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Introducing the unified measure of university mattering: Instrument development and evidence of the structural integrity of scores for transfer and native students

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Introducing the Unified Measure of University Mattering: Instrument Development and Evidence of the Structural Integrity of Scores for Transfer and Native Students

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Abstract

The psychological construct *university mattering* is defined as the feeling that one makes a difference and is significant to his or her university's community. University mattering emerged from the theory of general mattering, which describes mattering as a complex construct consisting of the facets *awareness*, *importance*, *ego-extension* and *reliance*. The Revised University Mattering Scale (RUMS), created by writing items to represent these facets, was developed for use in the current study.

The purpose of this study was twofold. First, the model-data fit of the RUMS was evaluated using confirmatory factor analysis (CFA). Five a priori models were tested using two independent samples: (a) a one-factor model, (b) a four-factor model, (c) a higher-order model, (d) a bifactor model, and (e) an incomplete bifactor model. The incomplete bifactor model had the best overall fit. When investigating unstandardized factor pattern coefficients, all items loaded strongly to the general mattering factor; thus, providing empirical support for one underlying construct. Therefore, items that cross-loaded to both the general mattering factor and their corresponding specific factor were removed. In addition, items associated with large correlation residuals were removed. As a result, 19 items were removed. The resulting 15-item measure fit a one-factor structure well and was named the Unified Measure of University Mattering-15 (UMUM-15).

The second purpose of this study was to assess the measurement invariance of the UMUM-15. Of particular interest to this study was the comparison of transfer student scores on university mattering to scores of native students (i.e., students who began at the institution with no transfer credit). Tests of measurement invariance began with testing

configural invariance, followed by metric invariance, and finally, scalar invariance. With the establishment of configural, metric, and scalar invariance, latent mean differences between transfer and native students were interpreted. As expected, transfer students had lower latent means than native students on university mattering. Not only did this study provide strong construct validity evidence for the UMUM-15, but this study also provided evidence for the need to reconceptualize our understanding of university mattering.

CHAPTER ONE

Introduction

“I'm just trying to matter”–June Carter Cash

In Reese Witherspoon’s acceptance speech for best actress during the 2006 Academy Awards, she referenced June Carter Cash, stating, “People used to ask June how she was doing. And she used to say, ‘I'm just trying to matter.’” Ms. Witherspoon went on to say she understood what Cash meant, and she too was “just trying to matter, live a good life, and make work that means something to somebody.” Many of us can relate to these sentiments; the simple desire to live a life that matters. Mattering is defined as feelings of significance, importance, and making a difference in the lives of others or to a larger social entity (Elliott, 2009; Elliott, Kao, & Grant, 2004; France & Finney, 2009; Rosenberg & McCullough, 1981). Some researchers even describe mattering as a fundamental human need (Dixon Rayle, 2006).

Sociologists Morris Rosenberg and B. Claire McCullough presented a formal theory of mattering in 1981. Since their initial research, the theory of mattering has been expounded upon. Mattering has been developed into a complex construct consisting of multiple facets: awareness, importance, ego-extension, and reliance (Elliott, 2009; Elliott et al., 2004; France & Finney, 2009; Rosenberg & McCullough, 1981). The facet *awareness* is a cognitive experience (Elliott et al., 2004); that is, we matter because other people acknowledge our presence. *Importance* is the feeling that other people care about us and are concerned about our well-being (Elliott et al., 2004; Rosenberg & McCullough, 1981). *Ego-extension* is the feeling that we matter when other people feel or react to what happens to us the same way we do (Elliott et al., 2004; France & Finney, 2009). *Reliance* is the feeling that we matter because other people depend on us (Rosenberg & McCullough, 1981). Thus, we feel we matter when others seek us out for advice or support. In sum, we feel a sense of mattering when we are recognized, cared for, appreciated, and needed.

According to Rosenberg and McCullough (1981), people experience two forms of mattering: interpersonal mattering (i.e., mattering to specific individuals, such as a parent, sibling, or significant other) and societal mattering (i.e., mattering to a larger social entity or community such as a workplace, club, team, or school). Furthermore, people can experience different levels of interpersonal and societal mattering. For example, a person can have high feelings of mattering to his or her family, but low feelings of mattering to his or her workplace. Some examples of interpersonal mattering that have been examined include mattering to friends (Demir, Ozen, Dogan, Bilyk, & Tyrell, 2010), mattering to significant others (Mak & Marshall, 2004), and mattering to parents (Marshall, 2001). To date, societal mattering has been examined in career development contexts (Amundson, 1993) and counseling professions (Corbiére & Amundson, 2007; Dixon Rayle, 2006), but mostly in university settings (e.g., France & Finney, 2010; Schlossberg, Lynch, & Chickering, 1989). The experience of mattering has also been investigated with various populations, including adolescents and young adults (Dixon, Scheidegger, & McWhirter, 2009; Elliott, Colangelo, & Gelles, 2005; Mak & Marshall, 2004; Marshall, 2001; Rosenberg & McCullough, 1981), older adults (Dixon, 2007), high school African American males (Tucker, Dixon, & Griddine, 2010), non-traditional adult students (Schlossberg et al., 1989), African American students (Cuyjet, 1998), first-year college students (Dixon Rayle & Chung, 2007), upper-class college students (France &

Finney, 2010), transfer commuter students (Kodoma, 2002), and community college students (Tovar, Simon, & Lee, 2009).

Of particular interest to the current study is societal mattering in the university context, or, *university mattering* – the feeling that one makes a difference and is significant to his or her university's community (France & Finney, 2010). In addition, the current study investigates university mattering for native and transfer students. The term "native student" describes students who began their collegiate experience at the current institution and did not enroll with any transfer credits. The term "transfer student" broadly describes students who came to the current institution with 24 credit hours or more from at least one other institution. Transferring typically happens in one of two ways. Either students move from a community college to a four-year institution (vertical transfer) or from a four-year to another four-year institution (horizontal transfer).

Why Study University Mattering?

According to Rosenberg and McCullough (1981) mattering is a motive: "the feeling that others depend on us, are interested in us, are concerned with our fate, or experience us as an ego-extension exercises a powerful influence over our actions" (p. 165). In other words, mattering is so essential to humans that it dictates human behavior (Elliott, 2009). Applying this to college life, if students feel that they matter to their university, theoretically, they should be motivated to behave in a certain way (e.g., become involved with university activities, continue to enroll in courses).

At a traditional university or college, some would argue that highly involved students (Astin, 1999) are the most successful (i.e., they most often obtain a degree). Specifically, student involvement and engagement with the university are related to persistence and academic success (Astin, 1993; Tinto, 1987). A lack of attachment to the university and its professors, staff, and students has been related to less involvement in university activities, such as Student Government Association (France, Finney, & Swerdzewski, 2010). A potential precursor to becoming involved within one's university is feeling that one matters to the university community (Schlossberg, 1989). Likewise, being involved and joining various campus organizations may foster increased feelings of mattering. However, these theories have yet to be empirically tested.

To date, university mattering has only been researched using correlational studies. For example, mattering to college has been found to be negatively associated with academic stress (Dixon Rayle & Chung, 2007). Similarly, mattering to university friends was negatively related to depression and stress (Dixon & Robinson Kurpius, 2008). France and Finney (2010) found university mattering to be negatively correlated with social adequacy concern (similar to social anxiety) and maladaptive help-seeking behaviors (i.e., seeking help to avoid work).

University mattering has also been found to be positively related to numerous desirable variables. For example, mattering to university friends was found to be positively related to self-esteem (Dixon & Robinson Kurpius, 2008). Furthermore university mattering has been positively associated with mastery-approach and performance approach goal orientation, academic self-efficacy, and instrumental help-seeking (i.e., seeking help to internalize a concept more deeply; France & Finney, 2010).

Measurement of University Mattering

A measure of university mattering is necessary for evaluating the effectiveness of university programs that claim to increase feelings of mattering and for identifying students with low feelings of mattering. A few measures exist that attempt to operationalize university mattering or mattering to college. First, Schlossberg, Lassalle, & Golec, (1989) developed the Mattering Scale for Adult Students in Higher Education (MHE). The MHE was developed to assess perceptions of mattering in relation to faculty, administration, and peers for students 25 years or older (i.e., non-traditional students). The authors provided scoring instructions and created five subscales: (a) Administration, (b) Advising, (c) Interaction with Peers, (d) Multiple Roles, and (e) Interaction with Faculty; however, the authors did not provide any factor analytic evidence to support these five dimensions of mattering.

More recently, Tovar et al. (2009) developed the College Mattering Inventory (CMI) to investigate undergraduate students' feelings of mattering. In Tovar et al.'s (2009) evaluation of the psychometric properties of the CMI using both exploratory factor analysis (EFA) and confirmatory factor analysis (CFA), they identified six factors which they named: (a) General College Mattering, (b) Mattering versus Marginality, (c) Mattering to Counselors, (d) Mattering to Instructors, (e) Mattering to Students, and (f) Perception of Value. Neither the MHE nor the CMI were written to map onto Rosenberg and McCullough's (1981) theory of mattering. That is, items on these measures do not map onto the awareness, importance, ego-extension, and reliance facets.

A third measure, the University Mattering Scale (UMS), was adapted from Elliott et al.'s (2004) measure of general mattering for use in a university context (France & Finney, 2010). The UMS differs from Schlossberg et al.'s (1989) MHE and Tovar et al.'s (2009) CMI in two important ways. First, unlike the MHE and CMI, the UMS was derived from Rosenberg and McCullough's (1981) theory of mattering by using the theoretical definitions of awareness, importance, ego-extension, and reliance to construct the items. Second, on the MHE and CMI the items specify to whom the students feel they matter (e.g., faculty, peers, and counselors). Alternatively, the instructions of the UMS were written to be general because the people and groups to whom students feel they matter can be vastly diverse in the university setting. The instructions were purposefully written in this way because it is not necessarily important that students feel they matter to a *particular* person or group; yet it is important that students feel they matter to *someone* or *some group*. That person could be their roommate, professor, counselor, or advisor. The group could be their Spanish class, the Student Government Association, or the basketball team. Thus, specifying whom students matter to in the item content could potentially constrict student responses. For example, it is possibly that a student feels a sense of mattering to his or her university, but he or she never met with a counselor. Therefore, this student would be unable to report feelings of mattering toward his or her counselor.

France and Finney (2010) completed a thorough construct validity study on the UMS. Their CFA results indicated that mattering represented by the factors awareness, importance, ego-extension, and reliance fit better than the other models tested. However, this study uncovered more questions than it answered. For example, it was unclear if awareness and importance or if importance and ego-extension were distinct factors due to their high correlations, $r = .94$ and $r = .92$ respectively. Additionally, it was evident that more items needed to be written to better cover the breadth of the ego-extension facet; the awareness factor had 10 items but the ego-extension facet only had 3. Furthermore, there were a large number of negatively worded items on the awareness and importance factors (possibly contributing to their high correlation). Finally, some of the items had low factor loadings, possibly because they contained confusing vocabulary. As a result, the overall common factor variance for several factors was too low, indicating that revisions were necessary to reduce the error variance in the scores.

The Revised University Mattering Scale

Given that the items on the MHE and the CMI do not appropriately reflect the facets of mattering theorized by Rosenberg and McCullough (1981), these measures were considered unacceptable for use in the current study. Furthermore, according to the *Standards for Educational and Psychological Testing*, “A test should be amended or revised when new research data…may lower the validity of test score interpretations” (Standard 3.25; AERA, APA, NCME, 1999; p. 48). Therefore, in order to address the concerns raised by France and Finney’s (2010) findings, numerous items on the UMS were revised and new items were written by France for use in the current study. A 34-item measure was created and named the Revised University Mattering Scale (RUMS). Of the original 24 UMS items, 13 were unchanged and retained on the RUMS. Eight of the original items on the UMS were revised for the RUMS. Five of these revisions dealt with changing the item wording from the negative to the positive. For example, “People of the JMU community tend not to remember my name” was revised to “People of the JMU community tend to remember my name.” The other three items were revised because the item wording from the UMS appeared to be confusing. For example, the item “I have noticed that people at JMU will sometimes inconvenience themselves to help me” was revised to “I have noticed that people at JMU will take the time to help me.” Three items from the UMS were deleted. Two of these items (“No one would notice if one day I disappeared" and "There is no one who really takes pride in my accomplishments") were deleted because they were extreme and demonstrated poor utility (i.e. low factor loadings) in the analysis of the UMS. The third item ("Much of the time, people are indifferent to my needs") was deleted because it demonstrated poor utility. The researchers' hypothesized students might have been confused by the word "indifferent" or unsure of its meaning. In addition to these revisions, 13 new items were created for the RUMS. Of these 13 new items, six were written to represent the *ego-extension* facet (which was only previously represented by three items on the UMS), four new items represented the facet of *importance*, two new items represented *reliance*, and one new item represented *awareness*.

Thus, these changes resulted in a new 34-item measure (see Appendix A for a comparison of the UMS to the RUMS) with nine items representing the awareness facet, eight items representing the importance facet, eight items representing the ego-extension facet, and nine items representing the reliance facet. In addition, eight items of the 34 items were stated in the negative, but unlike the UMS, these negatively worded items were distributed evenly across the facets (i.e., two negatively worded items per facet). Additionally, more items were written by France than needed with the expectation that some items would perform poorly after evaluating the factor structure of the RUMS and would thus be discarded. France also changed the response scale. The UMS response scale ranged from 1 ("strongly disagree") to 5 ("strongly agree") and contained a midpoint anchor of "neither agree nor disagree". The RUMS response scale was changed to range from 1 to 6 (1 = "strong disagree", 2 =”disagree", 3 = "slightly disagree", 4 =

"slightly agree", 5 = "agree", and 6 = "strongly agree"), thus eliminating this neutral midpoint and hopefully presenting less ambiguity to participants.

University Mattering and Transfer Students

The psychological construct of university mattering is characterized by students' feelings that their university community pays attention, cares for, and relies on them. Recall that university mattering has been examined using various student populations (e.g., non-traditional adult students, African American students, community college students). Interestingly, other than Kodoma's (2002) study of transfer commuter students, university mattering has not been examined for transfer students, despite the fact that transfer students constitute a large proportion of the student body on many campuses. Approximately 40.4% of students obtaining a bachelor's degree in the national 2002 graduating class had attended more than one university (Peter & Cataldi, 2005). In fact, research on transfer students is lacking in general, even though the number of transfer students continues to grow in institutions of higher education.

University mattering might be especially pertinent to the transfer student population. Transfer students frequently report feelings of marginality (i.e., a lack of mattering) after relocating to their new college campuses. Although the term mattering is not always referenced in the literature, qualitative responses gathered from transfer students indicate that transfer students experience a lack of mattering. For example, transfer students report feeling a lack of awareness and expressing they feel like a number (Owens, 2010). Similarly, the larger class sizes of universities (compared to relatively small classes at community colleges) can decrease a students' sense of mattering. In Davies and Dickmann (1998) study of transfer students, one student reported that the "anonymity [was] overwhelming" (p. 551) after transferring to a larger institution. When asked what institutional supports could ease the transition for students, many transfer student responses reflected the definition of importance. For example, in Owens (2010) study of transfer students, one student said, "I believe that the supports needed to facilitate a successful transfer include having someone to ask questions to and *who is truly interested in how you are doing"* (italics added for emphasis; p. 109). On the contrary, as transfer students adjusted to their new campus they reported increased feelings of mattering. For instance, in Townsend and Wilson's (2009) study of transfer students the facet of reliance was reflected in one student's report on research with a professor indicating that working with a professor on research made him feel like he was part of something bigger. Overall, low feelings of mattering may hinder transfer students' adjustment to their new institution, possibly making it more difficult for them to get involved and build relationships with their faculty and peers. In turn, a lack of involvement may lead to lower persistence or poor academic performance.

It is possible a measure of university mattering could function differently for transfer students given the observable differences between transfer students and native students. Demographically, transfer students tend to vary more in age and ethnicity and are less prepared academically than native students (Eggleston & Laanan, 2001). Transfer students are also less likely to live on campus, more likely to work off campus, and more likely to care for dependents than native students (McCormick, Sarraf, BrckaLorenz, & Haywood, 2009). In addition, transfer students differ from native students academically. For example, on average transfer students take longer to obtain a degree than native students (Peter & Cataldi, 2005). The increased time to degree is especially apparent for students who transferred more than once (Adelman, 2006). Also, transfer students may experience a drop in GPA after transferring to their new institution. This phenomenon is known as "transfer shock" (Hills, 1965). Diaz (1992) found that the majority of transfer students experienced a drop in GPA of about half a grade point after their transition to their new school.

Transfer students also differ from native students behaviorally. Transfer students are less involved with the university community than native students (Ishitani & McKitrick, 2010; NSSE, 2009; Wang & Wharton, 2010). Transfer students report spending less time interacting with faculty and becoming engaged in research with faculty (NSSE, 2009). Lower rates of involvement among transfer students in comparison to native students is problematic because campus involvement (e.g., time spent with faculty and peers, participation in campus organizations, living in the dorm, attending courses, time spent studying) has been related to academic success and retention (Astin, 1999; Tinto, 1987). Transfer students also express distress about the difficulty of integrating into the campus environment. One student noted that the most difficult part of transferring was making friends because the native students already had established "groups" (Britt & Hirt, 1999). Due to these differences in involvement and academics, transfer students have been identified as being "at risk" compared to native students (Ishitani & McKitrick, 2010).

Taken together, transfer students are a different population of students than students who began at the university as first-years. As such, transfer students could conceptualize university mattering differently than native students. Or, certain items on a measure of university mattering may be more salient to native students than transfer students, given that the university culture is built around students beginning their careers at that university. Students learn the traditions, culture, and receive messages that they are the "school" in their first year. Therefore, it is imperative to establish measurement invariance for transfer and native students on instruments used in higher education settings before comparing scores across these subgroups.

Purpose of the Study

The purpose of this study is to gather construct validity evidence for a revised measure of university mattering. Benson (1998) provides a useful three-stage framework for developing instruments with strong construct validity. The first stage is the substantive stage where the construct is defined theoretically and empirically. That is, items are written to operationalize the theory. In the case of university mattering, the theory defines mattering in terms of awareness, importance, ego-extension, and reliance, and items on the RUMS were written to represent each of these four facets. Benson's (1998) second stage is the structural stage, which involves examining the inter-item relationships, factor structure, and reliability of the measure. France and Finney (2010) had examined the structural stage for the UMS, but because the UMS was revised, it is necessary to examine the structural stage for the revised measure. Finally, Benson's third stage is the external stage, which involves examining whether scale scores obtained from a measure result in theoretically predictable outcomes. One way to gather validity evidence for the external stage is to examine if the scale scores obtained from the measure correlate in expected ways with other measures of theoretically related constructs. France and Finney (2010) gathered validity evidence for the external stage for the UMS by relating the scores of the measure to other variables (e.g., help-seeking attitudes, feelings of worry, sense of belonging). Another source of validity evidence for the external stage is to obtain known-groups validity. That is, do the scale scores accurately capture theoretically expected differences across known groups. For example, people who are diagnosed as clinically depressed should score high on a measure of depression and people who are not clinically depressed should score significantly lower on the same measure. The current study aims to gather known-groups validity evidence for the revised measure by comparing native and transfer students' scores on university mattering. This study is broken into two parts. Study 1 addressed model-data fit, the fit of various factor models for the RUMS scores (i.e., the structural stage). Study 2 addressed establishing measurement invariance of the revised measure and examining latent mean differences for native and transfer students (i.e., the external stage).

Study 1: Model-Data Fit

Of the proposed factor models, which model fits best? Model-data fit of the RUMS was evaluated by testing five hypothesized models using confirmatory factor analysis (CFA). The following models were specified a priori:

(a) One-Factor Model (*Figure 1*)

(b) Correlated Four-Factor Model (*Figure 2*)

(c) Second-Order Model (*Figure 3*)

(d) Bifactor Model (*Figure 4*)

(e) Incomplete Bifactor Model (*Figure 5*)

A detailed description of each model is presented in Chapter 3. The models were tested using two independent samples of native students. After evaluating the fit of the five models, further modifications (i.e., deletion of items) were made to improve model-data fit.

Study 2: Measurement Invariance and Latent Mean Differences

Given an interpretable factor structure from Study 1, is measurement invariance supported for transfer students? Study 2 consists of two steps. Given the interpretable model ultimately championed from Study 1, invariance of measurement parameters (configural, metric, and scalar) were assessed across native and transfer student groups. More generally, a measure can function differently for different groups. "Subgroups may be found to differ with respect to appropriateness of test content, internal structure of test responses, the relation of test scores to other variables, or the response processes employed by individual examinees" (AERA, APA, NCME, 1999, p. 80). Without establishing measurement invariance, differences in scale means cannot be attributed solely to differences in the underlying construct. Thus, the measurement invariance of any instrument used to examine differences between transfer and native students needs to be established before making inferences regarding the scores on that instrument.

Given the establishment of measurement invariance, do transfer students have a different latent mean than native students on university mattering? If measurement invariance is established, then latent mean differences across subgroups can be interpreted. Of particular interest to this study is the latent mean difference on university mattering for transfer students compared to native students. Given the current research on transfer students (e.g., Davies & Dickmann, 1998; Owens, 2010; Schlossberg, 1989; Townsend & Wilson, 2009), it was hypothesized that transfer students will have a lower latent mean on university mattering than native students. Recall that transfer students often report feeling a lack of mattering, isolation, or express difficulty in building relationships at their new institution (Owens, 2010; Townsend & Wilson, 2006). Some researchers have hypothesized that transfer students lack a sense of mattering because they are such a heterogeneous group; they have difficulty finding students similar to themselves with whom they can identify (Weiss, McKelfresh, & Yang, 2006). Likewise, it has also been hypothesized that people going through a transition often feel that they do not matter (Schlossberg, 1989). As a result, it is expected that transfer students will report lower feelings of university mattering compared to native students.

