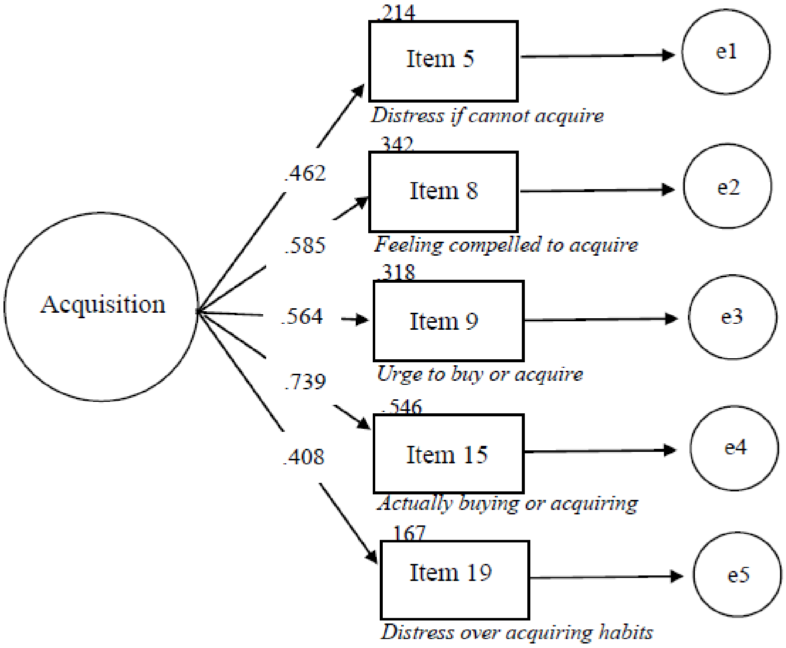

Fig. 1 *From left to right, the first circle represents the latent construct of acquisition. The values overlaying the first set of arrows represent the standardised regression weights for each item. Each rectangle represents the final items included in the subscale, with the squared multiple correlations and item wordings above and below the items. Finally, the individual error variance for each item is represented by the final column of circles*

Figure 2

Final Congeneric Model: Difficulty Discarding

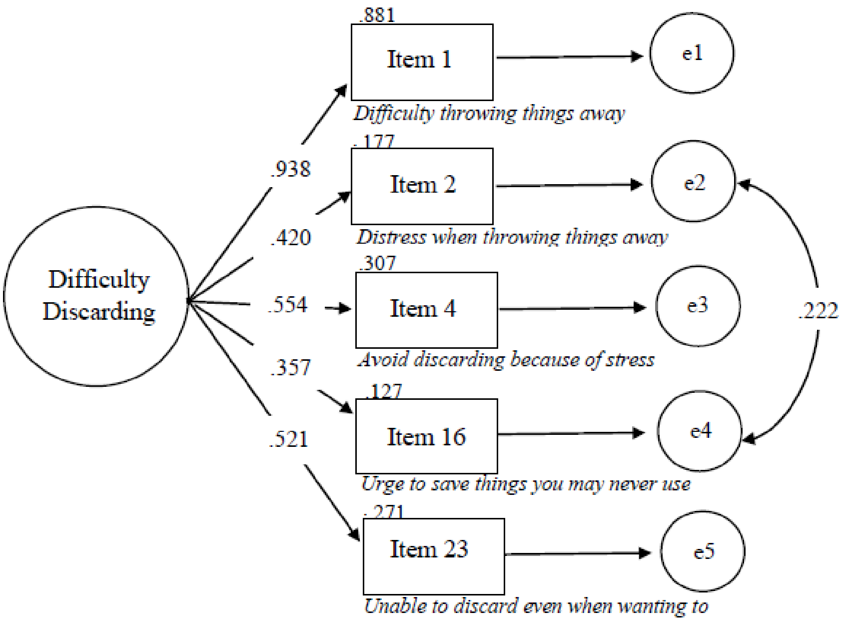

Fig. 2 *From left to right, the first circle represents the latent construct of difficulty discarding. The values overlaying the first set of arrows represent the standardised regression weights for each item. Each rectangle represents the final items included in the subscale, with the squared multiple correlations and item wordings above and below the items. The individual error variance for each item is represented by the final column of circles. Finally, the curved line on the far right represents the covariance between the errors of items 2 and 16, correlated at .222*