In sum, university mattering is of interest to higher education researchers (e.g., Schlossberg, 1989) and has been researched with various student populations. However, transfer students represent one population for which university mattering has not been examined. This study aims to both improve the measurement of university mattering by evaluating the factor structure of the RUMS and to assess whether this measure can be used with both native and transfer student subgroups by assessing measurement invariance. The establishment of measurement invariance then facilitates the comparison of native and transfer student university mattering latent means. If transfer students have lower latent levels of university mattering than native students, this would provide strong known-groups validity for the measure.

CHAPTER TWO

Review of the Literature

Rosenberg and McCullough (1981) first introduced the concept of mattering – the belief that we are significant to and make a difference in the world around us – to the field of sociology. Rosenberg began this work in the later years of his life, yet was unable to completely test his theories before his death. However, Gregory Elliott, a student of Rosenberg's, was able to continue much of Rosenberg and McCullough's initial work on mattering (see Elliott, 2009) following Rosenberg's death. Elliott (2009) proposed that mattering is instilled when a person is recognized and selected from a larger group of people. If others notice us in a crowd of people, care specifically for us, and try to meet our needs, or if others seek us out for our support and advice, even when there are plenty of other people around to turn to, we know we offer something independent of others that is of value (Elliott, 2009). In other words, we matter.

This study focuses on mattering in a specific context: mattering to one's university community. University mattering involves students' perceptions of mattering given their encounters and experiences with the community, made up of university faculty, staff, and peers. For example, students feel they matter when the university community is aware of them, when the community responds to their needs, and when students can contribute positively to the community (France & Finney, 2010). University mattering is derived from Rosenberg and McCullough's (1981) general theory of mattering. As such, this general theory of mattering is presented first, followed by a discussion of mattering in higher education, measures of university mattering, a review of research of university mattering and various student populations, and a discussion of the transfer student population.

The Theory of Mattering

Importantly, mattering is a person's *subjective* perception of his or her significance to others or a larger social entity (Rosenberg, 1985) and people can have different notions of how mattering is expressed (Elliott, 2009). That is, for a person to feel that he or she matters, he or she must interpret another's actions as signifying mattering. Otherwise, feelings of mattering will not develop.

Mattering has been defined as a motive that influences how people behave (Rosenberg & McCullough, 1981, p. 165). Elliott (2009) expanded upon this point succinctly stating:

> Different people, with different socialization experiences, may find themselves at different points along the mattering continuum. Some may believe they matter a great deal. They have experienced the attention, investment and reliance from others. Others may have learned from the significant others in their lives that they are nearly superfluous in this world. It is the placement along this dimension that helps to account for differences in behavior (p. 17).

In general, feelings of mattering instill knowledge that we are socially integrated with society which leads to positive behaviors (Elliott, 2009). That is, people who believe they matter are motivated to maintain their meaningful connections to others, and thus act in socially acceptable ways to avoid jeopardizing these relationships. However, a lack of mattering leads to negative behaviors. According to Rosenberg and McCullough (1981), not mattering is so devastating to the individual that the individual may act out in negative ways. These negative responses to feeling a lack of mattering include two possibilities: (1) acting in a way that demands attention (i.e., anti-social behaviors) or (2) social isolation so the individual does not have to face the reality that no one needs him or her (Elliott, 2009). Both responses can be harmful to the individual and to those around him or her.

To whom one matters has been discussed in terms of *interpersonal mattering* and *societal mattering* (Rosenberg & McCullough, 1981; Rosenberg, 1985). Interpersonal mattering refers to mattering to specific others, such as a significant other, parents, or children. For example, a husband feels he matters to his spouse because the spouse pays attention to him, relies on him, and he relies on his spouse. On the other hand, societal mattering refers to mattering to a larger social group, such as a family, school, team, or corporation. An example of societal mattering is when an employee feels she matters to her company because she is recognized for her effort and attention to detail on an important project. Again, the measure employed in this study assesses a form of societal mattering – mattering to one's university community.

Defining the Construct of Mattering

Within the literature, mattering has generally been described as a complex construct, consisting of either three or four facets. Rosenberg and McCullough (1981) originally described mattering as having three distinct facets: awareness, importance, and reliance.

The first facet of mattering is *awareness*. Awareness is a cognitive experience; we matter because other people acknowledge our existence (Elliott, 2009; Elliott et al., 2004). Awareness is experienced when other people remember our name or greet us when we enter a room. We also know we matter through awareness when people notice our absence. As described by Elliott (2009), "a person who matters is distinguishable from the masses" (p. 5). Furthermore, when others are aware of us, when they recognize us, they confirm our individuality. Awareness is on a continuum in that a person can be recognized by a large number of people (e.g., the President of the United States) or a person can be recognized by almost no one. On this far end of the continuum, the unacknowledged individual may feel as if they are invisible and do not matter. One way in which university staff can indicate they are aware of students is by personalizing the information students receive at orientation.

In addition to awareness, two other facets of mattering described include *importance* and *reliance*. Elliott (2009) proposed that importance and reliance are more complex than awareness because these facets of mattering involve a relationship between a person and the others to whom one matters. Relationships are bidirectional with each side taking and giving from the other. Importance is the "taking" side. It is the feeling that other people care about us and are concerned about our wellbeing (Elliott et al., 2004; Rosenberg & McCullough, 1981). In other words, we feel we matter when other people's behavior is supportive and caring. For example, other people indicate we matter by providing advice and emotional support, making sure our needs are met, and listening to our problems (Elliott, 2009). Universities can instill importance by ensuring the community is considerate and available to meet students' essential needs (e.g., safety).

Reliance, like importance, is also a characteristic of a relationship. Reliance is the "giving" side of a relationship (France & Finney, 2009). It is the feeling that we matter because others depend on us or need us (Rosenberg & McCullough, 1981). Thus, we feel we matter when others seek us out for advice or support. Although feeling that others rely on us informs our sense of mattering, this reliance can be arduous. Fulfilling the needs of others who depend on us can sometimes precede fulfilling our own needs (Elliott, 2009; Rosenberg & McCullough, 1981). Thus, experience an extreme sense of reliance can be problematic for that individual, leading to increased stress. Students may feel a sense of reliance at a university if they are called upon to participate in various university activities and organizations or if their peers look to them for advice.

In addition to awareness, importance, and reliance, researchers have proposed additional facets of mattering, including being missed (Marcus, 1991; Rosenberg, 1985), interest (Marcus, 1991), appreciation (Schlossberg, 1989), and ego-extension (Marcus, 1991; Rosenberg, 1985). Being missed is the reciprocal of awareness. Just as we need people to be aware of our presence, we hope they are cognizant of our absence (Rosenberg, 1985). However, being missed is too narrow to stand alone as a fourth dimension of mattering. If people are aware of us, they should also notice when we are not present. If people rely on us, they should also miss us when we are gone. Thus, being missed is not theoretically distinct from the other components of mattering. Similarly, interest is not distinct from awareness. Marcus (1991) stated that “feeling we are the object of another person’s interest” (p. 6) is an additional component of mattering. Rosenberg (1985) however, used “interest” as a synonym for awareness. Thus, it does not appear that interest is distinct from awareness, given the brief definition provided by Marcus (1991). Schlossberg (1989) proposed appreciation as an additional component of mattering. Appreciation embodies the feeling that when a person invests time into others or their work, this investment is valued. For example, an employer may take her employees out to lunch to show her appreciation for their hard work. However, it is not clear if appreciation is distinct from awareness, importance, and reliance. Elliott et al. (2004) used the term appreciation in their description of reliance: "reliance flows from a sense that others appreciate the resources that one has to offer" (p. 342).

Finally, the term *ego-extension* has been suggested as an additional facet of mattering. Ego-extension is when other people feel or react to what happens to us the same way we do (Elliott et al., 2004; Rosenberg & McCullough, 1981). Parents taking pride in their children's accomplishments is an example of ego-extension. It is the idea that our actions reflect on those who we matter to most. Rosenberg and McCullough (1981) originally defined importance using the term ego-extension (France & Finney, 2009). Elliott (2009) also defines ego-extension in terms of importance, implying they are not distinct. In his later research, Rosenberg (1985) defined ego-extension as distinct from importance. Given this inconsistency, France and Finney (2009) empirically tested the distinction between ego-extension and importance using CFA. They found some support for the distinction between ego-extension and importance, as the four-factor model (representing the factors awareness, importance, ego-extension, and reliance) fit statistically significantly better than a three-factor model that represented both importance and ego-extension as one factor. Still, in the four-factor model, the factors were all highly correlated, leaving to question the utility of this model over a more parsimonious model.

Mattering and the Self

Rosenberg (1985) posited that mattering is an essential dimension of one's self-concept. According to Elliott (2009), "the self-concept is an organized representation of the self stored in the mind" (p. 15). Feelings of mattering contribute to an individual's understanding of himself or herself and his or her place in society (Elliott et al., 2004). The self-concept is strongly related to one's psychological well-being in that an unhealthy self-concept leads to depression, anxiety, and dissatisfaction with one's life (Rosenberg, 1985). Given this, low feelings of mattering threaten one's self-concept. On the contrary, a characteristic of a healthy self-concept is high feelings of mattering.

The development of a sense of mattering and its relationship to the self-concept is explained from two paradigms: (a) cognitive social psychology and (b) structural symbolic interactionism (Elliott, 2009). From the cognitive social psychology perspective mattering is developed through reflected appraisal, social comparison, and self-attribution. Reflected appraisal has to do with how other people respond to us. "The feedback we get from significant others in our lives goes a long way in determining whether we matter" (Elliott, 2009, p. 18). For example, consider students at a university. Students assess the extent to which they matter to their university through their interactions and the feedback they receive from others. If fellow students say hello to them as they pass on campus, this indicates that others are aware of them. If their professors provide useful comments on their work and spend time, above and beyond what is necessary for instruction to make sure their students understand a concept, this communicates to students that they matter. Similarly, a residence hall director who invites a student he knows is homesick to join him for dinner indicates this student matters. When peers seek out another student for her opinion on the best way to go about solving a chemistry problem, they are demonstrating to this student that she matters.

As indicated by the term "social comparison," a person's sense of mattering is also informed by how individuals behave toward that person relative to their behavior towards others (Elliott, 2009). Using another university example, a student who notices his advisor treats him differently than the other advisees would be using social comparison to assess how much he matters to his advisor. If this advisor provides this student less resources and time in comparison to the other advisees, this student may deduce that he matters less than the other advisees.

Finally, according to the cognitive social psychological perspective, we infer how much we matter through self-attribution (Elliott, 2009): "one's self-understanding can be based on observations of one's own behavior and the conditions under which it occurs" (p. 18). Self-attribution is similar to reflected appraisals, except that we infer mattering not by others' behaviors, but our own. Therefore, reflecting on how we respond to others' requests for support and advice, and how frequently this occurs, informs our sense of mattering. For example, an alumnus who does not feel a sense of mattering to the university community may not respond to requests for monetary donations.

Whereas the previous concepts examined the relationship of mattering and self-concept through a psychological lens, the following concept, structural symbolic interactionism, used a sociological perspective. This paradigm describes the formation of one's various identities (Elliott, 2009). Identity refers to the different meanings people attach to their self, given the various roles they play in society (Stryker & Burke, 2000). More specifically, structural symbolic interactionism attempts to "explain how social structure effects self and how self effects social behaviors" (Stryker & Burke, 2000, p. 285). Of importance to mattering is one's *role identity*. Role identity is our internalization of how we should behave given our various roles in society. People can have multiple role identities; however, some are more prominent than others. For example, a woman can have the role identities of mother, wife, daughter, friend, co-worker, and so on. Her most salient role identities may be mother, wife, and daughter and mattering in these roles is most important. It may not be that damaging to this woman's identity if she does not feel a strong sense of mattering to some of her fellow co-workers; yet, it would be extremely damaging if she felt she did not matter to her children or her spouse. Failing to matter in this sense "deprives us of the legitimacy required to assume and maintain that desired role identity" (Elliott, 2009, p. 24). Therefore, from this sociological perspective, mattering is important for the construction of our identity. Again, this paradigm demonstrates how mattering informs our understanding of who we are.

Mattering and Related Constructs

Mattering falls under the large umbrella of relatedness constructs, such as the need to belong, sense of belonging, social support, and interpersonal relationships. It is important to discuss how these constructs, although related, are distinct from mattering. Unfortunately, a thorough treatment of the theoretical background (i.e., substantive stage) of each of these concepts is somewhat lacking. As stated by Hagerty, Williams, Coyne, and Early (1996), many descriptions of constructs such as sense of belonging "have been narrative and anecdotal rather than theoretical or empirical" (p. 236).

Belonging. Maslow (1970) was one of the first researchers to discuss belonging as an essential human need. Maslow theorized a hierarchy of needs in which once one's vital needs for food, water, and safety are met, the need for love and belonging becomes salient. Likewise, Baumeister and Leary (1995) summarized a large body of research, from multiple disciplines, to support their belief that the need to belong is a basic human need. In this substantial literature review, they gathered evidence that the need to belong influences people's cognitive processes and emotional reactions.

A sense of belonging has been defined as "the experience of personal involvement in a system or environment so that persons feel themselves to be an integral part of that system or environment" (Hagerty, Lynch-Sauer, Patusky, Bouwsema, & Collier, 1992; p. 173). Furthermore, Hagerty et al. (1992) described two dimensions of belonging: (a) valued involvement and (b) fit. Valued involvement is affective; it consists of feeling needed and accepted. Fit has to do with a person's perception that he or she is similar to others in the same system or environment. Both valued involvement and fit are necessary for a person to feel a sense of belonging. For example, a student may be a valued member of a university community, yet lack fit with the community because he comes from a modest upbringing whereas all the other students come from wealthy families. On the other hand, a student may be similar to her peers. She may live in the same dorm and study the same major as her peers. However, this student feels that the other students do not like her or value her. Both of these students would lack a sense of belonging but for different reasons. The male student lacks fit with his environment; the female student lacks the sense that she is valued. Empirical research supports these claims. For example, Clegg (2006) conducted a phenomenological study investigating the experience of not belonging; not belonging was often proceeded by feeling different or a lack of fit. Additionally, Hagerty et al. (1996) found sense of belonging was inversely related to anxiety.

Baumeister and Leary (1995) define belonging as “a need to form and maintain at least a minimum quantity of interpersonal relationships” (p. 499) and this need is innate, has an evolutionary basis, and thus, is found across all humans and cultures. These researchers stated the need to *belong* requires frequent personal contacts that are free from negative affect and conflict (ideally they involve positive affect) and these bonds are stable, expected to continue into the future. Baumeister and Leary (1995) further distinguish belonging from a need for intimate attachment because intimate attachment can be fulfilled by the knowledge that an emotional bond exists between two people. Belonging, however, requires personal contact. To clarify, the need for intimate attachment may be fulfilled in the child who has moved away from home to attend college. This child knows that his parents love him, and he talks to them occasionally on the phone, thus a positive emotional bond exists between the child and his parents, but his need to belong is not fulfilled. In order to meet the need to belong, he needs to establish positive, meaningful relationships with a few significant others at his new campus. Finally, the need to belong is so fundamental, if it is not met, an individual will suffer negative effects, such as stress or depression (Baumeister & Leary, 1995). Participants who experienced not belonging reported negative emotions: feelings of sadness, anxiety, anger, embarrassment, and physical exhaustion (Clegg, 2006).

In sum, both Hagerty et al. (1992; 1996) and Bausmeister and Leary (1995) identified belonging as vital for individuals’ well-being in that a lack of belonging leads to negative outcomes (e.g., anxiety, pathology). However, their definitions of belonging are slightly different. Both emphasize the importance of emotional bonds that promote positive affect and are characterized by feeling valued and cared for. However, Hagerty et al. (1992) emphasize fit as an integral aspect of belonging. Baumeister and Leary (1995) focus on proximity and frequent contact as an essential component.

Mattering has some similarities with these definitions of belonging. First, mattering is similar to Hagerty et al.'s (1992) dimension of valued involvement in that mattering also involves feeling valued, needed, and accepted by others. However, mattering has little to do with perceived fit. In fact, a person may not be similar to others in an environment, yet he or she can still feel a sense of mattering to those in the environment if he or she is noticed, supported, and relied upon. Mattering is similar to Baumeister and Leary's (1995) definition of belonging in that both belonging and mattering are characterized by satiation and substitution (Elliott, 2009). Satiation refers to the volume of relationships a person has with others. For both belonging and mattering, there are diminishing returns for how many people an individual feels he or she matters to or shares a sense of belonging with; only a few meaningful connections to other people are necessary for either need to be met. In other words, once a person fulfills each need, he or she should be less motivated to seek out additional relationships (Baumeister & Leary, 1995). However, the absence of all meaningful relationships is devastating to an individual's feelings of mattering and sense of belonging.

Substitution has to do with the replacement of previous relationships. For both belonging and mattering, old relationships that are lost can be substituted with new relationships (Baumeister & Leary, 1995; Elliott, 2009). When old relationships end, there is a sense of not belonging or not mattering (e.g., students transferring to a new university leaving friends behind); however, once new, meaningful relationships are established, a person will feel that he or she belongs and is significant to others. Finally, another similarity between mattering and belonging is that mattering, like belonging, is positively associated with psychological well-being and inversely related to depression and anxiety (France & Finney, 2009; Rosenberg & McCullough, 1981).

Despite these similarities, Elliott (2009) outlined four ways in which belonging and mattering differ. One way the two constructs differ is that belonging requires an emotional attachment to another. Whereas an emotional bond is possible for mattering (i.e., mattering to one's family), it is not necessary (i.e., mattering to your employer). That is, mattering involves an element of caring, but this is less extreme than the emotional bonding associated with belonging (Elliott, 2009). Another way in which belonging and mattering differ is how each need is met. To meet the need to belong, individuals are driven to initiate interactions with others. Mattering, however, cannot be forced upon others. The need to matter is only met by others' actions toward us–when others pay attention to us, demonstrate they care about us, or come to us for support. A third difference between belonging and mattering is that the need to belong is only fulfilled through frequent and personal interactions with others (Baumeister & Leary, 1995). Yet, mattering does not necessarily depend on frequent interactions. Once a person establishes that they matter to others, this is a generally stable concept. Furthermore, feelings of mattering can be induced without face-to-face interaction. An individual knows she matters when a friend who lives far away calls her on the phone; she does not have to interact with this friend in person to feel she matters. Finally, Elliott (2009) suggests that mattering and belonging differ in how people behave to achieve these needs. Specifically, people will act in a socially desirable ways when attempting to meet their need to belong. Acting in an undesirable way would perturb their chances of building meaningful relationships. However, people who do not feel that they matter may act out in negative ways because it is better to be noticed, even negatively, than to not be noticed at all (Elliott, 2009; Rosenberg & McCullough, 1981).

It has been theorized that mattering fosters belonging (Corbière & Amundson, 2007). There is some empirical support for the relationship between mattering and belonging. France and Finney (2009) found moderate correlations between a measure of sense of belonging and general mattering. Likewise, Tovar et al. (2010) also found moderate correlations between a measure of belonging to school and mattering to college.

In addition to belonging, there are other concepts that appear to be similar to mattering. Although, like belonging, these concepts are related to mattering, they differ from mattering in specific ways. These include social support and self-esteem.

Social Support. Social support can be material, psychological, or emotional and is defined as the extent to which others provide for us in times of need (Elliott, 2009). Social support is most like the importance facet of mattering (Elliott et al., 2004). Both concepts involve other people providing some resource (e.g., advice, emotional support). However, mattering differs from social support in that the dimension of importance is more general and does not necessarily relate to a specific form of support (Elliott, 2009). We can feel we are important even when we do not have immediate needs. Another distinction between mattering and social support is that feelings of mattering are only fostered if we believe the other person is acting out of altruism (Elliott, 2009). It may be that other people provide social support with an ulterior motive. In this case, feelings of mattering will not develop. For example, consider a new transfer student that has become acquainted with some of his or her peers from class. These classmates invite the new transfer student to lunch and seem to be interested in being friends. However, the transfer student soon discovers that these classmates were only being friendly because they knew he or she is bright and they wanted the answers to the homework. Clearly, this transfer student would not feel that she matters to these other students.

Self-Esteem. Mattering is also distinguishable from self-esteem. Self-esteem has been defined as one's evaluation of their personal self worth; the positive or negative appraisal of one's value (Leary & Baumeister, 2000; Rosenberg, 1979). Thus, emotion is an essential component of self-esteem, in addition to one's cognitive self-evaluation (Leary & Baumeister, 2000). Self-esteem is characterized by feelings of self-acceptance, self-respect, and generally liking one's self (Rosenberg, 1985). An individual with healthy self-esteem is satisfied with who he or she is, despite his or her shortcomings. On the other hand, a person with low self-esteem tends to be anxious, depressed, and have low life satisfaction (Rosenberg, 1985). Given this, self-esteem has been described as a motive; people want to maintain or confirm positive feelings about themselves (Leary & Baumeister, 2000).

Mattering differs from self-esteem in that mattering involves interactions with others; it is "an attribution of one's connection to the social order" (Elliott, 2009, p. 10). In other words, it is an awareness of one's relation to others and society. Unlike self-esteem, mattering does not involve an appraisal of one's self worth. Mattering is one's sense of his or her ability to make an impact in the lives of others or to a larger social entity. Self-esteem involves both cognitive and affective processes. Thus, mattering is one variable that influences an individual's level of self-esteem. Specifically, feelings of mattering contribute to higher levels of self-esteem, and feeling a lack of mattering contributes to lower levels of self-esteem (Elliott, 2009).

Higher Education and Mattering

University mattering is a form of societal mattering where the university is the larger social entity to which students experience a sense of mattering (France & Finney, 2010). Students feel they matter when the university community is aware of them, when the community responds to their needs, and when students can contribute positively to the community. Recall however, that mattering is a person's subjective experience (Rosenberg & McCullough, 1981). Thus, university administrators may provide numerous services for students, such as writing centers, counseling centers, and career advising. By providing these services, the university administrators may believe they are demonstrating the students matter to the university. However, if students take part in these services, but do not feel as if they are recognized, cared for, or needed, the students will not develop a sense of mattering.

Likewise, according to mattering researchers (e.g., Elliott, 2009), mattering is essential to social integration and mattering influences behavior because social connections are essential to an individual's psychological well-being (Baumeister & Leary, 1995; Elliott, 2009). This is of relevance to the university community because individuals who feel they are part of a society adopt the beliefs, goals, and values of that society (Hogg & Abrams, 1988). Thus, it can be hypothesized that students who feel they matter and are integrated into the university community are much less likely to break the rules (e.g., cheat, vandalize property) and more likely to give back to the community (e.g., participate in organizations, donate money).

Within higher education, university mattering is often referenced in the student affairs literature. Specifically, interest in mattering stems from Tinto's (1987) theory of student departure, which proposes that students who are not successfully integrated into the institution, both academically and socially, are most at risk to leave that institution. In other words, students who fail to form attachments feel a sense of isolation–especially if they are away from home and their high school peer groups–and tend to leave their institution, whereas students who form supportive relationships with faculty and peers tend to persist at their institution. This relates Baumeister and Leary's (1995) research on the need to belong which posits that peoples' relationships must be positive and proximal. If students move away from home to attend college, it is not enough to have supportive relationships with their family and high school friends; they need to form meaningful relationships within the college campus to fulfill their need to belong.

Similarly, Astin's (1999) theory of student involvement states that the more involved students are with their institution, the more likely they are to persist, succeed academically, and be satisfied with their experience. Astin broadly defined involvement as "the amount of physical and psychological energy that the student devotes to the academic experience" (p. 518). Thus, "involvement" is operationalized as any behavior that relates to university life, such as attending faculty office hours, participating in class, spending time studying, joining a campus organization, living in the dormitories, attending campus events and socials, and working on-campus. It is possible that the relationship between mattering and involvement is recursive; a sense of mattering leads to increased involvement and increased involvement leads to a greater sense of mattering.

However this is an empirical question that has never been tested. Before such theoretical models can be evaluated, a sound measure of university mattering needs to be developed.

Measures of Mattering in Higher Education

The measure used in this study, the RUMS, focuses on mattering to one's university community. Items on the RUMS refer to student experiences with university faculty, staff, and peers and were written to represent the four facets of mattering: awareness, importance, ego-extension, and reliance. Prior to the RUMS, there are only three known instruments that have been developed and used to measure mattering in higher education: the Mattering Scale for Adult Students in Higher Education (MHE; Schlossberg et al., 1990), the College Mattering Inventory (CMI; Tovar et al., 2009), and the University Mattering Scale (UMS; France & Finney, 2010). Each measure is discussed below. Issues associated with each measure are also discussed, justifying the development of the RUMS for use in the current study.

Mattering Scale for Adult Students in Higher Education. The MHE was developed to assess perceptions of mattering in relation to faculty, administration, and peers for students over 25 years old (i.e., non-traditional students). It appears items were written to represent mattering in five contexts: (a) administration, (b) advising, (c) interaction with peers, (d) multiple roles, and (e) interaction with faculty. For example, one item on the *interaction with peers* subscale states, "I have a good relationship with my younger classmates." Another item on the advising subscale states, "there has always been an advisor available to talk with me if I need to ask a question."

Unfortunately, the authors did not appear to follow an appropriate process for instrument development. For example, the theory from which the items were developed (i.e. Benson's substantive stage) was not described; what is clear is that the items were not written based on Rosenberg and McCullough's (1981) theory of mattering. In addition, there is no information provided about how the five subscales were derived (i.e., no factor analytic support for the subscales). Without this information, it is impossible to deduce whether using subscales is an appropriate way of scoring the MHE. That is, following Benson's (1998) program of construct validity, the structural stage of the MHE has not been established. Finally, the measure was developed for non-traditional adult students and the items were written in a way that is only appropriate for this subgroup. Given this, the MHE cannot be employed with other student subgroups.

College Mattering Inventory. Unlike the authors of the MHE, Tovar et al. (2009) developed the CMI especially for use with traditional students. They argued that mattering is contextual in that students can matter to different individuals in the university (e.g., faculty, administrators, peers). This conceptualization of mattering to specific contexts aligns with interpersonal mattering (Elliott, 2009; Elliott et al., 2004; Rosenberg & McCullough, 1981), but Tovar et al. (2009) did not address the concept of societal mattering. Therefore, they focused the measurement of mattering on specific people at one's institution (e.g., faculty, peers). They also wrote items pertaining to the following themes: (a) being the object of attention of others, (b) perception of support in various student endeavors by others, (c) supportive learning environment, (d) sense of fit with the college, and (e) perceived marginality owing to personal characteristics. Tovar et al. (2009) only named these themes and did not provide a thorough definition of each. The first two themes align with Rosenberg and McCullough's (1981) components of awareness and importance; however, the three additional themes do not align with the theory of mattering.

Tovar et al. (2009) first developed 55 items based on their five themes. Some items referred generally to the campus community (e.g., "People on campus are generally supportive of my individual needs"). Other items were written referencing specific people (e.g., "Sometimes my instructors simply do not listen to what I have to say" or "Counselors at the college generally show their concern for students' well-being"). Data were collected online from two institutions; one was a community college and the other a university. Combining these two data sources, a total of 3,139 students completed the CMI. To evaluate the structural stage for this measure, the sample of 3,139 students was randomly divided into two groups. One group consisted of 1,578 students and was used for an exploratory factor analysis (EFA). The other consisted of 1,561 students and was employed for a confirmatory factor analysis (CFA).

Principal axis factoring with varimax rotation was employed to examine the dimensionality of the 55 items. Tovar et al. (2009) removed items with communalities less than .30, any item that cross-loaded, and items with loadings less than .40. Thirty-four items and six factors were retained. They named the first factor "General College Mattering" and defined it as the college community showing interest in students and noticing when they come and go (thus, similar to Rosenberg and McCullough's [1981] definition of awareness). They labeled the second factor "Mattering Versus Marginality" and defined this factor as students' perceptions of belonging, fit, acceptance, or rejection. The third factor was named "Mattering to Counselors" and these items dealt with counselors' support and concern for students. The fourth factor was named "Mattering to

Instructors," and was similar to the counselor items except that these items referred to instructor support and concern for students. The fifth factor was named "Mattering to Students" and these items pertained to students' perceptions that other peers pay attention, support, and care about them. Finally, the sixth factor was labeled "Perception of Value" and the items on this factor assessed students' sense of their value or contribution to the college community.

Following the EFA, Tovar et al. (2009) used the second sample to test the fit of this six-factor model using CFA. The fit of the hypothesized six-factor model was poor (i.e., NFI = .85, CFI = .87, TLI = .86, RMSEA = .06). Model modifications were made based on modification indices. Four items were deleted and errors were allowed to correlate. However, this model still had poor fit (i.e., NFI = .91, CFI = .92, TLI = .91, RMSEA = .05). Thus, a fifth item was removed and the model was refit. This modified, 29-item measure with six-factors was championed (i.e., NFI = .92, CFI = .94, TLI = .93, RMSEA = .046) by the authors.

Tovar et al. (2009) went on to conduct invariance of the CMI for gender; however, it was unclear which sample they used for the invariance test. The revised six-factor model was first fit for males and females separately. Next, a model constraining all factor loadings, variances, and covariances to be equal was tested, but this model had poor fit. Tovar et al. (2009) relaxed the constraints to test the invariance of only the factor loadings. Concluding the item factor loadings were gender invariant, they tested 19 models varying in the degree of constraints. They championed one of these nineteen models, claiming partial invariance and decided to proceed to testing latent mean differences for males and females. Females and males were not statistically significantly different on any of the six mattering factors (no latent effect size was reported). Finally, they correlated the six mattering factors with a measure of college belonging consisting of the following five subscales: Perceived Peer Support, Perceived Faculty Support, Perceived Classroom Comfort, Perceived Isolation, and Empathetic Faculty Understanding. In general, the mattering factors correlated .10 to .45 with the belonging subscales, indicating mattering is related to these various forms of belonging but still distinct.

University Mattering Scale. The UMS was adapted by France and Finney (2010) from Elliott et al.'s (2004) general mattering scale. Elliott et al. (2004) created a measure of general mattering (an example item reads: "Often, people trust me with things that are important to them") based on Rosenberg and McCullough's (1989) theoretical framework. Elliott et al. (2004) wrote items to represent the concepts of awareness, importance, and reliance and examined the psychometric properties of their scale. They championed the three-factor structure; however, they did not test competing models.

France and Finney (2010) were interested in examining students' feelings of mattering to their university. Therefore, they adapted Elliott et al.'s (2004) measure of general mattering for use within a university (e.g., "Often, the people of the JMU community trust me with things that are important to them"). They noted that of the importance items Elliott et al. (2004) had written, three items appeared to fit the definition of ego-extension. This allowed for the testing of whether ego-extension and importance were in fact distinct, as alluded to by Rosenberg (1985) in his later work. Two hundred ninety upper-class students completed the UMS. To evaluate the structural stage of the UMS, six competing models were tested: (a) a four-factor model (awareness, importance, reliance, and ego-extension), (b) a higher-order model, (c) a three-factor model (awareness, importance (with the ego extension items treated as importance items), reliance), (d) a two-factor model combining importance, ego-extension, and reliance into one factor, (e) another two-factor model combining awareness, importance, and ego-extension into one factor, and (f) a one-factor model. Of these models, the four-factor model had the best overall fit. Interestingly, the second-order model did not converge to an admissible solution. Specifically, there was a negative disturbance term associated with the first-order importance factor.

France and Finney (2010) also gathered evidence for the external stage of the UMS. In general, they found the components of university mattering to be positively correlated with more adaptive non-cognitive constructs such as mastery-approach and performance approach goal orientation, academic self-efficacy, and instrumental help-seeking. They found the components of university mattering to be negatively correlated with more maladaptive non-cognitive constructs such as social adequacy concern, help-seeking threat, and help-seeking avoidance.

Results from this study led to a number of considerations for the revision of the UMS. These revisions led to the development of the Revised University Mattering Scale (RUMS), the instrument used in the present study. For example, it was unclear if awareness and importance or if importance and ego-extension were distinct factors due to their high correlations (.94 and .92 respectively). Additionally, there were a number of weaknesses of the UMS that could be addressed by rewriting some items. Specifically, there were disproportionate numbers of items on each factor; the awareness factor had 10 items but the ego-extension factor only had three. More items needed to be written to cover the breadth of ego-extension. Furthermore, there were a large number of negatively worded items on the awareness and importance factors (possible contributing to their high correlation). Finally, some of the items had low factor loadings. The variance extracted for the awareness, importance, and ego-extension factors were all below .50; that is, there was less variance explained by the factors in the items than error. It appeared that some items were confusing and could be rewritten to be clearer. Therefore, in an attempt to improve the measure, additional items were written to create the revised scale employed in this study (i.e., RUMS).

University Mattering and Student Populations

As noted in Chapter 1, university mattering has been investigated with various student subgroups. For example, Dixon Rayle and Chung (2007) examined mattering to college using 533 first-year college students (68% female). They found a negative relationship between mattering to college and academic stress. Likewise, Dixon and Robinson Kurpius (2008) examined the relationship between mattering to college and depression for 455 undergraduate students (56% female; 57% freshman). They proposed a regression model with gender, self-esteem, mattering, and stress as predictors of depression. All four variables were significant predictors of depression. France and Finney (2010) also examined mattering using a college student population. As noted above, they measured university mattering for 291 upper-class students (i.e., students who had accumulated between 45 and 70 credit hours; 67% female). University mattering was positively related to professor caring, social acceptance, mastery and performance approach orientation, academic self-efficacy, and instrumental help-seeking.

University mattering was negatively related to social adequacy concern, help-seeking threat, help-seeking avoidance, and executive help-seeking.

University mattering has also been examined for African American students. Specifically, African American students and white students were asked about their perceptions of mattering in relation to six general areas of campus life: academic advising, interactions with campus administrators, classroom climate, interactions with faculty, interactions with peers, and the delivery of campus services (Cuyjet, 1998). The responses from these two groups were then compared. It was found that African American students scored significantly lower than white students on all aspects of campus life except academic advising. Phillips (2005) replicated these results, using the same design and instrument.

Kodama (2002) examined transfer commuter students' feelings of mattering in comparison to native commuter students. No statistically significant differences were found between the two groups. However, on-campus support was found to be a significant predictor of mattering for transfer commuter students. In addition, transfer commuter students who were employed on-campus reported statistically significantly higher levels of mattering than transfer commuter students who were unemployed.

Although Schlossberg et al. (1989) studied mattering with non-traditional adult students and Tovar et al. (2009) studied mattering with community college students, both these studies used these subgroups for instrument development. They did not examine how these populations differ in mattering in comparison to other student populations.

Transfer Students

Other than Kodama's (2002) study, which focused on transfer commuter students, the transfer student population has been essentially left out of the university mattering literature. Transfer students are a unique subpopulation at institutions of higher education. For example, age, ethnicity, academic preparation, and employment patterns are just some of the ways in which transfer students differ from native students (Eggleston & Laanan, 2001). Specifically, transfer students tend to be older, more ethnically diverse, less academically prepared, and more likely to be employed off-campus than native students. Transfer students also make up a sizable group on many college campuses. Since the 20th century, the number of transfer students has grown. From 1972 to 1982 students who attended more than one institution grew from 39% to 52% (McCormick, 2003). More recent data indicates that 40.4% of students pursuing higher education (including public two-year, public four-year, and private not-for-profit institutions) had attended more than one institution by the year 2002 (Peter & Cataldi, 2005). Despite the fact that a large proportion of students enrolled in institutions of higher education are transfer students, research on transfer students is lacking. Two areas dominate the transfer student literature. The majority of the research focuses either on a specific type of transfer student (students who transfer from community colleges) or on differences in GPA between transfer and native students (Glass & Harrington, 2002). There is a need for research focusing on the adjustment and psychological development of transfer students (Laanan, 2001).

Types of Transfer Students

During the 20th century, many institutions of higher education adopted a standardized credit system designed to aid in the management of students' increasingly diverse curricular experiences (McCormick, 2003). Interestingly, a by-product of these standardized credit systems was the facilitation of student mobility across institutions. Students could more easily transfer their course credit from one institution to another. McCormick and Carroll (1997) define transfer as "a transition between postsecondary institutions in which the second institution (the destination, or receiving institution) typically grants the student credit for coursework taken at the first institution (the origin, or sending institution)" (p. 1). Currently, many states have formal transfer agreements between their two- and four-year institutions (Miller & Hillis, 2006), which also facilitates students' ability to move more easily from one institution to another.

Given the ease of student mobility across institutions, some of the difficulty in studying transfer students may originate from the fact that transfer students are a heterogeneous population. Traditionally, the term transfer student may bring to mind the student who completes two years of coursework at a community college and then transfers to a four-year institution to complete his or her last two years and receive a bachelor's degree (Miller & Hillis, 2006). However, many students do not follow this linear path to degree completion (Borden, 2004). Students may transfer more than once and attend multiple institutions. Some students begin at a four-year institution and transfer to a two-year institution (i.e. "reverse transfer"); still other students may be enrolled in two institutions at the same time. Students who are concurrently enrolled in two different institutions have been labeled as "double dippers" (Gose, 1995), whereas "swirling" is a term describing students who transfer back-and-forth between institutions (de los Santos & Wright, 1990). A further distinction among transfer students is whether they transfer from a two-year institution to a four-year institution (i.e., vertical transfer) or between institutions of the same type, two-year to another two-year or a four-year to another four-year (i.e., horizontal or lateral transfer respectively) (McCormick & Carroll, 1997).

Miller and Hillis (2006) described four types of transfer students: (a) community college transfers, (b) quilters, (c) reverse transfers, and (d) peer transfers. Community college transfers are analogous to vertical transfers and represent the more traditional conceptualization of transfer students moving from two-year institutions to four-year institutions. Quilter students are defined as students "who enroll in multiple institutions, whether simultaneously or individually to bring together the required courses for an academic degree" (p. 299). Reverse transfer students begin at four-year institutions and move to two-year institutions. These students have reported numerous reasons for making this type of transfer, such as not having the necessary academic skills, discovering their occupational interests were more aligned with a certificate program offered at a community college, personal reasons, to work full-time, to complete their education online, or geographic reasons. Finally, Miller and Hillis's (2006) definition of peer transfers is akin to horizontal transfers ("peer" refers to the type of institutions students are transferring between). Miller and Hillis suggest students transfer between similar institutions for specific academic programs or for social reasons.

Clearly, there are many pathways students can take to obtain a degree. Also, there are a variety of reasons why students choose to transfer. This indicates that transfer students are not only different from native students, but a heterogeneous group as a whole. As a result, it is challenging to categorize transfer students as one subpopulation.

However, the common thread among all transfer students is that they have attended at least one other institution prior to transferring, and thus bring with them previous collegiate experiences and expectations (Wang & Wharton, 2010). Furthermore, all transfer students have to adjust to their new institution. They face similar challenges socially; many native students have already formed relationships. They also face similar challenges academically and must assimilate to their new institutional culture (Ishitani & McKitrick, 2010). However, transfer students do not want to be treated like first-year students. Transfer students have distinct needs in comparison to first-year students.

Characteristics of Transfer Students

Time to degree. In general, there is more variability in the amount of time to degree completion for transfer students (Ishitani & McKitrick, 2010). Furthermore, Peter and Cataldi (2005) looked at data from both the Beginning Postsecondary Students Longitudinal Study and the Baccalaureate and Beyond Longitudinal Study. They found a relationship between attending multiple institutions and slowed progress toward the bachelor's degree; possibly a result of difficulty in transferring credits, different requirements at different institutions, gaps in enrollment, or extenuating factors such as a move, job changes, or changes in family life. Specifically, with data from the Beginning Postsecondary Students Longitudinal Study they found that six-year persistence was negatively associated with transferring even after controlling for income, GPA, and various risk factors. Likewise, using data from the Baccalaureate and Beyond Longitudinal Study, time-to-degree was found to vary depending on how many institutions students attended and the type of institutions from which students transferred. The students who began at a two-year institution and transferred multiple times (i.e., swirlers) took the longest to receive their degree (11 years on average). Similarly, Adelman (2006) found a negative relationship between bachelor attainment and transferring multiple times. Finally, transfer students who took time off in between institutions at which they enrolled had the lowest probability of completing their degree (Li, 2002).

Academic Achievement. Transfer students' community college GPA has repeatedly been identified as the best predictor for transfer students' GPA at their senior institution. For example, community college GPA and four-year institution GPA were correlated r = .58 (which is considered a medium to large effect [Cohen, 1992]) in one study (Townsend, McNerny, & Arnold, 1993). Also community college/post-secondary GPA is cited as the most important variable for transfer admissions into four-year institutions (Adelman, 2005).

Transfer shock is the term used to describe the drop in GPA experienced by transfer students when they move from a two-year institution to a four-year institution (Hills, 1965). Diaz (1992) conducted a meta-analysis of the transfer shock phenomenon using 62 studies. Transfer shock was reported in 79% of the studies with students' GPAs dropping on average half a grade point or less. However, most of these students (67%) recovered from transfer shock within their first year. Specifically, of the studies that reported recovery rates, 34% showed students completely recovered, 34% showed students nearly recovered, and 32% showed students partially recovered.

However, some researchers have found that transfer students show an increase in GPA after they move to a senior institution. This has been labeled "transfer ecstasy" (Nickens, 1972). Possibly, the relationship between transferring and GPA is more complex, leading to these mixed results (i.e., transfer shock vs. transfer ecstasy). One study examined the phenomenon of transfer shock by dividing transfer students into five groups based on their discipline: business, education, fine arts and humanities, mathematics and sciences, and social sciences and controlling for high school GPA (Cejda, 1997). Interestingly, transfer students majoring in education, fine arts and humanities, and social sciences tended to experience an increase in GPA. Transfer students majoring in business and mathematics and sciences experienced a drop in their GPA, indicating that the relationship between transferring and GPA may be moderated by area of discipline.

Another study compared transfer and native student GPAs (Glass & Harrington, 1992). Fifty transfer and 50 native students were randomly selected. Transfer students GPAs (on average 2.74) were statistically significantly lower than native students' GPAs (on average 3.03) even after controlling for high school GPA. In addition to transfer shock, transfer students may increase the amount of time they spend studying and preparing for class at their senior institution compared to their two-year institution. Specifically, transfer students at UMass reported studying about 4.5 hours a week more after transferring (Berger & Malaney, 2003).

Engagement. A few researchers have gone beyond these general descriptions of transfer students, investigations of time to degree, and investigations of academic achievement to examine how well transfer students engage with their new institution. Student involvement and engagement with the university are related to persistence and academic success (Astin, 1993; Tinto, 1987).

The 2009 annual report of National Survey of Student Engagement (NSSE) investigated how native students, horizontal transfer students, and vertical transfer students differ in academic engagement. Academic engagement was defined as student participation in “culminating senior experiences” (i.e., capstone courses, theses, and comprehensive exams). Forty percent of native students reported participating in senior culminating experiences, whereas only 30% of horizontal transfer students and 25% of vertical transfer students took part in these academic experiences. In addition to academic engagement, the 2009 NSSE report also gathered information about the percentage of students who worked with faculty on research. A similar pattern emerged for the three student groups as with academic engagement. Twenty-four percent of native students engaged in research with faculty, but only 17% of horizontal transfer students and 13% of vertical transfer students reported being involved in research experiences with faculty.