Final Congeneric Model: Clutter

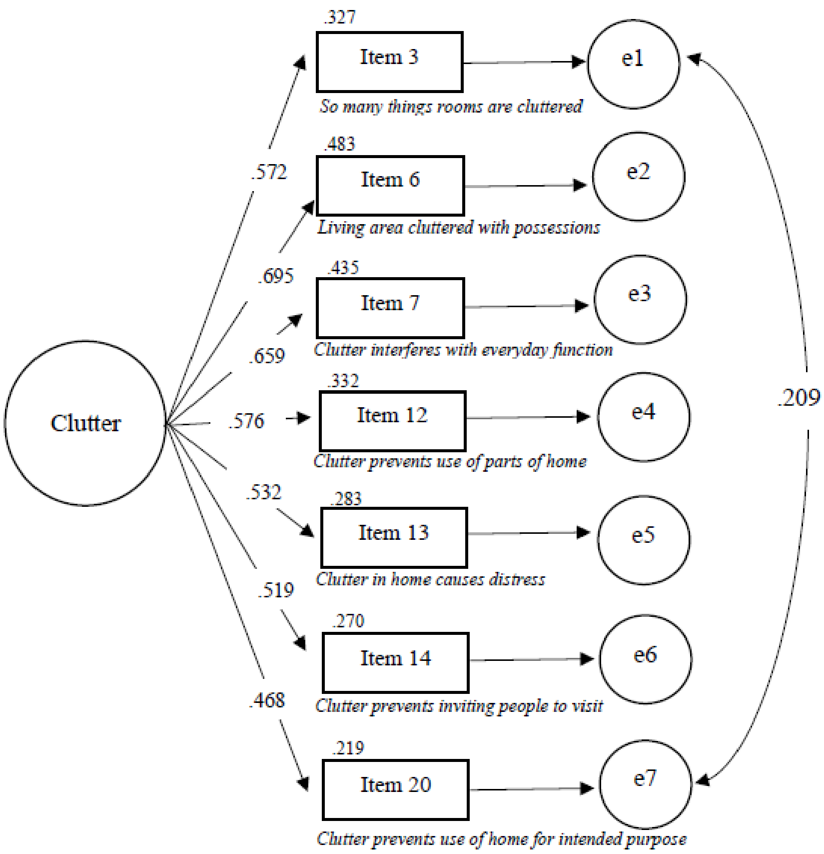

Fig. 3 *From left to right, the first circle represents the latent construct of clutter. The values overlaying the first set of arrows represent the standardised regression weights for each item. Each rectangle represents the final items included in the subscale, with the squared multiple correlations and item wordings above and below the items. The individual error variance for each item is represented by the final column of circles. Finally, the curved line on the far right represents the covariance between the errors of items 3 and 20, correlated at .209*

Figure 4

Path Diagram: Three-Factor SI-R Model

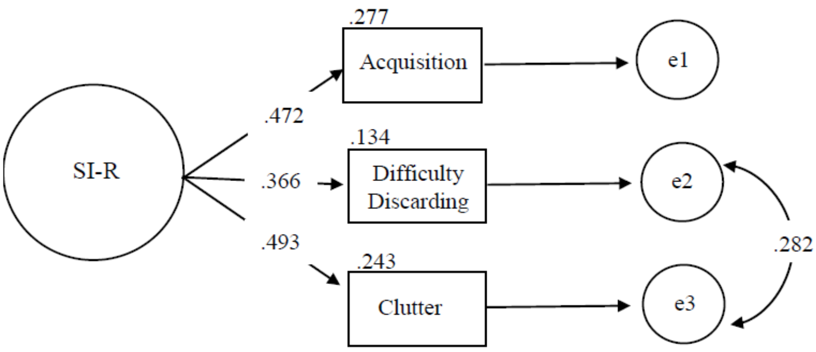

Fig. 4 *From left to right, the largest circle represents the latent construct underpinning the SI-R, with each value overlaying the first column of arrows representing the standardised regression weights for each factor. Each rectangle represents the factors included in the SI-R, including the squared multiple correlations above each factor. The final column of circles represents the individual error variance of each factor. The curved line on the far right represents the covariance between the errors of the difficulty discarding and clutter factors, correlated at .282*

Table 1

Fit Indices of Existing CFA Studies of the SI-R

	Clinical hoarding status	Best fitting model	χ^2	RMSEA	CFI	TLI
Ayers et al. (2017)	Clinical	First-order three factor model	529.986	0.092	0.832	Not reported
Kalogeraki et al. (2020)	Sub-clinical	First-order three-factor model	607.20	0.071	0.89	0.87
Lee et al. (2016)	Sub-clinical	First-order, three-factor model	1026.02	0.095	0.86	0.85
Melli et al. (2013)	Sub-clinical	Three-correlated-factor model	812.38	0.076	0.95	0.97
Raines et al. (2015)	Sub-clinical	Bifactor: Four-factor model	92.49	0.05	0.95	Not reported
Tortella-Feliu et al. (2006)	Sub-clinical	First-order three-factor model	613.298	0.06	.87	.85

Note. χ^2 = chi square. RMSEA = root mean square error of approximation. CFI = comparative fit index. TLI = Tucker-Lewis index.