Other studies investigating student engagement have found similar patterns of lower engagement for transfer students compared to native students. For example, community college transfer students were found to have lower scores than native students on collaborative learning, student faculty interaction, and enriching educational experiences based on measures from the NSSE (Ishitani & McKitrick, 2010). Furthermore, Wang and Wharton (2010) developed a scale to assess transfer student engagement and campus involvement. The scale consisted of six subscales: independent and active learning, outside class academic-related interaction, social involvement, participation in student organizations, awareness of student support services, and use of student services. Generally, transfer students reported statistically significantly lower levels of social involvement, student organization participation, awareness of support services, and usage of student services than native students.

Finally, one study purposefully sampled “involved” and “uninvolved” transfer students based on their participation in campus activities (Ose, 1997). Transfer students were interviewed with respect to three areas: motivation, satisfaction, and their sense of connection to their university. Involved transfer students were more motivated than uninvolved transfer students to make social connections, whereas the uninvolved transfer students were more motivated to perform well academically. Involved and uninvolved transfer students were most similar on reported satisfaction with their experience at the university; however, uninvolved transfer students reported slightly lower satisfaction. Finally, involved and uninvolved transfer students reported feeling a lack of connection to the university when they first transferred. Specifically, they reported “feeling like an outsider” (p.43). However, over time, the involved transfer students reported they felt more connected to the university, whereas the uninvolved transfer students reported they felt more connected to their work environment or the local community in comparison to the university.

Taken together, these studies highlight differences in behavior between transfer and native students. Given these differences, transfer students have been labeled as an “at risk” subgroup (Ishitani & McKitrick, 2010). Specific risk factors include, transfer students take longer to obtain a degree, their GPAs tend to be lower, and they are less engaged with their institution than native students. Despite these known risk factors, there are fewer college initiatives focused on transfer students compared to first-year students (Townsend & Wilson, 2006). For example, most institutions of higher education have first-year orientation programs and first-year learning communities. Some institutions also offer transfer students orientation programs. However, transfer orientation programs tend to be shorter than first-year orientation programs. Other institutions combine transfer and first-year student orientation programs. Thus, these programs are less tailored to the specific needs of transfer students (Eggleston & Laanan, 2001). A better understanding of transfer students and transfer adjustment would aid in the development and evaluation of transfer student programs.

Transfer Students and Feelings of Mattering

Transfer students' feelings of university mattering–the perception that a student is significant and makes a difference in his or her school community–is of particular interest for three reasons. First, most of the research on transfer students focuses on GPA and persistence and is lacking in the area of adjustment and students' emotional and psychological development (Laanan, 2001). Thus, a better understanding of transfer students' feelings of university mattering may help university faculty and student affairs administrators aid these students in their transition between institutions. Second, given the research on transfer students, transfer students frequently report feelings of marginality after relocating to their new college campuses. The term "marginality" has been used to define this lack of mattering. That is, at the far end of the continuum of mattering, feeling a lack of acceptance, a lack of significance, or that one is a nonentity is to feel marginal (Schlossberg, 1989). Moreover, qualitative reports reveal that transfer students frequently feel isolated, lonely, lost, or that they are on their own (Owens, 2010; Townsend & Wilson, 2006), all of which are feelings that indicate a lack of mattering. Possibly, transfer students feel marginal because they are such a diverse group (Weiss et al., 2006); these students do not identify with native students but also, may not easily identify with the other transfer students. Finally, by definition, transfer students may lack feelings of mattering because they are in transition. Schlossberg (1989) theorized, "…people in transition often feel marginal and that they do not matter" (p. 6). Until these students are able to establish meaningful relationships and connect to their new community, their sense of mattering will suffer. Practically, a measure of university mattering could prove useful in evaluating the effectiveness of university transfer programs that claim to increase feelings of mattering. Also a sound measure would be useful for identifying transfer students with low feelings of mattering for program selection purposes.

Conclusion

To summarize, there is a clear need for a quality measure of university mattering. To meet this need the UMS was revised for use in the current study. There are numerous reasons why the previously created measures of university mattering are not appropriate. For example, the MHE was developed specifically for an adult population and would need to be adapted for use with an undergraduate population. Second, the MHE and CMI were not developed using a strong methodology for instrument development. That is, following Benson's (1998) framework, it is important to ensure the items of an instrument operationalize the theory (i.e., substantive stage). The items on the UMS were written to represent the proposed facets of mattering: awareness, importance, ego-extension, and reliance. Given France and Finney's (2010) suggestions to revise and hopefully improve the UMS, the RUMS was created. Thus, this study attempts to evaluate the model-data fit of the RUMS (i.e., the structural stage) by testing five theoretically derived models. Furthermore, the measurement invariance across transfer and native students will be assessed. Finally, with the establishment of measurement invariance, latent mean differences on university mattering can be compared for transfer and native students. If transfer student have significantly lower latent means than native students, this will provide validity evidence for the external stage (Benson, 1998) of the university mattering measure, as well as inform the transfer student literature.

CHAPTER THREE

Methods

The purpose of this chapter is to describe the samples, procedures, and analyses used to gather construct validity evidence for a measure of university mattering. The chapter begins with a description of the participants and the data collection process. Importantly, because there is not a universally accepted definition of transfer students, I describe in detail how transfer students were defined for this study. Second, I address how I answered the first research question by presenting confirmatory factor analysis (CFA). CFA theory posits that the covariation among a set of items is caused by an underlying latent variable (or multiple latent variables; DeVellis, 2003). A latent variable is "a hypothetical construct" and as a result, is not directly measurable or observable (Crowley & Fan, 1997, p. 510). For example, a person's level of university mattering is a latent variable because "mattering" is unobservable, but a person's height is not; height can be observed and directly measured. A strength of CFA is that it can be used to test theoretical competing models using empirical data (Crowley & Fan, 1997). Therefore, five theoretically-based models were evaluated using CFA. These models are presented in detail below.

Following this, I present the planned analyses for measurement invariance, which pertains to my second research question. Contingent on the establishment of measurement invariance, the third research question pertaining to latent mean differences can be addressed. Similar to a latent variable, a latent mean is not directly measureable or observable. Using the same example of height, one can compare the mean height of men to the mean height of women, but height is observable. The purpose of the third research question is to compare transfer students latent mean of university mattering to native students latent mean of university mattering. However, unlike height, university mattering is unobservable; the latent means must be estimated through modeling techniques. It is expected that transfer students will have lower university mattering than native students given the challenges transfer students face with respect to integrating into their new university community. A latent mean difference between transfer and non-transfer students would provide additional construct validity evidence for this measure of university mattering. That is, this would provide evidence for the external stage (Benson, 1998) of the validity process.

Participants and Procedures

Data were collected at a large, mid-Atlantic, public university where all incoming first-year students are required to complete assessments in August immediately prior to the beginning of classes and again, once they have earned between 45 and 70 credit hours (typically during the spring of their sophomore year). At both administrations, students were randomly assigned by the last two digits of their student identification number to a classroom where the assessments were administered. Depending on the size of the classroom, there were twenty-five to 300 students assigned to the classrooms with two to seven trained proctors in each room who administer the assessments. Students completed a series of assessments over a three-hour time period. The RUMS was administered to all students across all rooms in the Spring of 2009 and the Spring of 2010. The RUMS was part of a battery of non-cognitive assessments (i.e., measures focusing on attitudinal, affective, or behavioral dispositions) that students completed at the beginning of the testing period. In addition to these non-cognitive assessments, students also completed a number of cognitive assessments (i.e., direct measures of learning outcomes) for the purpose of evaluating the university's general education courses. Only the archival data from the RUMS were used for the current study.

Splitting data sets. An important consideration for this study was how to define transfer students. Technically, any student who enters the university with credit from another institution could be considered a transfer student. However, the student who takes a summer course at his or her local community college to prepare for the first year is different from the student who completes his or her associate's degree at a community college and then transfers to the university. To be eligible for transfer admissions at the current institution, students must have completed or be in the process of completing 24 credit hours at their previous institution. Therefore, for the purpose of this study, the transfer subgroup was defined as any student who transferred to the current institution with 24 or more credit hours. The number of transfer credits per student were gathered from university records. Students may have transferred from two- or four-year institutions; that is, students did not necessarily transfer from the same type of institution to be categorized in the transfer subgroup. Furthermore, transfer students may have transferred more than once prior to transferring to the current institution. Thus, a transfer student may not have accumulated all their transfer credits from the same institution. Despite these differences within the transfer subgroup, all students who transferred to the current institution brought with them the experience of attending at least one additional institution of higher education. Similarly, all transfer students faced the same challenge of adjusting socially and academically to their new institution.

A combined total of 4,838 students completed Spring assessments in 2009 and 2010. Prior to splitting this larger sample into three smaller samples of native students and one sample of transfer students, missing data was assessed. There were 353 cases with missing data that were listwise deleted, resulting in a total of 4,485. Of those 4,485 students, 708 had 24 or more transfer credits and were classified as "transfer students" for the purpose of this study. Of the remaining 3,777 students who had completed assessments, 1,286 students had between 1 to 23 transfer credits. These students were removed, leaving a subgroup of 2,491 native students who entered the university as first-year students with no transfer credits. By randomly splitting this sample of 2,491 participants into three subgroups, three samples of approximately 830 native students each were created.

Given the large sample size of native students, removing the subgroup of students with 1 to 23 transfer credits did not create a sample size issue. More specifically, factor analytic and invariance studies require large sample sizes. As a guideline, a ratio of 10:1 (cases: parameters) has been suggested for the estimation of stable parameters in factor analysis (Kline, 2005). The most complex model, the proposed bifactor model, has 102 parameters (34 factor loadings to the general factor, 34 factor loadings to the specific factor, and 34 uniquenesses) to estimate; thus, ideally, each sub-group should have about 1,000 students. Although a sample size of 830 is slightly lower than the suggested 10:1 ratio, these three samples were necessary for cross-validation. That is, the five proposed models were initially tested using Sample 1 and Sample 2 and necessary modifications were made based on these two samples. Prior to assessing measurement invariance, Sample 3 was used to test the modified model that resulted from Study 1 to avoid the capitalization on idiosyncrasies of the data (MacCallum, Roznowski, & Necowitz, 1992). Thus, Samples 1 and 2 were used to address the first research question pertaining to model-data fit. Sample 3 and the Transfer Sample were used to address the second and third research questions: measurement invariance and latent mean differences between transfer and native students.

Demographics for the four samples are presented in Table 1. The demographics for the native samples and transfer sample closely paralleled the actual native and transfer populations at this university. In general, the three native samples were very similar to one another on demographic variables. The transfer students differed from the native students in that they were slightly older and had more variability in age. Consistent with previous findings on transfer student GPA, transfer students also had a lower average GPA and more variability in GPA than native students. A higher percentage of transfer students were male than native students. In addition, a higher percentage of transfer students were in-state, compared to native students.

Measure

Revised University Mattering Scale. During campus assessment activities, students completed the RUMS, a 34-item measure composed of items written to represent four components of university mattering: awareness, importance, reliance, and ego-extension (see Appendix B). Participants were given specific directions to think about all the members of their university community (e.g., peers, faculty) as a whole when responding to the items. Participants were asked to respond to the items by indicating the degree to which they agreed with each statement using a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The eight negatively worded items were reverse scored; thus, higher scores indicate higher levels of university mattering.

Planned Data Analysis

Study 1: Model-Data Fit using Confirmatory Factor Analysis

Based on CFA theory, students' responses to the 34 items on the RUMS are assumed to be driven by their unobservable (i.e., latent) degree of university mattering. A student who truly feels he or she matters to a lot of people at the university should select responses on the RUMS that constitute a high score. Another student who feels he or she matters little to the university should tend to select responses that result in a low score on the RUMS.

The equation for the common factor model, when modeling continuous normally distributed variables, is

$$y_j = \lambda_{j1}\eta_1 + \lambda_{j2}\eta_2 + \ldots + \lambda_{jm}\eta_m + \varepsilon_j$$

where y_j represents the observed score from indicator (item) j, λ_{jm} represents the factor pattern coefficient relating variable j to the mth factor η, and ε_j represents variance unique to y_j (and thus is unrelated to all ηs and all other εs; Brown, 2006, see equation 2.1). A more thorough discussion of the common factor model can be found in Brown (2006) and McDonald (1999). However, it is important to note that when employing CFA the researcher specifies the structure of a measurement model based on theory. That is, the number of factors and which items represent which factors are specified a priori. When specifying a measurement model, parameters (e.g., factor pattern coefficients) can be specified to be free, fixed, or constrained (Crowley & Fan, 1997). Free parameters are estimated from the empirical data. Fixed parameters are specified to be zero and thus, are not estimated. For example, if a model is specified where item 1 represents the factor "awareness", the path coefficient from item 1 to the awareness factor will be freely estimated using the sample data. However, the paths from item 1 to all other factors will be fixed to zero. Finally, a coefficient can also be constrained to a specific value, such as 1, or be constrained to be equal to another coefficient that is estimated in the model (as in tests of metric and scalar invariance).

Recall that the goal of Study 1 was to test the following five competing models described below: (a) a one-factor model, (b) a correlated four-factor model, (c) a higher-order model, (d) a bifactor model, and (e) an incomplete bifactor model. Specifically, the five models were fit to Sample 1 and Sample 2 data. Scale modifications (i.e., removal of items) were only made when the same areas of misfit emerged across the two data sets.

One-factor model. The first proposed model is a unidimensional model, in which all 34-items represent one underlying factor of university mattering (see Figure 1). This model has 527 degrees of freedom, with 68 free parameters (34 direct paths and 34 error variances) estimated from 595 observations[1]. In a unidimensional model, each item is modeled as interchangeable (i.e., homogenous) with any of the other 33 items. In other words, the items are said to be *factorially simple*, only representing one latent construct (Reise et al., 2010). However, based on France and Finney's (2010) findings, this model is expected to fit poorly. Even if the items on the RUMS are truly good indicators of university mattering, this model could result in poor model-data fit for two reasons, one being theoretical and the other statistical. Theoretically, university mattering may be multidimensional (e.g., Rosenberg & McCullough, 1981), and therefore, a unidimensional model would be a poor representation of the true underlying structure.

On the other hand, the one-factor model could have poor fit for statistical reasons. The goal of CFA is to assess how well the model reproduces the covariance matrix. This is indicated by the fit indices. Given that the number of items is positively related to the size of the covariance matrix, as the covariance matrix increases in size, it becomes more difficult to reproduce that matrix. This could result in poor global fit (i.e., global fit indices such as the CFI are influenced by the number of variables being modeled). However, poor global fit does not necessarily mean bad model-data fit. When fitting a unidimensional model with a large number of items, it is most important to interpret correlation residuals to assess local misfit. In this situation, small correlation residuals (< .10) would lend support for an underlying unidimensional structure.

Another reason to test the one-factor model is because the parameter estimates from the one-factor model can serves as base-lines to compare to the parameter estimates obtained from the bifactor model (Reise et al., 2010). Specifically, the unstandardized factor pattern coefficients, which represent the relationship between the items and the factor, for the one-factor model can be compared to the unstandardized factor pattern coefficients for the general factor of the bifactor model. If these parameters are similar, this would provide support for one underlying university mattering factor.

Correlated four-factor model. The second proposed model is a multidimensional model (see Figure 2) where the four RUMS factors (awareness, importance, reliance, and ego-extension) are correlated. This model has 521 degrees of freedom, with 74 free parameters (34 direct paths, 34 error variances, and 6 covariances) estimated from 595 observations. This model is based on Rosenberg and McCullough's (1981) theory of mattering where mattering was discussed as being comprised of multiple facets. This model is conceptually different from the one-factor model in that the items represent different factors and are not interchangeable (e.g., an importance item is not the same as a reliance item). As a result, championing this model would mean four separate subscale scores should be calculated when scoring the RUMS. Although this is a plausible model based on theory, previous research on the UMS (France & Finney, 2010) found high correlations among the four factors, calling into question the utility of this model.

Higher-order model. In addition to the one-factor and four-factor models, a higher-order model will be tested (see Figure 3). This model has 523 degrees of freedom, with 71 free parameters (38 direct paths and 34 error variances) estimated from 595 observations, and thus is a simpler model than the four-factor correlated model. A commonly cited example of a higher-order model is Spearman's (1927) model of intelligence. In this model, there are numerous lower-order factors of specific intelligence-related abilities, each assessed by multiple items. A second-order general intelligence factor is theorized to account for the commonality among the specific abilities. That is, the relationships among the first-order factors are explained by a higher-order factor. In the case of the current study, the relationship between the general second-order mattering factor and each item is mediated through the first-order factors (i.e., an indirect effect; Reise et al., 2010). Given the high correlations among the four factors of the UMS (see France & Finney, 2010), the higher-order model is a plausible alternative model to test. However, in evaluating the psychometric properties of the UMS, this model did not converge to an admissible solution due to a negative disturbance term associated with the importance factor (France & Finney, 2010). The disturbance term represents variance in the set of items not explained by or independent of the second-order factor; this indicates that the importance items do not share additional variance after controlling for the second-order mattering factor (Chen, West, & Sousa, 2006; Reise et al., 2010). Moreover, variances cannot be negative, thus causing the estimation problem.

Bifactor model. The fourth model tested is the bifactor model. This model has 493 degrees of freedom, with 102 free parameters (68 direct paths and 34 error variances) estimated from 595 observations and is the most complex model. The bifactor model is similar to the one-factor model in that one general factor explains the common variance across all the items. However, an important difference between the one-factor model and the bifactor model is that in the one-factor model, the items are considered unidimensional (or factorially simple), meaning the total variance associated with each item can *only* be partitioned into variance explained by the common factor (i.e., university mattering), and variance not explained by the factor (residual variance). In the bifactor model, the items are *factorially complex* (Reise et al., 2010), meaning the common variance associated with each item can be partitioned into variance explained by the general factor (i.e., university mattering) and variance explained by a specific factor (see Figure 4). These specific factors are orthogonal (i.e., unrelated) to the general factor. That is, the specific factors represent variance shared among subsets of items above and beyond the variance shared by all the items as explained by the general factor.

The bifactor model in this study has four specific factors; one associated with the items representing each of the mattering facets (awareness, importance, ego-extension, and reliance). However, it is important to distinguish these specific factors from the mattering facets. In other words, the specific factor associated with the awareness items does not represent “awareness”. This specific factor represents what is common across the awareness items *after* controlling for the common variance across all the mattering items (i.e., general university mattering which includes awareness). Thus, specific factors can manifest due to a method effect (e.g., common item wording) or they can be substantively meaningful (e.g., representing some other latent construct such as extroversion). For example, the ego-extension items include vocabulary referring to various emotions (e.g., pride, sad, excitement); therefore, it is possible the specific factor associated with these items reflects this “emotion” component. Thus, the specific factors are not comparable to the factors from the correlated four-factor model or the four first-order factors from the higher-order model. Instead, these specific factors are analogous to the disturbance terms from the higher-order model (Chen et al., 2006). That is, the specific factors represent additional shared variance across a subset of items after controlling for the general mattering factor. Therefore, to avoid confusion with the awareness, importance, ego-extension, and reliance factors, the specific factors were arbitrarily named A (corresponding to the awareness items), B (corresponding to the importance items), C (corresponding to the ego-extension items), and D (corresponding to the reliance items). Benefits of using a bifactor framework in instrument development include the ability to assess whether items primarily measure a single common latent construct and if so, how well (Reise et al., 2010).

Incomplete bifactor model. Finally, the incomplete bifactor model was hypothesized as a plausible model due to previous findings related to the higher-order model in the psychometric evaluation of the UMS (France & Finney, 2010). This model has 501 degrees of freedom, with 94 free parameters (60 direct paths and 34 error variances) estimated from 595 observations. As previously stated, the higher-order model tested for the UMS did not converge to an admissible solution due to a negative disturbance term associated with the importance factor. For the incomplete bifactor model, the importance items only represent the general factor; specific factor B was removed (see Figure 5). In other words, it was hypothesized that all of the common variance in the importance items can be explained by the general factor and there was no additional variance shared among that subset of items; thus, there was no reason to model a specific factor for these items. More clearly, if there were no additional variance among these items after controlling for the general factor, this would manifest as a negative disturbance term in a higher-order model. Given previous research on the UMS (France & Finney, 2010), this model was hypothesized to best represent the data of the RUMS.

Study 2: Measurement Invariance

When comparing scores on a measure from two qualitatively distinct groups (e.g., males and females, African Americans and Hispanics, transfer students and native students), there is an assumption that the structure of the underlying construct and parameters are equivalent across groups (Byrne, Shavelson, & Muthén, 1989). If an instrument functions differently for different subgroups, the instrument is said to lack measurement invariance. That is, establishing measurement invariance is "a precondition for conducting substantive group comparisons" (Vandenberg & Lance, 2000, p. 12). There can be numerous causes of a lack of invariance. It may be the actual construct manifests differently for different subgroups (i.e., the construct is multidimensional for one group but unidimensional for another group) or that the subgroups use the response scale differently (i.e., one group tends to use the extremes of the response scale whereas the other group tends to be more conservative and use the middle of the response scale). Despite the cause, if the instrument functions differently, observed differences in scores across various groups cannot necessarily be attributed to *true* differences in the underlying latent construct. Likewise, if no group differences are observed, but measurement invariance has not been established, there may be real differences on the underlying latent construct that are not observable due to a lack of invariance.

For this study, the evaluation of measurement invariance was conducted using a step-by-step procedure introducing more equality constraints on the model across groups at each step (Meredith, 1993; Steenkamp & Baumgartner, 1998). Tests of measurement invariance began with testing configural invariance, followed by metric invariance, and finally, scalar invariance. Following the establishment of measurement invariance across the two groups, latent means were interpreted.

Conclusion

In summary, the purpose of this study is to gather construct validity evidence for the RUMS. First, model-data fit was evaluated for the five competing models using two samples of native students. The incomplete bifactor model was expected to fit significantly better or just as well as the other proposed models. Next, measurement invariance was assessed for transfer and native students on university mattering. The establishment of measurement invariance facilitates the investigation of latent mean differences. Transfer students were expected to have lower latent means on university mattering, providing known-groups validity for university mattering.

CHAPTER 4

Results

The results are reported in two parts. First, the results for Study 1 pertaining to research question 1 (i.e., of the five proposed models, which model fits best?) are presented. Samples 1 and 2 were used to address research question 1. Model modifications were made to the RUMS resulting in a further refined instrument with an interpretable factor structure. Second, the analyses addressing research questions 2 (i.e., given an interpretable factor structure from Study 1, is measurement invariance supported for transfer students?) and 3 (i.e., given measurement invariance for transfer students, do transfer students have a different latent mean than native students on university mattering?) are presented. Sample 3 and the Transfer Sample were used in the assessment of measurement invariance and the comparison of latent means.

Study 1: Of the five proposed models, which model fits best?

Data Screening and Descriptive Statistics

Prior to running CFA analyses, the two native samples were screened for outliers using Mahalanobis' distance. Sample 1 had 830 complete cases (i.e., any cases with missing data were listwise deleted). Of those 830, fourteen cases were identified as outliers due to obvious response sets (e.g., 1, 1, 1, 1, 1) and removed, resulting in a data set of 816 cases. Sample 2 also had 830 complete cases; eight cases were removed as outliers, resulting in a data set of 822 cases.

Following the removal of outliers, data were examined for univariate and multivariate normality. Both samples appeared to be approximately univariately normally distributed. That is, none of the skewness values exceeded an absolute value of 2 and none of the kurtosis values exceeded an absolute value of 7 (Curran, West, & Finch, 1996; Finney & DiStefano, 2006). Similar patterns of skewness and kurtosis were replicated across the two samples. In general, for both Samples 1 and 2, 32 of the 34 items were slightly negatively skewed. The exceptions were items 5 and 34, which had skewness values close to zero in both data sets. In Sample 1, the most skewed item was item 7 (-1.30). However, item 16 was the most skewed (-1.33) in Sample 2. The least skewed item was item 5 in both samples (0.08 and 0.10, respectively). In Sample 1, item 7 was the most kurtotic (1.72); however, in Sample 2, item 16 was the most kurtotic (3.17). In both samples, item 21 was the least kurtotic (-.76 and -.72, respectively).

Multivariate normality was investigated for each sample by calculating Mardia's normalized multivariate kurtosis coefficient. Mardia's coefficient was 96.08 and 96.52 for Samples 1 and 2, respectively. Thus, it was concluded that the data were multivariately non-normal given that these values exceeded 3 (Bentler, 1998).

Item means generally fell just above the scale mid-point of 3.5. Specifically, means ranged from 3.31 (item 34) to 4.97 (item 7) in Sample 1 and 3.34 (item 34) to 4.96 (item 7) in Sample 2. In both samples, Item 3 had the least amount of variance (SD = .90 in both data sets) and Item 21 had the most variance (SD = 1.44 in both data sets). In Sample 1, items were correlated from .001 (items 15 and 34) to .69 (items 24 and 30). In Sample 2, items were correlated from .02 (items 7 and 34) to .70 (items 5 and 8). These widespread ranges in the magnitude of the correlations suggest that the one-factor model will have poor fit. On the other hand, if all the correlations were about the same magnitude, one would expect the one-factor model to fit well. Correlations and descriptive statistics for all 34 items from both samples are reported in Table 2.

Estimation Methods

Once models are specified, mathematical algorithms, such as Maximum Likelihood (ML), are used to estimate the population parameters and factor pattern coefficients of each specified model (Crowley & Fan, 1997). An appropriate estimation method must be chosen given the properties of the data, otherwise the resulting parameter estimates, fit indices, and standard errors may be biased (additionally, biased standard errors will impact the conclusions drawn from significance tests), potentially leading to erroneous conclusions about the theory being tested (Finney & DiStefano, 2006; in press). The data properties to consider include the distribution and the metric of the data (Finney & DiStefano, in press). More specifically, the distribution of the data can be normal or non-normal and the metric of the data can be continuous or categorical. For the current study, the data were multivariately non-normal (as indicated by the high values of Mardia's coefficient) and, although the construct of university mattering is theoretically continuous, Likert data (as in the case of the current study) is categorical in nature. That is, the RUMS yields data that are categorical (i.e., six ordered categories), not continuous.

When data are categorical, Finney and DiStefano (in press) suggest two approaches to model estimation: (1) analyzing a Pearson Product Moment (PPM) covariance matrix using ML with S-B adjustments (robust ML) or (2) analyzing a polychoric correlation matrix using robust Diagonally Weighted Least Squares (rDWLS). Finney and DiStefano recommend analyzing the specified models using both estimation methods and comparing the results. As long as both estimation methods result in the same substantive conclusions, results from either method can be interpreted. However, if the results diverge, one should interpret the rDWLS results because the parameter estimates from robust ML will be attenuated. Given the nature of the data (i.e., non-normally distributed and categorical), models were estimated using both covariances with ML with S-B adjustments and polychoric correlation rDWLS. These two estimation methods and their assumptions are discussed below. The results are then presented for each estimation method for Sample 1 and Sample 2.

Maximum Likelihood. As suggested by Finney and DiStefano (in press), the five CFA models were first analyzed employing ML with SB adjustments using item variances and covariances. Maximum Likelihood (ML) is a popular estimation method and frequently employed to analyze PPM covariance matrices of continuous data. That is, ML assumes the data are normally distributed and continuous in nature (Chou & Bentler, 1995; Olsson et al., 2000). If the data are continuous but non-normal, using ML with a PPM covariance matrix will result in attenuated standard errors and fit indices. In this situation, it is best to apply the Satorra-Bentler (SB) adjustment to adjust the χ^2 statistic, fit indices, and the standard errors of the estimated parameters using the degree of multivariate kurtosis present in the data (Satorra & Bentler, 1994). In the current study, covariance matrices were created in PRELIS 2.80 and analyzed using LISREL 8.80 (Jöreskog & Sörbom, 2005).

Robust Diagonally Weighted Least Squares. Following the analyses employing robust ML, the same models were evaluated employing rDWLS testing polychorics. More specifically, when data are categorical, it may be more appropriate to analyze a polychoric correlation matrix, which does not assume continuous data. More specifically, the polychoric correlation is used to correlate two ordinal variables when it is assumed that a continuous, normally distributed latent variable underlies the observed ordinal variables (Hershberger, 2005). The calculation of the polychoric correlation involves a correction that approximates what the PPM correlation would have been if the data were continuous. The rDWLS estimator available in LISREL was chosen over Weighted Least Squares (WLS) estimation. WLS consistently performs poorly (i.e., produces overestimated parameter estimates and underestimated standard errors) with small samples (< 1,000) and with large models (Dolan, 1994; Flora & Curran, 2004) and is not sensitive to model misfit (Olsson et al., 2000), and therefore is not appropriate for the current study. In the current study, polychoric correlation matrices were created also in PRELIS 2.80 and analyzed using LISREL 8.80.

It was expected that the two estimators would result in very similar results. That is, as the number of response categories increase, the data became more continuous in nature. That is, the PPM correlation coefficients and polychoric correlation coefficients become increasingly similar (Bollen & Barb, 1981). However, researchers have found that even with 5-category indicators, parameter estimates are more accurate when analyzing polychoric rather than PPM correlation matrices with ML estimation (Babakus, Ferguson, & Jöreskog, 1987; Dolan, 1994). Another study directly compared ML and categorical-DWLS (Beauducel & Herzberg, 2006) by simulating models of various complexity using indicators with 2 to 6 categories. Their results favored the categorical method for estimation of fit and standard errors, except for the estimation of factor correlations, which were less biased with ML estimation. Rhemtulla, Brosseau-Liard, and Savalei (in press) directly compared ML with SB adjustments to robust categorical least squares. They concluded that robust categorical least square performed best for data with 2 to 5 categories. However, factor pattern coefficients, factor correlations, and robust standard errors were more accurately estimated with robust ML than with robust categorical least squares when data have 6 or 7 categories. Furthermore, depending on the normality of the data, one estimation method may be better than the other. Specifically, categorical estimation methods assume the data are normally distributed (Flora & Curran, 2004) and when this assumption is violated, ML with SB adjustments performs better than robust categorical methods (Rhemtulla et al., in press). Taken together, this research suggests that ML with SB adjustments may be a better choice of estimation method than rDWLS for the current study, given that the data consists of six categories and were multivariate non-normal.

Assessing Model-Data Fit

Model-data fit was evaluated using numerous criteria. The criteria changes depending on the estimation method employed. Therefore, fit criteria for both ML with SB adjustments, as well as fit criteria for rDWLS are presented. For ML estimation with SB adjustments, overall or global model fit was evaluated using the Satorra-Bentler adjusted chi-square (χ^2_{SB}), the standardized root mean square residual (SRMR), the robust root mean square error of approximation (RMSEA $_{SB}$), and the robust comparative fit index (CFI $_{SB}$). The χ^2_{SB} is actually a "badness" of fit test; therefore, a non-significant χ^2 indicates the model fits the data well. However, the χ^2 is sensitive to sample size and is an exact test of fit. Therefore, Hu and Bentler (1998; 1999) recommended reporting at least one absolute fit index (e.g., RMSEA, SRMR) and one incremental fit index (e.g., CFI, TLI) in addition to the χ^2.

Like the χ^2, the SRMR and $RMSEA_{SB}$ are both absolute fit indices, meaning they assess how well the hypothesized model reproduces the sample covariance matrix in an absolute sense. The SRMR ranges from 0 to 1, with smaller values indicating better fit; the SRMR has been found to be sensitive to misspecified factor covariances (Hu & Bentler, 1998; 1999). The RMSEA takes model complexity into account, providing a measure of misspecification per degree of freedom. In addition, the RMSEA has been found to be sensitive to misspecified factor pattern coefficients (Hu & Bentler, 1998; 1999). The CFI is an incremental fit index, meaning it assesses model fit relative to a null model. Like the RMSEA, the CFI has been found to be sensitive to misspecified factor pattern coefficients. The CFI ranges from 0 to 1 with larger values indicating better model fit (Hu & Bentler, 1999). When using the Satorra-Benter adjustment, the suggested cut-off for the SRMR is < .07, < .05 for the RMSEA_{SB}, and > .96 for the CFI_{SB} (Yu & Muthén, 2002).

For the models analyzed using rDWLS, the same fit indices were examined. Unfortunately, there is a paucity of research with regard to appropriate cutoffs for the SRMR, CFI, and RMSEA when employing rDWLS. Nye and Drasgow (in press) used a simulation study to investigate cutoff values with rDWLS estimation and concluded, unlike ML with SB adjustments, there are no clear rules of thumb for fit index cutoff values. Specifically, appropriate cutoffs for the RMSEA and SRMR depend on sample size and amount of skew or kurtosis present in the data. For example, for large samples (N = 1,000) a RMSEA value of .01 may be appropriate, but in smaller samples (N = 400), this value will result in a larger number of Type 1 error rates; thus, a more liberal RMSEA value should be used (e.g., .03). Nye and Drasgow (in press) also found the DWLS-based CFI to be a poor indicator of model misspecification because most CFI values fell between .98 and 1.00. In sum, these values are reported, but should be interpreted with caution until more research on rDWLS fit indices is conducted.

The global fit indices described above only represent overall model-data fit (how well the estimated model reproduces the actual data). Yet, areas of localized misfit (mis-specified relationships among item pairs) can be masked by these summative indices. Therefore, correlation residuals were investigated to identify local areas of misfit[2]. Correlation residuals indicate how well the observed correlations among the items are reproduced by the model. More specifically, the value of the residual is the difference between the model-implied correlation and the observed correlation. For example, if the observed correlation between item 1 and 2 is .54, but the model-implied correlation between item 1 and 2 is estimated to be .40, the correlation residual will be .14. Large residuals (i.e., greater than | 0.1 |) indicate the relationship between that item pair is not reproduced well by the model (Kline, 2005). Positive residuals indicate the model is underestimating the relationship between items; whereas, negative residuals indicate the model is overestimating the relationship between items (Brown, 2006).

Sample 1: Assessing Model-fit using ML with S-B adjustments. First, the five models using Sample 1 data were analyzed employing ML with S-B adjustments. The bifactor model did not converge to an admissible solution. This occurred due to a negative error variance associated with an item written to represent importance. This suggests the importance items only reflect general mattering and do not share common variance above and beyond the general mattering factor (Chen et al., 2006). As stated by Rindskopf (1984), estimation problems of this nature occur because of model identification problems due to factor overextraction (i.e., overfactoring). More specifically, a structure was being forced on the data with the importance items modeled as factorially complex – loading to both the general mattering factor and specific factor B, but this model did not converge because the importance items are factorially simple (i.e., unidimensional). After controlling for the general university mattering factor, there is no additional variance shared among the items representing importance; essentially specific factor B does not exist.

Table 3 presents the fit indices for the four models that converged. As predicted, when evaluating the fit of these models, the incomplete bifactor model fit best overall. Specifically, the SRMR and the CFI_{SB} met Yu and Muthén's (2002) suggested cut-offs of .07 and .96, respectively. The $RMSEA_{SB}$ fell slightly above their suggested cut-off of .05 at .07. For the other three models, the SRMR, CFI_{SB}, and $RMSEA_{SB}$ values were greater than the suggested cut-offs.

In addition to overall fit indices, the results from the correlated four-factor and higher-order models also supported the incomplete bifactor model as the best fitting model. Specifically, in the correlated four-factor model, the factors were highly correlated (.64 to .93), suggesting that the four factors are not distinct. Likewise, in the higher-order model there was a great deal of common variance across the four first-order factors. This was evident by the large R^2 values for the first-order factors (awareness: R^2 = .67, importance: R^2 = .97, ego-extension: R^2 = .82, and reliance: R^2 = .69). Thus, the second-order factor could explain the majority of variance in the first-order factors (and nearly all of the variance for the first-order importance factor). As a result, the disturbance terms were small. In fact, the disturbance term for the importance factor was non-significant; further revealing why the bifactor model would not converge to an admissible solution. As described above, once the general mattering factor was controlled for, there was no additional unique variance shared among the importance items.

In addition, model fit was evaluated using the chi-square difference test because all models were nested within the incomplete bifactor model. As the incomplete bifactor model is the most complex, the other models cannot fit better than the incomplete bifactor model. However, it is possible that they could fit just as well. Therefore, a non-statistically significant chi-square difference would indicate the other models fit just as well as the incomplete bifactor model. When testing the chi-square difference between the incomplete bifactor model and the four-factor model (which is the most complex model next to the incomplete bifactor model), the chi-square was statistically significant (χ^2_{SB} (20) = 571.82, $p < .001$), suggesting that the four-factor model fit statistically significantly worse than the incomplete bifactor model (and all the other models would also fit significantly worse). However, one caveat to the χ^2 difference test is that the test is sensitive to sample size, just like the χ^2, and will be significant when the sample size is large. Thus, fit indices and correlation residuals are more informative.

Correlation residuals from the incomplete bifactor model were examined to assess localized misfit. There were numerous items associated with large residuals (> | .10|). Specifically, items 2, 5, 7, 8, 12, 15, 30, and 32 were associated with 8 or more large residuals. These residuals will be used to inform scale modifications but only after assessing which replicate when employing rDWLS and in Sample 2. In conclusion, although the incomplete bifactor model fit statistically better than the other three models, the fit could still be improved given the $RMSEA_{SB}$ value and the amount of localized misfit.

Sample 1: Assessing Model-fit using rDWLS with polychoric correlations. When using rDWLS to analyze polychoric correlation matrices, model fit was extremely similar to the results employing robust ML with PPM covariances (see Table 3). Theoretically, the fit should improve using rDWLS, because rDWLS adjust the fit indices and standard errors for the categorical nature of the data. Fit did improve for the CFI in all four models, although the improvement in fit was negligible. Interestingly, the RMSEA value estimated with rDWLS was slightly larger than the RMSEA estimated with ML and the S-B adjustment for most models. As with robust ML with PPM covariances, the incomplete bifactor model had the best overall fit and the bifactor model did not converge to an admissible solution.

The results from the correlated four-factor and higher-order models were examined and provided corroborating evidence for the interpretation of incomplete bifactor model as the best fitting model. Again, the factors were highly correlated (.70 to .95) in the four-factor model. In the higher-order model, the R^2 values for the first-order factors were large (awareness: R^2 = .76, importance: R^2 = .94, ego-extension: R^2 = .79, and reliance: R^2 = .78) indicating there was a great deal of common variance among the first-order factors.

Correlation residuals were also examined from the incomplete bifactor model. As found when using robust ML estimation, items 2, 5, 7, 8, 15, 30 and 32 were associated with a large number of large residuals. However, items 11 and 16 were also associated with many large residuals when using rDWLS.

Thus, the same general conclusions can be made despite the difference in estimation method employed. This similarity in results across estimation methods is most likely due to the fact that as the number of categories increases, the more similar polychoric correlations are to PPM correlations. However, it was important to conduct parallel analyses with Sample 2 to ensure the same patterns emerged.

Sample 2: Assessing Model-fit using ML with S-B adjustments. Model fit for Sample 2 was similar to the fit of Sample 1 (see Table 4). Unlike Sample 1 however, the bifactor model did converge to a solution in Sample 2. Yet, the higher-order model did not converge to an admissible solution for Sample 2 due to a negative disturbance term associated with the importance items. This again, was most likely due to factor overextraction related to the importance items (Rindskopf, 1984). That is, the importance items only represent the second-order mattering factor and are over-factored when modeling this first-order factor (Chen et al., 2006). As with Sample 1, the results from the correlated four-factor were examined. Again, the factors were highly correlated (.73 to .94) in the four-factor model, suggesting the four factors are not distinguishable.

When comparing fit across models, the bifactor model fit slightly better than the incomplete bifactor model as indicated by the CFI, SRMR, and the χ^2 difference test (χ^2_{SB} (8) = 123.25, p < .001). However, after examining the statistical significance of the unstandardized factor pattern coefficients for the importance items to their specific factor, only four (3, 6, 11, and 16) of the eight items written to represent importance had statistically significant pattern coefficients to specific factor B. The lack of statistical significance for half of the importance pattern coefficients reveals why the higher-order model would not converge to a solution; once the general mattering factor was controlled for, there was little addition unique variance shared across the importance items. Given this, correlation residuals for the incomplete bifactor model were examined. Items 5, 7, 9, 15, 17, 23, and 28 were associated with numerous large residuals. Of these items, only 5, 7, and 15 were also associated with large residuals using Sample 1 data and both estimation methods. Thus, this indicates that importance of examining stability of misfit with multiple samples.

Sample 2: Assessing Model-fit using rDWLS with polychoric correlations. Fit was similar using rDWLS with polychorics to the results when employing robust ML for Sample 2 (see Table 4). As with Sample 1, the fit slightly improved. Interestingly, all five models, including the higher-order and bifactor models converged to a solution. The bifactor and incomplete bifactor model appeared to fit equally as well, as indicated by the RMSEA, CFI, and SRMR indicating support for the incomplete bifactor model since it is simpler. Moreover, in the bifactor model only two items (3 and 6) of the eight items written to represent importance had statistically significant pattern coefficients to specific factor B.

Likewise, in examining the results of the four-factor and higher-order models, the results support the incomplete bifactor model. The four factors were correlated from .76 to .94 in the four-factor model. By examining R^2 values for the first-order factors in the higher-order model (awareness: R^2 = .76, importance: R^2 = .99, ego-extension: R^2 = .82, and reliance: R^2 = .83), it was apparent that the general mattering factor could explain nearly all of the variance in the importance first-order factor. It is surprising the higher-order and bifactor models converged for this analysis and not in the other analyses given this high R^2 value for the importance factor. This result is most likely due to some idiosyncrasies in the data. However, these differences in model convergence across analyses highlight the stability of the incomplete bifactor model in relation to the bifactor and higher-order models. That is, the incomplete bifactor model converged to a solution in all four analyses (Sample 1 and 2 using robust ML and rDWLS). When examining localized misfit of the incomplete bifactor model, the same items associated with large correlation residuals when employing robust ML were associated with large residuals when employing rDWLS (items 5, 7, 9, 15, 17, 23, and 28) in Sample 2.

In sum, supporting the incomplete bifactor model has implications for scoring the RUMS. Specifically, the resulting scores are not unidimensional (as would be the case if the one-factor model was championed). Furthermore, one cannot calculate four subscale scores (if the correlated four-factor model was championed). A total score from the RUMS would include systematic variance due to the general mattering factor *and* systematic variance resulting from each specific factor. Thus, correlation residuals among item pairs were examined to resolve issues of model misfit. Additionally, parameter estimates were examined to better understand the scores and the development of measure that should emerge.

Model Modifications

The purpose of Study 1 was first to evaluate the fit of the five hypothesized models and given these results, make the necessary modifications to the RUMS before proceeding to fitting the invariance models. Even though the incomplete bifactor model fit best overall in Sample 1 and appeared to be the most parsimonious model for Sample 2, there was substantial localized misfit identified across both samples. That is, a number of items were associated with large correlation residuals. Thus, this section describes how the RUMS was modified before moving on to research questions 2 and 3.

Recall that a large number of items were written with the intention of deleting poor functioning items. However, items were only removed if they appeared to fit poorly in both samples. Item quality was evaluated based on two criteria: the number of large correlation residuals an item was associated with and an item's strength of loading to its specific factor in comparison to its loading to the general factor (i.e., whether the item was factorially simple or complex). First, if items were associated with large correlation residuals across the two samples, these items were also flagged for removal because these items contributed to localized misfit. That is, items associated with large correlation residuals shared variance even after controlling for the general mattering factor and specific factors. These criteria had to be met for the same item in both samples before an item was removed to avoid capitalizing on change idiosyncrasies of the data (MacCallum, Roznowski, & Necowitz, 1992). That is, if an item was associated with a large number of residuals in Sample 1, but no large residuals in Sample 2, the item was not removed.