Table 2

Participant Demographic Information (N = 139)

	N	%
Sex		
Female	112	80.58
Male	28	19.42
Relationship status		
Single	32	23.0
In relationship	20	14.4
Married	73	52.5
Divorced	11	7.9
Widowed	3	2.2
Work status		
Full-time employed	58	41.7
Part-time employed	35	25.2
Casually employed	13	9.4
Full-time student	3	2.2
Unemployed	30	21.6
Highest level of education		
Primary school	1	0.7
Secondary school	25	18
TAFE qualification	35	25.2
Undergraduate degree	62	44.6
Postgraduate degree	16	11.5
Country of birth		
Australia	130	93.5
New Zealand	2	1.4
England	2	1.4
Fiji	1	0.7
Iran	1	0.7
Malaysia	1	0.7
Saudi Arabia	1	0.7
Venezuela	1	0.7

Table 3

Acquisition, Difficulty Discarding and Clutter: Item Structures and Factor Reliabilities

	Items	*H*
Acquisition		.727
	Item 5: How distressed or uncomfortable would you feel if you could not acquire something you wanted?	
	Item 8: How often do you feel compelled to acquire something you see?	
	Item 9: How strong is your urge to buy or acquire free things for which you have no immediate use?	
	Item 15: How often do you actually buy (or acquire for free) things for which you have no immediate use or need?	
	Item 19: How upset or distressed do you feel about your acquiring habits?	
Difficulty Discarding		.895
	Item 1: To what extent do you have difficulty throwing things away?	
	Item 2: How distressing do you find the task of throwing things away?	
	Item 4: How often do you avoid trying to discard possessions because it is too stressful or time-consuming?	
	Item 16: How strong is your urge to save something you know you may never use?	
	Item 23: How often are you unable to discard a possession you would like to get rid of?	
Clutter		.789
	Item 3: To what extent do you have so many things that your room(s) are cluttered?	
	Item 6: How much of the living area in your home is cluttered with possessions?	
	Item 7: How much does the clutter in your home interfere with your social, work or everyday functioning?	
	Item 12: To what extent does clutter prevent you from using parts of your home?	
	Item 13: To what extent does the clutter in your home cause you distress?	
	Item 14: How frequently does the clutter in your home prevent you from inviting people to visit?	
	Item 20: To what extent does the clutter in your home prevent you from using parts of your home for their intended purpose?	

Note. H represents the construct reliability of each SI-R subscale.

Table 4

Bivariate Correlations Between SI-R Items

	1(D)	2(D)	3(C)	4(D)	5(A)	6(C)	7(C)	8(A)	9(A)	**10(A)**	**11(D)**	12(C)	13(C)	14(C)	15(A)	16(D)	**17(D)**	**18(C)**	19(A)	20(C)	**21(C)**	**22(A)**	23(D)
1(D)	1	.39**	.46**	.52**	-.26**	.16	.27**	.10	.12	.01	.27**	.11	.33**	.26**	.10	.33**	.18*	.14	.26**	.40**	.46**	-.06	.49**
2(D)		1	.20*	.28**	.18*	.13	.20*	.09	.27**	.19*	.29**	.29**	.31**	.08	.05	.33**	.35**	.17*	.27**	.17*	.27**	-.09	.20*
3(C)			1	.41**	-.10	.40**	.29**	.19*	.20*	.03	.31**	.38**	.28**	.37**	.19*	.24*	.05	.41**	.26**	.42**	.48**	.06	.24**
4(D)				1	-.07	.12	.16*	.25**	.14	.09	.29**	.07	.34**	.28**	.29**	.16*	.09	.10	.19*	.27**	.47**	-.06	.23**
5(A)					1	-.10	-.02	.20*	.27**	.44**	-.01	.02	.09	.02	.34**	.38**	.12	-.02	.22**	.30**	.01	.24**	-.13
6(C)						1	.45**	.05	.01	-.04	.16	.45**	.34**	.38**	.02	-.05	.10	.30**	.22**	.24**	.29**	-.10	-.11
7(C)							1	.21*	.18*	.11	.24**	.37**	.43**	.35**	.05	.10	.15	.27**	.42**	.33**	.36**	.02	.11
8(A)								1	.31**	.19*	.25**	.05	.17*	.14	.47**	.22**	.05	.09	.22**	.22**	.13	.18*	.09
9(A)									1	.15	.33**	.22**	.20*	.03	.41**	.36**	.18*	.20*	.27**	.20*	.15	-.02	.08
10(A)										1	.08	-.01	.13	.07	.24**	.135	.01	.14	.37**	.04	.01	.27**	.03
11(D)											1	.24**	.17*	.26**	.14	.40**	.25**	.10	.15	.19*	.40**	-.12	.24**
12(C)												1	.25**	.22**	.04	.11	.07	.31**	.26**	.29**	.33**	.03	.07
13(C)													1	.22*	.15	.14	.20*	.24**	.39**	.33**	.42**	-.08	.22**
14(C)														1	.03	.06	-.02	.12	.19*	.26**	.42**	.01	.19*
15(A)															1	.37**	.02	.16	.24**	.24**	.16	.18*	.11
16(D)																1	.01	.08	.16	.18*	.27**	.01	.29**
17(D)																	1	.14	.11	.08	.09	-.16*	.10
18(C)																		1	.36**	.42**	.14	.26**	.14
19(A)																			1	.29**	.35**	.13	.10
20(C)																				1	.31**	.19*	.29**
21(C)																					1	-.06	.29**
22(A)																						1	-.04
23(D)																							1

* Correlation significant at $p < .05$

** Correlation significant at $p < .01$

Note. (A) = items from acquisition subscale; (D) = items from difficulty discarding subscale; (C) = items from clutter subscale

Emboldened items removed: 10(A), 11(D), 17(D), 18(C), 21(C), 22(A)