When comparing items with large residuals across the two samples, items 5, 7, and 15 were consistently associated with large positive correlation residuals. Specifically, item 5, an awareness item, tended to share variance, even after controlling for the general mattering factor and specific factor A, with items written to represent reliance. After considering the wording of item 5, this makes sense. Item 5 was written as an awareness item with the intent that the word “recognize” would be interpreted as “notice” or “to be aware of”. However, the word “recognize” has alternative interpretations. For example, people can be recognized for their accomplishments or recognized with an award. These alternative interpretations of "recognize" are more aligned with the concept of reliance than awareness. Thus, item 5 could represent either the awareness or reliance facet, depending on how students interpreted the word "recognize". Items 7 and 15 were both written as negatively worded ego-extension items. These items tended to share variance, after controlling for the general mattering factor and the specific factor C, with other negatively worded items. In addition, these items had large *negative* residuals with many positively worded items, indicating the relationships between these two negatively worded items and the positively worded items were being overrepresented by the model. In sum, all three items were problematic and therefore, removed.

Second, parameter estimates from the incomplete bifactor model were investigated (Tables 5 and 6; Sample 1 and 2, respectively). More specifically, results from the incomplete bifactor model can be used diagnostically to drive the development of a scorable measure. Importantly, the unstandardized factor pattern coefficients to the general mattering factor for all 34 items were .50 or greater (except item 34). These strong loadings to the general factor suggest the presence of a single underlying latent construct of university mattering (Reise et al., 2010). That is, most of the 34 items represented one general factor. On the contrary, if the loadings to the specific factors were generally higher than the loadings to the general factor, this finding would support the distinction of these factors. Given that the loadings to the general mattering factor were so strong, a unidimensional model was created. A unidimensional model was created by removing items that were factorially complex (i.e., items that higher loadings on their specific factor than the general factor or items that had higher loadings on the general factor were flagged for removal if they also loaded highly (< .50) on their specific factor) and retaining items that primarily represented the general mattering factor.

Comparing the one-factor model parameter estimates to the incomplete bifactor parameter estimates obtained for the general mattering factor provided additional support for the unidimensional structure. That is, any divergence in unstandardized factor pattern coefficients between the one-factor model and the incomplete bifactor model indicates misfit for the one-factor model (Reise et al., 2010). The parameter estimates for the one-factor model are also reported in Tables 5 and 6. In general, the pattern coefficients were similar across the one-factor and incomplete bifactor models for Sample 1 and 2, indicating further that the one-factor model represents the data rather well, despite misfit associated with a few items.

In Sample 1, all pattern coefficients for the general mattering factor from the incomplete bifactor model were .50 or higher except item 34 (.42), indicating a strong general factor was underlying the relationships among the items. Only items 2 ("When people at JMU need help, they come to me"), 5 ("The majority of people in the JMU community recognize me"), 7 ("There is no one at JMU who would share in my excitement about my accomplishments"), 8 ("Most people of the JMU community seem to notice me"), and 15 ("If I had a set back, there would be no one at JMU who would share in my feelings of unhappiness") had higher pattern coefficients on their corresponding specific factors than on the general mattering factor further demonstrating the majority of items primarily represented the general mattering factor. In addition to these items, items 9 ("People of the JMU community count on me to be there in times of need"), 12 ("Most people of the JMU community seem to notice when I come or go"), and 26 (“Quite a few people of the JMU community look to me for advice on issues of importance”), 30 (“The people of the JMU community generally know when I am around”), and 32 (“The people of the JMU community tend to rely on me for support”) loaded strongly to their specific factors (> .50) in addition to the general mattering factor, indicating that these items are factorially complex. Interestingly, item 4 (“My successes are a source of pride to the people of the JMU community”) was negatively related to specific factor C after controlling for the general mattering factor, potentially indicating the path from this item to the specific factor is not needed. Furthermore, the pattern coefficients to the specific factors for items 10 (“There are people of the JMU community who react to what happens to me in the same way they would if it happened to them”) and 22 (“There are people in the JMU community who would also experience my disappointment if I didn’t reach my full potential”) were not statistically significant indicating these items are essentially unidimensional and do not share systematic variance after controlling for the general mattering factor.

Similar results were found for Sample 2. Like Sample 1, all unstandardized factor pattern coefficients for the general mattering factor from the incomplete bifactor model were .50 or higher, except item 34 (.42). Like in Sample 1, items 5 and 8 loaded more strongly to their specific factor than the general mattering factor. Items 2, 9, 12, and 26 were factorially complex, loading strongly on both the general factor, and on their corresponding specific factor. The loadings to the corresponding specific factors for items 17 and 23 were not statistically significant. As in sample 1, item 4 had a negative loading on specific factor C. Thus, across the two samples, items 5 and 8 consistently loaded more highly to their specific factor than the general factor and items 2, 9, 12 and

26 appeared to be factorially complex, loading strongly on both the general factor, but also on their corresponding specific factor. These items were removed. If these items were retained, summing the raw data would result in a total score that was composed of variance from both the general mattering factor and the specific factors. Thus, the relationship between that total score and external variables could not be attributed to only general mattering, but general mattering and some additional variance captured by each specific factor. Whereas for a measure that yields unidimensional data, the relationship between the total score and external variables can be attributed to that single construct. Although, multidimensional data can be modeled in an SEM framework (e.g., using a bifactor model), many researchers and practitioners who might use the UMUM-15 may not be able to employ SEM given sample size constraints or they may not be familiar with SEM techniques. Again, removing these items was justified because all 34 items loaded highly on the general mattering factor. This provides some empirical evidence for essentially unidimensional scores.

Finally, in addition to item 2, 5, 7, 8, 9, 12, 15, and 26, items 3 ("I have noticed that people at JMU will take the time to help me") and 6 ("People of the JMU community are concerned about my needs") were removed because they consistently had statistically significant loadings to specific factor B when examining the bifactor model results from Sample 2. A modified incomplete bifactor model was then tested after removing these 10 items. Since items that were salient to the specific factors were removed, one might expect the incomplete bifactor model to result in convergence problems. However, the incomplete bifactor model did converge, indicating that there was still common variance among sets of items in addition to the common variance pertaining to the general mattering factor. Therefore, the items were further evaluated based on fit and their salience to the specific factors in comparison to the general mattering factor.

24-Item Incomplete Bifactor Model

This modified incomplete bifactor model had general good fit in both samples (see Table 7 for robust ML results and Table 8 for rDWLS results). This is to be expected, given that poorly fitting items were removed (5, 7, and 15). Moreover, the removal of several items that were not as salient to the general mattering factor as to their specific factors (items 2, 3, 6, 8, 9, 12) resulted in a smaller covariance matrix to reproduce (i.e., it is easier to reproduce fewer covariances than more covariances), thus resulting in better fit.

Despite the improved model fit, there were still areas of misfit. Items 17 (“It is hard for me to get attention from people of the JMU community”), 21 (“Sometimes at JMU, I feel as if I were invisible”), and 28 (“People of the JMU community don’t care about my personal welfare”) were associated with large positive correlation residuals. All three items were negatively worded and tended to share variance with the other negatively worded items, after controlling for the general mattering factor and the specific factors. Thus, these three items were removed.

When investigating the items’ unstandardized factor pattern coefficients for both the general and specific factors, there were still items that loaded strongly to their specific factor in addition to the general mattering factor. For example, in both samples, items 18 (“There are people of the JMU community who would be sad if they knew I was sad”), 19 (“I am not someone the people of the JMU community would turn to when they need something”), 20 (“Some people at JMU would feel as enthusiastic as I would, if I were to achieve an important goal”), 27 (“People of the JMU community tend to remember my name”), 30 (“The people of the JMU community generally know when I am around”), and 32 (“The people of the JMU community tend to rely on me for support”) had loadings .40 or greater to the specific factor. Thus, these items were flagged for removal in the second round of revisions in order to support a unidimensional model as indicated by the empirical evidence of high general factor loadings and lower specific factor loadings.

The Unified Measure of University Mattering 15 (UMUM-15)

The incomplete bifactor model from both samples suggested scores from the items were essentially unidimensional (given the high loadings to the general mattering factor) with “bloated specifics”, which are nuisance factors that arise due to insignificant features of the items (e.g., negative wording, redundant wording) (Reise et al., 2007). This second round of revisions resulted in a measure consisting of 15-items. As expected, after making the above modifications, a 15-item incomplete bifactor model did not result in an admissible solution in either sample because there was no systematic variance remaining among sets of items. That is, the incomplete bifactor model did not converge due to over-factoring – there was no variance above and beyond the general mattering factor shared among sets of items. Given this, the 15-item measure was modeled as one-factor. The resulting one-factor model fit well in both samples (see Table 7 for robust ML results and Table 8 for rDWLS results). In addition, the correlation residuals were small (< .10), indicating the model also fit well locally and suggesting that the mattering factor accounts for most of the covariance among the items. This 15-item measure will be referred to as the Unified Measure of University Mattering

15 (UMUM-15, see Appendix C) throughout the remainder of the document to distinguish it from the RUMS. The name "Unified Measure of University Mattering 15" was chosen to reflect these revisions and the unidimensional nature of the 15 remaining items from the RUMS.

Importantly, this reduced measure covers the breadth of the university mattering construct by retaining items from each facet of mattering. That is, two of the retained items were originally written as awareness items (items 1 and 24), five were written as importance items (11, 13, 16, 25, and 31), four were ego-extension items (4, 10, 22, and 33), and four were reliance items (14, 23, 29, and 34), ensuring that the various facets of mattering were represented in the final measure (Sijtsma, 2009). In addition, items 11 and 23 are negatively worded, which are useful for identifying obvious response sets.

Parameter Estimates and Reliabilities

Given that the one-factor model fit the data well, the unstandardized and standardized factor pattern coefficients, R^2 values, and standardized error variances estimated for this model were examined (see Table 9) for both samples. All unstandardized pattern coefficients, which represent the amount of change in an item for each standard deviation increase in the underlying factor, were statistically significant. The standardized pattern coefficients represent the standard deviation change in the item for each standard deviation increase in the factor. The standardized pattern coefficients can also be squared to produce the R^2 value; which represents the reliability of the indicator (i.e., how much variance in the indicator is explained by the factor). The error variance represents the amount of error associated with each indicator and is simply calculated by subtracting the R^2 value from 1. Ideally, R^2 values should be greater than

.50, meaning at least 50% of the variance in the indicator is explained by the factor. For Sample 1, the variance in the indicators explained by the factor ranged from 10% (item 34) to 62% (item 31). For Sample 2, the variance in the indicators explained by the factor ranged from 11% (item 34) to 67% (item 31). Although item 34 had the lowest variance explained by the factor by more than 20% compared to the other 14 items, Item 34 was retained because it added to the breadth of the mattering construct. That is, only participants with very high levels of mattering may endorse item 34 ("If I were not a JMU student, the JMU community would suffer"). Finally, reliability was calculated as coefficient omega (ω) (McDonald, 1999). Coefficient omega was .91 for both samples, suggesting adequate reliability.

Study 2: Factorial Invariance

Data Screening and Descriptive Statistics

As in Study 1, prior to running analyses, both Sample 3 and the Transfer Sample were screened for outliers. There were 828 complete cases in Sample 3; however, 11 cases were identified as outliers due to obvious response sets (i.e., 1, 1, 1, 1, 1). Therefore, Sample 3 resulted in a sample size of 817 cases. The Transfer Sample contained 708 compete cases; however 12 cases were identified as outliers. Thus, the transfer sample resulted in a data set of 696 cases.

After removing outliers, univariate and multivariate normality were examined. First, univariate normality was examined for the native sample. Overall, the data appeared to be approximately univariately normal as the skewness and kurtosis values did not exceed values of | 2 | or | 7 |, respectively (Curran, West, & Finch, 1996; Finney & DiStefano, 2006). All fifteen items were slightly negatively skewed, except item 34. Item

16 was the most skewed (-1.13) and kurtotic (1.99) item. Item 34 was the least skewed (0.15) and kurtotic (-0.71) item. For the transfer sample, the data also appeared to be approximately univariately normal as all skewness and kurtosis values did not exceed values of | 2 | or | 7 |, respectively (Curran, West, & Finch, 1996; Finney & DiStefano, 2006). Similar to the native sample, all items from the transfer sample were slightly negatively skewed, except item 34. Likewise, the most skewed and kurtotic item was item 16 (-1.09 and 1.38, respectively). The least skewed and kurtotic item was item 34 (.28 and -.77, respectively).

When investigating multivariate normality, Mardia's coefficient was 60.49 for the native sample and 42.72 for the transfer sample. Thus, the data were multivariate non-normal. Item means from both samples fell slightly above the mid-point of the scale (i.e., 3.5). For the native sample, inter-item correlations ranged from .12 (items 16 and 34) to .68 (items 25 and 31 and items 31 and 33). For the Transfer Sample, inter-item correlations ranged from .13 (items 16 and 34) to .66 (items 13 and 14 and items 31 and 33). This range of inter-item correlations foreshadows the variability in the size of factor loadings (see below). Descriptive statistics and inter-item correlations are reported for both samples in Table 10.

Estimation Method

Given that robust ML produced comparable fit indices to rDWLS, robust ML was employed for the invariance analyses. As with Study 1, all models were analyzed in LISREL 8.80 (Jöreskog & Sörbom, 2005).

Assessing Model Fit

Like in Study 1, multiple indicators of fit were examined to assess the overall and relative fit of each invariance model. For overall fit, the χ^2_{SB}, robust comparative fit index (CFI_{SB}), and robust root mean square error of approximation ($RMSEA_{SB}$) were used to evaluate the fit of the configural, metric, and scalar invariance models. The same guidelines for cutoffs employed in Study 1 were used for the evaluation of the invariance models: $CFI_{SB} > .95$ and $RMSEA_{SB} < .05$ (Yu & Muthén, 2002). However, as these cutoffs have been criticized as too strict given the complexity of invariance models, Vandenberg and Lance (2000) more liberal cutoffs, < .08 as an upper-bound for the RMSEA and > .90 as a lower-bound for the CFI, were also considered.

In addition, $\Delta\chi^2_{SB}$ values and ΔCFI_{SB} values were calculated to relative model fit. Recall that the invariance models are nested. Specifically, both the metric invariance model and scalar invariance model are nested within the configural invariance model. The configural model is the most complex model with the least constraints, whereas the scalar model is the least complex with the most constraints. As with the CFA models, because the configural model is the most complex, the metric and scalar models cannot fit statistically significantly better than the configural model, but they can fit just as well. A non-significant $\Delta\chi^2_{SB}$ test supports metric and scalar invariance. However, the $\Delta\chi^2_{SB}$ can be problematic when assessing fit because it provides an exact test of comparative fit and is influenced by sample size. Luckily, ΔCFI can be used to assess approximate comparative fit across nested models (Quintana & Maxwell, 1999; Steenkamp & Baumgartner, 1998). More specifically, a $\Delta CFI > .01$ indicates a meaningful decline in fit (Cheung & Rensvold, 2002). Unfortunately, the $\Delta\chi^2_{SB}$ and ΔCFI can result in different substantive conclusions (French & Finch, 2006). Therefore, changes in standardized covariance and mean residuals were also examined. If the residuals were larger (i.e., > | 3 |) for the restricted model in comparison to the more complex model, this would be taken as evidence that the more complex model was a better representation of the data.

Testing the One-Factor Structure

Prior to assessing measurement invariance, the 15-item one-factor model was fit to each sample separately to ensure there were no gross areas of misfit. First, inter-item correlations are presented in Table 11. In Sample 3, item correlations ranged from .12 (items 16 and 34) to .68 (items 31 and 33). In the Transfer Sample, item correlations ranged from .14 (items 16 and 34) to .67 (items 31 and 33). The data from Sample 3 and the Transfer Sample fit the one-factor model well. The fit indices for both samples are reported in Table 11. For both samples, the SRMR (.04 for both samples) and CFI_{SB} (.98 for both samples) fell within Yu and Muthén's (2002) recommended cutoffs. The $RMSEA_{SB}$ (.06 for both samples) fell within Vandenberg and Lance's (2000) suggested cutoff of .09. In addition, the standardized covariance residuals were small across all items in both samples, providing evidence that the one-factor model represented the data well. These results also provided further support for the one-factor model. That is, in Study 1, the modifications made to the RUMS were post-hoc. Testing the one-factor model with these independent samples were a priori, providing the first actual test of the one-factor structure.

Configural Invariance

Given that the one-factor model fit well in both samples, configual invariance was already established for the UMUM-15 across native and transfer students in this previous step. That is, the same factor structure represents the inter-item relationships in both groups (Steenkamp & Baumgartner, 1998). In other words, it can be concluded that generally, native and transfer students conceptualize university mattering as a single construct. However, a multi-group analysis, in which the one-factor model was fit to the native and transfer groups simultaneously was conducted to obtain overall fit indices (see Table 12). The fit indices from this multi-group configural model are used as baselines to compare subsequent invariance models (e.g., $\Delta\chi^2_{SB}$ and Δ CFI). Parameter estimates for this model are reported in Table 13. All unstandardized pattern coefficients were statistically significant. For Sample 3, the amount of variance in an indicator explained by the factor ranged from 14% (item 34) to 72% (item 31). For the Transfer Sample, the amount of variance in an indicator explained by the factor ranged from 14% (item 34) to 66% (item 31). Coefficient omega for both samples was .92, indicating adequate reliability.

Metric Invariance

Following the establishment of configural invariance, metric invariance was assessed. Establishing metric invariance indicates the items are equally salient across transfer and native students, providing evidence that the corresponding factors have the same meaning across groups. In other words, whereas configural invariance tests whether the same items represent the same factors across groups, metric invariance tests whether the magnitude of the factor loadings is the same across groups. Thus, metric invariance is met when the unstandardized factor pattern coefficients (λ) of each item are essentially equal across groups. Equal unstandardized factor pattern coefficients would mean one unit of change in one group is equal to one unit of change in the other group (Chen, Sousa, & West, 2005). In order to test for metric invariance, the unstandardized factor pattern coefficients from the configural invariance model were constrained to be equal across the native and transfer student groups.

Prior to assessing metric invariance however, it is important to set the metric of the latent factor. In order to set the metric of the latent factor, one item is chosen as a referent item. It is necessary to ensure the item chosen as a referent item is itself invariant across groups, otherwise the factor pattern coefficient estimates from the transfer and native groups will be based on different metrics because a different scaling constant would be used to adjust the parameter estimates of each group (Johnson, Meade, & Duvernet, 2009). Tests were conducted to establish that the item chosen as the referent item was indeed invariant across groups before it was used to set the metric of the latent variable. This was done by freely estimating the unstandardized pattern coefficient for the referent item (item 1) and then constraining this path to be equal across the two groups, using each of the other items as referent indicators (Cheung & Rensvold, 1999). This constrained the factor variance to be on the same metric as item 1. Metric invariance was then tested by constraining the pattern coefficients of the 15 items to be equal across groups. The fully metric invariant model did not fit statistically significantly worse than the configural model (p = .16, ΔCFI < 0.01). Standardized covariance residuals were also examined. The residuals remained small in the metric invariant model and comparable to the residuals from the configural model. Thus, it was concluded that metric invariance was established; indicating the strength of each item-factor relationship was approximately equal across groups.

Scalar Invariance

Given that metric invariance was established, scalar invariance was assessed. For continuous data, scalar invariance is met if the intercepts (τ) of each item are essentially equal across groups. The intercept represents the predicted value of the observed variable when the latent trait value equals zero. That is, scalar invariance is established if individuals with the same latent level of university mattering obtain the same value on the observed variable, regardless of their group membership. More conceptually, a native and transfer student with the same latent level of university mattering should use the response scale in the same way (i.e., choose the same response option; Steenkamp & Baumgartner, 1998). To test scalar invariance, the intercepts of each item were constrained to be equal across the two groups. The establishment of scalar invariance allows for the comparison of factor means because scalar invariance presumes scores from different groups not only have the same unit of measurement (metric invariance) but also the same origin (equal intercepts) (Chen et al., 2005). The fit of this model was compared to the fully metric invariant model. Although the $\Delta\chi^2$ was statistically significant ($p < .001$), the ΔCFI fell within the accepted amount (0.0016), indicating support for scalar invariance across the two groups. Given this disparity in model fit, the mean residuals were also examined. All standardized mean residuals were small (fell below $|3|$), supporting scalar invariance.

Latent Mean Differences

With the establishment of configural, metric, and scalar invariance, latent mean differences between native and transfer students were interpreted (see Table 14). First, the latent mean of the native group was fixed to zero, which allows for the estimation of the latent mean difference by freely estimating the latent mean for the transfer group. The latent mean difference between the groups was significant and negative (κ = -.28, p < .01) indicating that, as predicted, transfer students were statistically significantly lower on university mattering than native students. In addition to statistical significance, one should also always interpret practical significance or the magnitude of the difference. This can be done by calculating an effect size. Dividing the latent mean difference by the pooled latent variances places the latent mean difference on a standardized metric (analogous to Cohen's *d*; Hancock, 2001). The latent effect size was estimated as -.40, which is considered a moderate effect (Hancock, 2001). That is, transfer students were .40 standard deviations lower in latent university mattering than native students. This value is comparable to Cohen's *d* which was calculated as -.39 using the observed data. The .01 difference in these values is a result of measurement error, which attenuates the effect size. That is, when using the observed scores, the university mattering composite score includes random measurement error. When using a latent variable technique (e.g., SEM) to model the latent mean difference, the random measurement error is removed. However, because the UMUM-15 had high reliability (.91 in Samples 1 and 2, and .92 in Sample 3 and the Transfer Sample), this difference is negligible.

Conclusion

In Study 1, the incomplete bifactor model was used diagnostically to modify the RUMS. In general, all 34 items loaded strongly to the general mattering factor, indicating the presence of this underlying latent construct. However, there were areas of localized misfit. Items associated with large correlation residuals were removed. It was suspected that the reason for these large residuals was the result of item wording; many of these items were negatively worded. Furthermore, a few items loaded strongly to both the general factor and their specific factor. These items were removed to create a unidimensional measure. After two rounds of modifications, 15 items remained and a one-factor model represented the data well. This measure was named the UMUM-15. In Study 2, Sample 3 and the Transfer sample were used to cross-validate the results from Study 1. The 15-item one-factor model represented the data well in both samples. Furthermore, configural, metric, and scalar invariance were established for the UMUM-15 across both student groups. As a result, latent means could be compared, and as expected, transfer students had meaningfully lower means than native students on university mattering.

CHAPTER 5

Discussion

The Revised University Mattering Scale (RUMS) was created to assess students' perceived sense of mattering to their university (France & Finney, 2010). Since the psychometric properties of the RUMS had not been examined, this dissertation evaluated the factor structure of the RUMS (Study 1). The result of Study 1 was a new measure of university mattering (UMUM-15) retaining 15 of the items from the RUMS. In Study 2, the structural integrity of the UMUM-15 was tested and external validity gathered by conducting a measurement invariance study comparing native and transfer students. This chapter begins with a summary of the findings for Study 1 followed by the implications of these results for the measurement and theory of mattering. Next, the findings from Study 2 are discussed along with implications for transfer students. Finally, the chapter concludes with a discussion of limitations and possible directions for future research.

Discussion of the Findings

Summary of Study 1 Results

The purpose of Study 1 was to test five hypothesized models using CFA and identify which model best represented the data using two independent samples. If none of the models represented the data well, model modifications would be made to improve fit. The models tested were: (1) a one-factor model, (2) a correlated four-factor model, (3) a higher-order model, (4) a bifactor model, and (5) an incomplete bifactor model. France and Finney (2010) had previously fit the first three models, but not the bifactor and incomplete bifactor models. Findings from this study generally replicated findings from France and Finney (2010), even given the revisions to the UMS. Similar to France and Finney (2010), the one-factor model in the current study did not represent the data well in either Sample 1 or 2. Also, like France and Finney, the factors were highly correlated (.64 to .93 in Sample 1 and .72 to .94 in Sample 2) in the correlated four-factor model for both samples in the current study. However, the results for the higher-order model replicated France and Finney's findings for only one of the samples tested here. When France and Finney tested the higher-order model, it would not converge to an admissible solution. In the current study, the higher-order model did not converge to a solution using Sample 2 data with robust ML estimation; however, it did converge using Sample 1 data and Sample 2 data with rDWLS estimation, but the disturbance for the importance first-order factor indicated that the remaining variance among the importance items was minimal after controlling for the second-order mattering factor.

In addition to the models examined by France and Finney (2010), this study fit a bifactor model and an incomplete bifactor model. Including these models proved to be useful for identifying ways to strengthen the measurement of university mattering. As predicted, for Sample 1, the incomplete bifactor model provided the best model-data fit in comparison to the other models. The bifactor model did not converge to an admissible solution due to a negative error variance associated with an item written to represent importance. In Sample 2, the bifactor model did converge to a solution and fit slightly better than the incomplete bifactor model. It is important to note however, that neither the incomplete bifactor nor bifactor model were championed due to numerous areas of localized misfit that replicated across both models. Instead, a series of model modifications were undertaken to identify a better fitting model.

In the first iteration of modifications, items were removed if they were associated with large correlation residuals; thus, causing localized misfit. Three items (5, 7, and 15) were removed because they were associated with large correlation residuals across both samples. Items were also removed if they were factorially complex – loading strongly to their specific factor in addition to the general mattering factor (demonstrating multidimensionality). This was done because factorially complex items are problematic for scoring a measure because what is common across the items is not necessarily due to one underlying construct (e.g., university mattering). This process of removing items would not have been justified if the specific factors were more saturated with common variance than the general mattering factor. Furthermore, this process of removing factorially complex items was justified because the general mattering factor explained the majority of variance among the items (i.e., the loadings to the general mattering factor were large whereas the loadings to the specific factors were small) indicating empirical support for the essential unidimensionality of the data. Five items (2, 8, 9, 12, and 26) were removed because they were factorially complex. Finally, items 3 and 6 were also removed because they were the only two importance items that had significant factor pattern coefficients with their specific factor in the bifactor model from Sample 2.

After this first round of modifications, an incomplete bifactor model was tested for the reduced 24-item measure. Although model-data fit improved, there were still areas of concern. Specifically, items 17, 21, and 28 were associated with large correlation residuals and removed. Finally, items 18, 19, 20, 27, 30, and 32 were removed because they were factorially complex, having strong loadings on the general mattering factor and their specific factors.

Following this second round of modifications, the RUMS was reduced to a 15-item measure. A unidimensional structure was fit to this reduced measure and demonstrated adequate fit across both samples. This modified measure was named the Unified Measure of University Mattering 15 (UMUM-15) to distinguish it from the RUMS. Even though many items from the RUMS were deleted, the UMUM-15 still covers the breadth of the university mattering construct, retaining items from each of the four facets: awareness (items 1 and 24), importance (items 11, 13, 16, 25), ego-extension (items 4, 22, and 33) and reliance (items 14, 23, 29, and 34). Furthermore, the UMUM-15 had acceptable reliability (across four samples) and the item R^2 values were generally high, indicating that university mattering accounts for more variance in the items than random measurement error. Some researchers may argue that item 34 has low utility and therefore should be removed. Specifically, item 34 had the lowest R^2 value across all four samples. However, this item was retained because it is believed that it is an important item in order to represent the breadth of the university mattering construct.

Implications of Study 1

The findings from Study 1 have implications for the measurement and theory of mattering. Importantly, the development of the UMUM-15 supports a unified view of university mattering. Prior to this study, researchers (e.g., Elliott, 2009; Rosenberg & McCullough, 1981) discussed mattering as multifaceted, consisting of the various components awareness, importance, ego-extension, and reliance (see Figure 6). Describing mattering in this way led to the development of instruments that produced item responses reflecting multiple, yet highly correlated, individual factors (Reise et al., 2010). For example, Elliott et al. (2004) modeled these facets as three distinct factors (awareness, importance, and reliance) and France and Finney (2010) modeled these facets as four distinct factors (awareness, importance, ego-extension, and reliance). Conceptualizing and modeling university mattering three or four individual, factors has implications for scoring. Specifically, the measure would be scored using subscale scores for each factor. For example, a single student would receive four subscale scores: one for awareness, importance, ego-extension, and reliance. Thus, a person would have a university mattering "profile", with four scores from each factor.

Modeling certain constructs in this way makes sense if there is empirical support that the factors are moderately correlated (e.g., .30 to .60). However, when the factors are so highly correlated (e.g., < .80), subscale scores present problems. Specifically, Reise et al. (2010) named two issues when using subscale scores with factors that are highly correlated: (a) multicollinearity, and (b) reliability. First, mullticollinearity interferes with one's ability to judge the unique contribution of each of the subscales in predicting some important outcome. For example, if awareness and importance are so highly correlated, neither factor will contribute any unique variance to the prediction of student involvement. Likewise, a frequent argument for using subscales, as opposed to a total score, is that the subscale scores could have differential correlates with external variables. For example, using the same example, it may be true that awareness is a better predictor of student involvement than importance and would thus exhibit a stronger correlation with student involvement than importance would with student involvement. Although, this is true and may be important for factors that are low to moderately correlated, when factors are highly correlated Reise et al. (2010) state this is a "weak justification for 'cutting up' a measure" (p. 554) and the subscales scores will be less reliable measures than the total score. In addition, in the case of the current study, subscale scores would reflect variation on both the general mattering factor and the specific factors. Thus, the subscale score may appear to be reliable, but in fact, that reliability is a function of the general mattering factor, not the specific subdomain (Reise et al. 2010).

Conversely, the present study yielded an instrument, the UMUM-15, which measures university mattering as a single construct. Even so, the UMUM-15 covers the breadth of the university mattering construct by retaining items from each of the four mattering facets. In other words, it is possible to have a single construct that is substantively complex. Conceptualizing mattering in this way, these facets fall along the mattering continuum, yielding unidimensional data.

More specifically, one can think of university mattering as a continuum (see Figure 7). This conceptualization of university mattering is different from thinking of mattering as the combination of factors. However, conceptualizing university mattering as a continuum is not entirely new. Elliott (2009) referred to mattering as a continuum, even though he also defined the various facets of mattering. At the low end of the continuum are items that are relatively easy to endorse, such as Item 16 (“There are people at JMU who give me advice when I need it”), which had the highest mean across all four samples. Item 16 appears to be an easy item to endorse in comparison to item 34 (“If I were not a JMU student, the JMU community would suffer”). The further one moves down the mattering continuum, the harder the items become to endorse. That is, a person has to have a higher sense of mattering to the university in order to continue replying with either “agree” or “strongly agree” to these “more difficult” mattering items.

Using Item 34 as an example, it is believed that only students with an extremely strong sense of mattering would endorse this item with "agree" or "strongly agree". Item 34 had the lowest observed mean across samples reflecting the "difficulty" of endorsing this item compared to the other items. Therefore, although this item may not have as much utility in reflecting mattering (R^2) as the other items, it improves the measure by more broadly covering the breadth of mattering. Furthermore, it can "discriminate" between those examinees with an above average sense of mattering compared to examinees with an average sense of mattering better than items that fall in the middle or low end of the mattering continuum. Students that have an above average level of university mattering may endorse these "easy" items just as much as students with an average level of university mattering, but only students with an especially high level of university mattering will endorse item 34. On the contrary, item 16 may better distinguish between students who are average on university mattering and students who fall below average on the university mattering continuum.

Summary of Study 2 Results

The one-factor model (the UMUM-15) championed from Study 1 was tested using a third sample of native students and a sample of transfer students. This model represented the data well in both groups; thus, configural invariance was established, indicating that native and transfer students' generally conceptualize university mattering in the same way. In addition, metric and scalar invariance were established, facilitating the comparison of native and transfer students' latent mean differences on university mattering. Transfer students were expected to have a lower sense of mattering to the university than native students because transfer students often express feelings of loneliness and anonymity, as well as struggles with meeting people, making friends, and building relationships with faculty (e.g., Owens, 2010). As predicted, transfer students had lower latent means than native students on university mattering. This finding provided known-groups validity evidence for the UMUM-15 and empirical evidence for differences in the characteristics of transfer and native students.

Implications of Study 2 Results

The results of the latent mean comparison in Study 2 align with theoretical expectations about transfer students (Davies & Dickmann, 1998; Owens, 2010). As theorized by Schlossberg (1989), transfer students have lower university mattering than students who are not experiencing a transition (i.e., native students). Previous research has found university mattering to be negatively related to academic stress (Dixon Rayle & Chung, 2007), social adequacy concern (similar to social anxiety), help-seeking threat, and help-seeking avoidance (France & Finney, 2010), and positively related to mastery-approach and performance approach goal orientation, academic self-efficacy, and instrumental help-seeking (France & Finney, 2010). Thus, if transfer students tend to be lower in university mattering, we can hypothesize that they may also have similar patterns on these academic variables and experience more difficulty in college. Of course, it is important to remember that university mattering was found to only correlate with these variables. In other words, any causal relationships among these variables have yet to be determined. Moreover, unknown or unexplored variables may account for the relationships between university mattering and these variables. In sum, further research exploring the relationships between university mattering, specifically utilizing the UMUM-15, and external variables is needed.

Although more research utilizing the UMUM-15 is necessary, it appears that the UMUM-15 may be helpful for evaluating the effectiveness of university programs for both transfer and native students. Assuming that a person's level of university mattering can be changed, university programs can be developed with the intention of increasing transfer students' university mattering. For example, university mattering could be measured at different time points during the program to assess which aspects of the program increase (or do not increase) university mattering. Based on the theory of mattering (e.g., Rosenberg & McCullough, 1981), programming that is personalized for each individual student and demonstrates to that student that he or she is a valued member of the community should foster a stronger sense of university mattering.

Limitations and Future Research

In terms of future research, it is primarily important to replicate the findings from the current study using different student samples. The students used in the current study and in previous research on the UMS (i.e., France & Finney, 2010) came from the same public institution. This university is large (about 20,000 students), located in a Southeastern state, and the students are generally homogenous (majority female and Caucasian). Furthermore, the students used across these studies had accumulated between 45 and 70 credit hours (i.e., sophomore status). In future studies, researchers should examine the psychometric properties of the UMUM-15 for students at institutions with different characteristics (e.g., smaller universities, private institutions, two-year institutions, institutions located in various parts of the United States or outside the United States), as well as students with different characteristics (e.g., first-years, seniors, alumni, students of various ethnic backgrounds, first generation students, students belonging to various minority groups). Until the factor structure of the UMUM-15 is examined using students that differ from the current study, the generalizability of these results are unknown.

Another limitation of this study was that measurement invariance was only examined for two groups of students: native and transfer students. As discussed previously, transfer students are a heterogeneous population, but were treated as one population in this study. If sample size had permitted, transfer students could have been further divided into subgroups. For example, groups could have been formed depending on the type of institution students transferred from (e.g., a two-year group and a four-year group). Alternatively, groups could have been formed based on the number of times students had transferred prior to attending their current institution (e.g., a single transfer group and a multiple transfer group). Furthermore, there are many subgroups of students present on university campuses in addition to transfer students. Researchers should assess the measurement invariance of UMUM-15 for students of various ethnic backgrounds, first generation students, adult or non-traditional students, part-time students, LGBT students, graduate students, etc. in future studies. If measurement invariance of the UMUM-15 is established for these additional populations, the measure can be used to evaluate the effectiveness of university programs for these specific students groups in addition to transfer and native students.

In addition to evaluating measurement invariance of the UMUM-15 across groups, researchers may be interested in evaluating the invariance of the UMUM-15 over time. A previous noted limitation of this study was that all students were sophomores. If the UMUM-15 was given to first-years or seniors, invariance of the parameter estimates for these groups would also need to be established prior to interpreting scores from the UMUM-15. For example, it is possible that first-year students conceptualize university mattering differently than sophomore students, given that they have not had as much time as sophomores to assimilate to their campus environment. To examine the measurement invariance of university mattering longitudinally, the UMUM-15 would have to be administered to students in their first year and the three years after, until they graduate. Establishing longitudinal measurement invariance would provide the necessary support that scores from the UMUM-15 can be compared across years. It would also facilitate the ability to examine how university mattering develops over time.

Future studies are needed to gather additional validity evidence for the external stage of the UMUM-15. Rosenberg and McCullough (1981) theorized mattering is a motive. Therefore, future studies are needed testing this hypothesis. For example, does low university mattering predict which students decide to leave the university? According to Elliott (2009), a low sense of mattering leads people to engage in anti-social behaviors. Thus, is there a relationship between students who engage in delinquent behavior (e.g., vandalism of university property, underage drinking, illegal drug use) and a low sense of mattering? Future research could compare university mattering scores of students who have been sanctioned to Judicial Affairs to students who have not been sanctioned, expecting students who have been sanctioned to have lower levels of university mattering. Furthermore, what are the implications for students with a low sense of university mattering? Do these students have lower academic self-efficacy or struggle with their academic course work? Finally, in addition to examining the ill effects of low mattering, the UMUM-15 could be used to evaluate the effectiveness of university programs over time.

General Conclusion

In closing, this research made several notable contributions to the study of university mattering. Findings from this study introduced a further revised measure of university mattering, the UMUM-15. This measure was derived by testing competing models that had been specified a priori based on theory. By using the incomplete bifactor model diagnostically, a one-factor model was derived through careful revision of the RUMS. More specifically, all 34 items loaded strongly to the general mattering factor; thus, indicating the data is essentially unidimensional. As a result, the UMUM-15 has strong psychometric properties that replicated across four independent samples. Importantly, the various facets of university mattering were retained in the final measure. As a result, the UMUM-15 supports a unified view of mattering. Measurement invariance across transfer and native students was also established for the UMUM-15. Transfer students had statistically significant and meaningfully lower levels of university mattering than native students. This finding provides strong known-groups validity evidence for the UMUM-15 (i.e., external stage, Benson, 1998). This finding also contributes to the literature on transfer student adjustment and psychological development. This study highlights the need for more studies on this growing population of students, suggesting transfer students may be more likely to suffer from the ills of having low mattering than native students.

Footnotes

[1]Degrees of freedom are calculated by subtracting the number of parameter estimates from the number of observations. Observations can be calculated using the formula: $k(k+1)/2$, where k equals the number of indicators.

[2]A covariance matrix was used to obtain all fit indices and parameter estimates with robust ML estimation, except to obtain correlation residuals. When using ML estimation to analyze a covariance matrix, standardized covariance residuals are printed in the LISREL output. Standardized covariance residuals are on a *z*-score metric. Therefore, values greater than $| 3 |$ are generally considered large, indicating local misfit. However, because I wanted to compare residuals produced from robust ML to residuals produced from rDWLS, a correlation matrix was read into LISREL to obtain correlation residuals with robust ML estimation.

Table 1

Demographics for Native Samples and Transfer Sample

	Sample 1	Sample 2	Sample 3	Transfer Sample
N	816	822	817	696
Age (*SD*)	20.07 (.62)	20.10 (.62)	20.08 (.67)	20.92 (2.48)
Female	61.90%	65.50%	65.10%	52.40%
White	78.70%	79.80%	80.80%	77.30%
Asian	5.00%	5.60%	6.00%	3.60%
Black	3.70%	3.60%	3.70%	4.20%
Hispanic	3.20%	2.40%	2.60%	3.40%
In-State	67.50%	67.40%	68.50%	86.80%
GPA (*SD*)	3.12 (.46)	3.11 (.44)	3.08 (.45)	2.57 (1.11)
Transfer Credits (*SD*)	0	0	0	42.09 (12.52)

Table 2

Iter-item Correlations and Descriptive Statistics for Sample 1 (below the diagonal) and Sample 2 (above the diagonal)

Item	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	Mean	*SD*	Skew	Kurt
1		0.45	0.53	0.48	0.45	0.52	0.31	0.51	0.41	0.43	0.44	0.46	0.48	0.43	0.29	0.36	0.44	0.38	0.34	0.42	0.39	0.33	0.37	0.46	0.47	0.34	0.43	0.34	0.42	0.50	0.49	0.42	0.39	0.22	4.49	1.01	-1.02	1.24
2	0.43		0.36	0.41	0.39	0.36	0.20	0.39	0.60	0.43	0.30	0.44	0.41	0.50	0.18	0.26	0.26	0.32	0.40	0.34	0.25	0.28	0.35	0.33	0.44	0.52	0.39	0.24	0.38	0.38	0.43	0.54	0.28	0.26	3.71	1.16	-0.26	-0.42
3	0.51	0.32		0.48	0.31	0.54	0.30	0.37	0.33	0.40	0.46	0.32	0.42	0.37	0.31	0.48	0.31	0.34	0.29	0.41	0.35	0.29	0.29	0.39	0.43	0.31	0.41	0.31	0.36	0.37	0.46	0.38	0.37	0.16	4.84	0.90	-0.88	1.34
4	0.47	0.36	0.45		0.42	0.58	0.26	0.42	0.41	0.41	0.41	0.44	0.43	0.42	0.22	0.39	0.29	0.33	0.33	0.40	0.32	0.33	0.31	0.38	0.44	0.37	0.38	0.29	0.40	0.42	0.44	0.42	0.30	0.19	4.19	1.15	-0.59	0.11
5	0.45	0.40	0.29	0.41		0.46	0.12	0.70	0.44	0.34	0.31	0.59	0.41	0.42	0.13	0.26	0.31	0.25	0.36	0.27	0.37	0.26	0.25	0.49	0.43	0.43	0.53	0.29	0.36	0.57	0.41	0.46	0.31	0.31	3.35	1.28	0.10	-0.69
6	0.55	0.37	0.54	0.55	0.43		0.26	0.50	0.43	0.44	0.49	0.45	0.50	0.43	0.23	0.40	0.33	0.37	0.34	0.40	0.34	0.34	0.27	0.43	0.50	0.33	0.41	0.35	0.38	0.44	0.52	0.41	0.37	0.21	4.04	1.12	-0.50	0.11
7	0.27	0.11	0.26	0.22	0.06	0.24		0.19	0.19	0.33	0.50	0.18	0.32	0.24	0.55	0.37	0.44	0.39	0.31	0.42	0.33	0.28	0.43	0.27	0.28	0.24	0.28	0.42	0.26	0.24	0.37	0.26	0.32	0.02	4.96	1.10	-1.21	1.30
8	0.48	0.41	0.30	0.35	0.67	0.41	0.11		0.52	0.39	0.35	0.67	0.47	0.47	0.18	0.34	0.38	0.33	0.33	0.36	0.40	0.34	0.33	0.61	0.50	0.41	0.56	0.33	0.36	0.64	0.48	0.49	0.32	0.29	3.79	1.19	-0.26	-0.43
9	0.42	0.59	0.31	0.38	0.44	0.40	0.17	0.47		0.51	0.31	0.50	0.49	0.58	0.14	0.31	0.22	0.36	0.41	0.39	0.25	0.36	0.39	0.41	0.52	0.52	0.43	0.28	0.42	0.47	0.44	0.58	0.31	0.33	3.74	1.16	-0.25	-0.31
10	0.44	0.35	0.39	0.38	0.29	0.44	0.30	0.33	0.46		0.42	0.44	0.55	0.52	0.35	0.44	0.32	0.49	0.35	0.57	0.28	0.44	0.36	0.39	0.48	0.39	0.40	0.37	0.35	0.41	0.50	0.46	0.35	0.18	4.15	1.19	-0.55	-0.07
11	0.43	0.20	0.41	0.32	0.21	0.43	0.48	0.24	0.31	0.43		0.32	0.47	0.38	0.49	0.45	0.52	0.41	0.45	0.46	0.46	0.33	0.50	0.37	0.45	0.32	0.37	0.51	0.33	0.36	0.50	0.36	0.41	0.11	4.52	1.03	-0.62	0.34
12	0.45	0.43	0.35	0.41	0.58	0.45	0.15	0.65	0.48	0.42	0.31		0.54	0.52	0.22	0.28	0.34	0.36	0.35	0.37	0.38	0.36	0.33	0.60	0.50	0.46	0.53	0.32	0.34	0.63	0.51	0.51	0.34	0.25	3.72	1.15	-0.23	-0.51
13	0.50	0.40	0.44	0.45	0.41	0.48	0.27	0.41	0.49	0.52	0.45	0.55		0.61	0.35	0.46	0.38	0.56	0.42	0.53	0.39	0.44	0.44	0.54	0.63	0.50	0.49	0.42	0.39	0.53	0.61	0.58	0.45	0.26	4.19	1.08	-0.44	0.07
14	0.43	0.54	0.36	0.37	0.42	0.38	0.22	0.48	0.60	0.51	0.37	0.54	0.61		0.30	0.40	0.34	0.45	0.48	0.47	0.34	0.41	0.41	0.49	0.53	0.58	0.50	0.38	0.40	0.54	0.58	0.63	0.35	0.24	4.27	1.03	-0.65	0.71
15	0.29	0.09	0.27	0.20	0.09	0.26	0.60	0.09	0.17	0.34	0.52	0.17	0.30	0.24		0.42	0.46	0.43	0.34	0.48	0.39	0.34	0.46	0.26	0.32	0.23	0.27	0.46	0.24	0.27	0.39	0.25	0.34	0.06	4.85	1.07	-0.89	0.40
16	0.35	0.17	0.45	0.30	0.14	0.32	0.37	0.18	0.28	0.39	0.39	0.26	0.39	0.36	0.43		0.39	0.52	0.33	0.54	0.34	0.43	0.39	0.40	0.44	0.34	0.44	0.37	0.34	0.37	0.48	0.37	0.41	0.14	4.93	0.94	-1.32	3.17
17	0.43	0.25	0.35	0.32	0.30	0.35	0.34	0.36	0.29	0.34	0.48	0.39	0.44	0.37	0.44	0.31		0.39	0.43	0.36	0.52	0.38	0.53	0.44	0.36	0.34	0.39	0.52	0.25	0.37	0.46	0.37	0.39	0.13	4.41	1.12	-0.71	0.32
18	0.31	0.22	0.33	0.26	0.12	0.29	0.29	0.18	0.30	0.43	0.39	0.29	0.46	0.38	0.33	0.44	0.28		0.34	0.62	0.32	0.50	0.43	0.42	0.52	0.41	0.43	0.41	0.28	0.41	0.55	0.43	0.48	0.12	4.47	1.13	-0.78	0.63
19	0.34	0.46	0.26	0.32	0.29	0.25	0.30	0.35	0.51	0.36	0.43	0.40	0.43	0.53	0.33	0.35	0.44	0.33		0.37	0.37	0.32	0.53	0.37	0.41	0.46	0.38	0.42	0.35	0.38	0.45	0.55	0.32	0.16	4.34	1.09	-0.55	0.23
20	0.40	0.26	0.39	0.38	0.23	0.39	0.38	0.27	0.36	0.53	0.42	0.33	0.47	0.44	0.38	0.51	0.36	0.53	0.38		0.36	0.53	0.48	0.44	0.50	0.41	0.43	0.44	0.38	0.43	0.55	0.46	0.45	0.14	4.52	1.01	-0.60	0.46
21	0.44	0.28	0.34	0.29	0.34	0.36	0.32	0.38	0.27	0.31	0.39	0.38	0.42	0.37	0.33	0.25	0.57	0.23	0.37	0.28		0.26	0.47	0.45	0.41	0.32	0.43	0.47	0.26	0.43	0.44	0.36	0.33	0.19	4.32	1.43	-0.53	-0.72
22	0.36	0.25	0.38	0.33	0.19	0.34	0.31	0.23	0.32	0.43	0.36	0.32	0.40	0.40	0.31	0.41	0.31	0.48	0.32	0.56	0.21		0.39	0.41	0.47	0.39	0.39	0.35	0.39	0.40	0.51	0.40	0.45	0.15	4.24	1.09	-0.53	0.13
23	0.36	0.35	0.32	0.35	0.30	0.28	0.42	0.30	0.41	0.39	0.41	0.34	0.41	0.47	0.44	0.40	0.41	0.36	0.55	0.45	0.42	0.36		0.39	0.47	0.46	0.39	0.53	0.34	0.37	0.49	0.49	0.37	0.12	4.76	1.08	-0.99	1.14
24	0.47	0.38	0.34	0.39	0.50	0.38	0.18	0.57	0.47	0.41	0.36	0.62	0.51	0.49	0.17	0.32	0.44	0.34	0.42	0.40	0.44	0.33	0.38		0.55	0.45	0.60	0.38	0.37	0.64	0.57	0.53	0.43	0.27	4.07	1.04	-0.57	0.34
25	0.46	0.33	0.42	0.43	0.39	0.48	0.31	0.37	0.46	0.45	0.44	0.48	0.58	0.49	0.33	0.41	0.41	0.41	0.39	0.45	0.41	0.46	0.42	0.55		0.52	0.55	0.45	0.44	0.55	0.65	0.60	0.48	0.29	4.01	1.09	-0.34	-0.04
26	0.36	0.53	0.30	0.33	0.43	0.32	0.17	0.43	0.53	0.42	0.32	0.48	0.45	0.57	0.22	0.32	0.32	0.34	0.51	0.40	0.32	0.34	0.45	0.51	0.49		0.52	0.32	0.33	0.49	0.50	0.68	0.35	0.28	3.96	1.09	-0.32	-0.22
27	0.36	0.35	0.31	0.30	0.46	0.27	0.15	0.50	0.42	0.35	0.30	0.52	0.44	0.50	0.17	0.35	0.37	0.31	0.39	0.37	0.40	0.30	0.37	0.57	0.47	0.53		0.41	0.39	0.65	0.58	0.56	0.43	0.29	4.10	1.15	-0.50	-0.01
28	0.40	0.24	0.37	0.33	0.26	0.38	0.46	0.28	0.32	0.40	0.57	0.36	0.46	0.39	0.50	0.39	0.50	0.35	0.47	0.42	0.52	0.33	0.47	0.38	0.46	0.34	0.36		0.30	0.37	0.52	0.39	0.39	0.12	4.55	1.03	-0.70	0.77
29	0.36	0.32	0.32	0.46	0.37	0.31	0.24	0.35	0.44	0.32	0.32	0.36	0.40	0.41	0.25	0.37	0.27	0.31	0.38	0.41	0.31	0.36	0.42	0.40	0.42	0.45	0.41	0.35		0.44	0.47	0.43	0.37	0.33	4.36	1.07	-0.58	0.44
30	0.46	0.42	0.32	0.41	0.58	0.40	0.15	0.61	0.48	0.42	0.32	0.66	0.51	0.55	0.20	0.28	0.41	0.30	0.41	0.37	0.42	0.33	0.35	0.69	0.52	0.58	0.65	0.36	0.48		0.59	0.59	0.42	0.31	3.94	1.05	-0.34	0.13
31	0.51	0.34	0.46	0.44	0.33	0.55	0.33	0.39	0.42	0.53	0.51	0.46	0.57	0.51	0.34	0.43	0.42	0.45	0.40	0.53	0.40	0.44	0.38	0.54	0.63	0.44	0.48	0.52	0.45	0.55		0.65	0.59	0.26	4.41	0.99	-0.68	0.97
32	0.37	0.54	0.28	0.38	0.45	0.36	0.15	0.48	0.59	0.47	0.31	0.51	0.47	0.62	0.20	0.29	0.32	0.36	0.53	0.39	0.37	0.36	0.49	0.56	0.52	0.69	0.52	0.34	0.45	0.62	0.54		0.46	0.34	3.94	1.06	-0.34	0.05
33	0.42	0.29	0.43	0.38	0.23	0.41	0.37	0.25	0.35	0.44	0.43	0.32	0.48	0.45	0.42	0.48	0.35	0.46	0.35	0.54	0.36	0.48	0.42	0.40	0.49	0.39	0.34	0.43	0.43	0.40	0.61	0.44		0.22	4.54	1.07	-0.97	1.28
34	0.22	0.23	0.13	0.27	0.32	0.17	0.03	0.29	0.29	0.21	0.12	0.27	0.24	0.24	0.00	0.08	0.12	0.12	0.22	0.19	0.21	0.20	0.16	0.25	0.24	0.27	0.24	0.13	0.28	0.37	0.24	0.35	0.21		3.34	1.39	0.11	-0.68
Mean	4.53	3.81	4.84	4.21	3.33	4.06	4.97	3.85	3.85	4.16	4.53	3.71	4.22	4.31	4.87	4.93	4.42	4.48	4.40	4.55	4.32	4.28	4.86	4.12	4.04	4.00	4.17	4.62	4.41	3.95	4.44	4.02	4.68	3.31				
SD	0.96	1.19	0.90	1.14	1.24	1.11	1.09	1.15	1.18	1.21	1.05	1.16	1.06	1.04	1.07	0.90	1.09	1.13	1.12	0.94	1.44	1.03	1.07	1.04	1.13	1.18	1.15	1.05	1.03	1.06	0.97	1.09	0.99	1.43				
Skew	-0.90	-0.30	-0.93	-0.58	0.08	-0.44	-1.30	-0.17	-0.23	-0.60	-0.64	-0.09	-0.39	-0.63	-1.02	-1.00	-0.47	-0.83	-0.48	-0.48	-0.51	-0.49	-0.86	-0.35	-0.35	-0.31	-0.48	-0.66	-0.43	-0.21	-0.62	-0.24	-0.73	0.16				
Kurt	1.11	-0.46	1.55	0.17	-0.62	-0.17	1.72	-0.42	-0.52	-0.05	0.52	-0.53	0.15	0.45	1.13	1.70	-0.12	0.66	-0.20	0.47	-0.76	0.25	0.54	-0.08	-0.08	-0.33	0.00	0.38	0.13	-0.06	0.80	-0.17	0.69	-0.75				

Note. Negatively worded items were reverse coded. The scale ranged from 1 to 6.

Table 3

Fit Indices of the Tested Models Sample 1 (N = 816)

CFA Models using ML with SB adjustments	χ^2_{SB}	*df*	$RMSEA_{SB}$	CFI_{SB}	SRMR
Model 1: One-factor Model	5793.20	527	.11	.90	.08
Model 2: Four-factor Model	3396.44	521	.08	.94	.07
Model 3: Second-order Model	3696.42	523	.09	.94	.08
Model 4: Bifactor Model	*Did not converge to admissible solution*				
Model 5: Incomplete Bifactor Model	2782.76	501	.07	.96	.07
CFA Models using rDWLS	χ^2	*df*	RMSEA	CFI	SRMR
Model 1: One-factor Model	5967.23	527	.11	.93	.09
Model 2: Four-factor Model	3591.20	521	.09	.96	.07
Model 3: Second-order Model	3885.73	523	.09	.96	.08
Model 4: Bifactor Model	*Did not converge to admissible solution*				
Model 5: Incomplete Bifactor Model	2849.99	501	.08	.97	.07

Table 4

Fit Indices of the Tested Models Sample 2 (N = 822)

CFA Models using ML with SB adjustments	χ^2_{SB}	*df*	$RMSEA_{SB}$	CFI_{SB}	SRMR
Model 1: One-factor Model	4975.03	527	.10	.91	.07
Model 2: Four-factor Model	3429.26	521	.08	.94	.07
Model 3: Second-order Model		*Did not converge to admissible solution*			
Model 4: Bifactor Model	2643.95	493	.07	.96	.06
Model 5: Incomplete Bifactor Model	2778.05	501	.07	.95	.05
CFA Models using rDWLS	χ^2	*df*	RMSEA	CFI	SRMR
Model 1: One-factor Model	5316.00	527	.11	.94	.08
Model 2: Four-factor Model	3772.69	521	.09	.96	.07
Model 3: Second-order Model	3896.06	523	.09	.96	.07
Model 4: Bifactor Model	2653.66	493	.07	.97	.06
Model 5: Incomplete Bifactor Model	2802.39	501	.07	.97	.06

Table 5

Unstandardized Factor Pattern Coefficients from Sample 1

Item	One-factor Model	Incomplete Bifactor Model			
		General Factor	Awareness	Ego-Extension	Reliance
1	.63*	**.63***	.16*		
2	.67*	.55*			**.63***
3	.51*	**.55***			
4	.70*	**.68***		-.16*	
5	.71*	.56*	**.73***		
6	.68*	**.71***			
7	.44*	.50*		**.63***	
8	.71*	.56*	**.75***		
9	.78*	**.67***			.58*
10	.78*	**.80***		.02	
11	.62*	**.68***			
12	.80*	**.69***	.62*		
13	.78*	**.78***			
14	.76*	**.69***			.42*
15	.46*	.53*		**.66***	
16	.48*	**.54***			
17	.63*	**.64***	.11*		
18	.61*	**.66***		.11*	
19	.70*	**.64***			.41*
20	.60*	**.64***		.11*	
21	.82*	**.80***	.23*		
22	.57*	**.62***		.08	
23	.66*	**.64***			.22*
24	.74*	**.66***	.45*		
25	.82*	**.83***			
26	.81*	**.69***			.60*
27	.75*	**.65***	.45*		
28	.64*	**.69***			
29	.61*	**.59***			.19*
30	.78*	**.67***	.55*		
31	.73*	**.76***			
32	.79*	**.68***			.59*
33	.63*	**.68***		.12*	
34	.50*	**.42***			.31*

Note. The higher of the two pattern coefficients per item is bolded for the incomplete bifactor results. * $p < .05$.

Table 6

Unstandardized Factor Pattern Coefficients from Sample 2

Item	One-factor Model	Incomplete Bifactor Model			
		General Factor	Awareness	Ego-Extension	Reliance
1	.66*	**.65***	.17*		
2	.68*	**.61***			.53*
3	.52*	**.54***			
4	.68*	.69*		-.12*	
5	.77*	.67*	**.74***		
6	.72*	**.73***			
7	.49*	**.52***		.34*	
8	.80*	.71*	**.74***		
9	.75*	**.67***			.53*
10	.77*	**.76***		.23*	
11	.63*	**.67***			
12	.78*	**.71***	.54*		
13	.81*	**.82***			
14	.74*	**.71***			.34*
15	.51*	**.54***		.40*	
16	.56*	**.59***			
17	.64*	**.66***	.02		
18	.72*	**.73***		.41*	
19	.64*	**.63***			.27*
20	.68*	**.69***		.43*	
21	.81*	**.81***	.15*		
22	.64*	**.64***		.26*	
23	.67*	**.68***			.10
24	.74*	**.70***	.35*		
25	.83*	**.84***			
26	.72*	**.66***			.51*
27	.82*	**.77***	.34*		
28	.61*	**.64***			
29	.60*	**.59***			.13*
30	.77*	**.72***	.42*		
31	.79*	**.81***			
32	.80*	**.75***			.46*
33	.65*	**.67***		.11*	
34	.47*	**.42***			.33*

Note. The higher of the two pattern coefficients per item is bolded for the incomplete bifactor results. * $p < .05$.

Table 7

Fit Indices for the Modified Models using ML with SB adjustments

	χ^2_{SB}	*df*	$RMSEA_{SB}$	CFI_{SB}	SRMR
		Sample 1 (N = 816)			
24-item Incomplete Bifactor Model	1102.95	234	.07	.97	.05
15-item One-Factor Model	299.716	90	.05	.98	.04
		Sample 2 (N = 822)			
24-item Incomplete Bifactor Model	1118.72	234	.07	.96	.05
15-item One-Factor Model	317.29	90	.06	.97	.04

Table 8

Fit Indices for the Modified Models using rDWLS

	χ^2_{SB}	*df*	RMSEA	CFI	SRMR
		Sample 1 (N = 816)			
24-item Incomplete Bifactor Model	1139.91	234	.07	.98	.05
15-item One-Factor Model	298.20	90	.05	.99	.04
		Sample 2 (N = 822)			
24-item Incomplete Bifactor Model	1136.16	234	.07	.98	.05
15-item One-Factor Model	345.60	90	.06	.98	.04

Table 9

Fit Indices for Modified 15-item One-Factor Model Sample 1 (Sample 2)

Item	Unstandardized Factor Pattern Coefficients	Standardized Factor Pattern Coefficients	R^2	Error Variance
1	.62 (.64)	.65 (.63)	.42 (.40)	.58 (.60)
4	.67 (.67)	.59 (.58)	.35 (.34)	.65 (.66)
10	.80 (.77)	.66 (.65)	.44 (.43)	.56 (.57)
11	.64 (.63)	.61 (.62)	.37 (.38)	.63 (.62)
13	.79 (.83)	.75 (.77)	.56 (.59)	.44 (.41)
14	.72 (.73)	.69 (.70)	.48 (.50)	.52 (.50)
16	.51 (.57)	.57 (.61)	.33 (.37)	.67 (.63)
22	.61 (.66)	.59 (.61)	.35 (.37)	.65 (.63)
23	.63 (.65)	.59 (.60)	.35 (.36)	.65 (.64)
24	.69 (.71)	.66 (68)	.44 (.46)	.56 (.54)
25	.85 (.85)	.75 (.78)	.56 (.60)	.44 (.40)
29	.61 (.61)	.59 (.57)	.35 (.33)	.65 (.67)
31	.76 (.81)	.79 (.82)	.62 (.67)	.38 (.33)
33	.68 (.67)	.69 (.63)	.48 (.39)	.52 (.61)
34	.46 (.45)	.32 (.33)	.10 (.11)	.90 (.89)

Table 10

Iter-Item Correlations and Descriptive Statistics from Sample 3 (above the diagonal) and Transfer Sample (below the diagonal)

Items	1	4	10	11	13	14	16	22	23	24	25	29	31	33	34	Mean	*SD*	Skew	Kurt
1		0.53	0.42	0.42	0.50	0.45	0.39	0.36	0.37	0.51	0.56	0.40	0.54	0.42	0.26	4.49	1.02	-1.09	1.52
4	0.45		0.34	0.44	0.44	0.39	0.30	0.33	0.32	0.41	0.45	0.45	0.44	0.37	0.29	4.22	1.14	-0.60	0.24
10	0.43	0.37		0.43	0.53	0.50	0.48	0.48	0.38	0.47	0.53	0.41	0.53	0.47	0.17	4.19	1.20	-0.62	0.06
11	0.39	0.36	0.42		0.49	0.37	0.44	0.36	0.44	0.45	0.45	0.35	0.52	0.51	0.15	4.55	1.04	-0.76	0.60
13	0.55	0.42	0.52	0.49		0.60	0.48	0.45	0.43	0.58	0.61	0.50	0.66	0.55	0.27	4.24	1.11	-0.67	0.53
14	0.50	0.44	0.53	0.38	0.66		0.45	0.40	0.43	0.52	0.53	0.47	0.59	0.51	0.27	4.33	1.06	-0.66	0.66
16	0.46	0.38	0.43	0.43	0.47	0.54		0.45	0.41	0.38	0.43	0.38	0.49	0.51	0.12	4.93	0.95	-1.13	1.99
22	0.38	0.39	0.51	0.37	0.49	0.48	0.54		0.38	0.38	0.49	0.41	0.50	0.46	0.22	4.27	1.04	-0.56	0.44
23	0.39	0.30	0.44	0.37	0.44	0.48	0.39	0.47		0.41	0.43	0.36	0.47	0.45	0.17	4.83	1.04	-0.91	0.94
24	0.51	0.38	0.45	0.34	0.56	0.59	0.41	0.45	0.47		0.61	0.47	0.67	0.52	0.33	4.14	1.02	-0.56	0.54
25	0.46	0.42	0.52	0.40	0.58	0.53	0.50	0.49	0.45	0.56		0.48	0.68	0.51	0.35	4.06	1.10	-0.38	-0.09
29	0.42	0.46	0.40	0.34	0.42	0.41	0.44	0.45	0.36	0.46	0.42		0.53	0.46	0.36	4.46	1.02	-0.40	0.10
31	0.52	0.47	0.54	0.48	0.64	0.55	0.54	0.56	0.46	0.54	0.59	0.54		0.68	0.32	4.44	1.01	-0.75	0.96
33	0.39	0.35	0.46	0.42	0.53	0.50	0.50	0.53	0.41	0.46	0.50	0.48	0.66		0.26	4.64	1.01	-1.01	1.57
34	0.26	0.24	0.26	0.15	0.30	0.23	0.13	0.18	0.22	0.35	0.28	0.40	0.30	0.24		3.34	1.40	0.14	-0.71
Mean	4.25	4.13	3.85	4.37	3.87	3.90	4.68	4.06	4.32	3.74	3.68	4.20	4.16	4.32	3.13				
SD	1.13	1.19	1.30	1.12	1.19	1.19	1.10	1.11	1.25	1.16	1.18	1.11	1.12	1.17	1.47				
Skew	-0.82	-0.63	-0.33	-0.68	-0.42	-0.59	-1.09	-0.54	-0.64	-0.38	-0.34	-0.69	-0.72	-0.90	0.28				
Kurt	0.46	0.10	-0.57	0.40	-0.07	0.01	1.38	0.20	-0.01	-0.28	-0.37	0.52	0.75	0.90	-0.77				

Table 11

Fit Indices for UMUM-15

	χ^2_{SB}	*df*	$RMSEA_{SB}$	CFI_{SB}	SRMR
		Sample 3 (N = 817)			
One-factor Model	340.76	90	0.06	0.98	0.04
		Transfer Sample (N = 696)			
One-factor Model	317.60	90	0.06	0.98	0.04

Table 12

Results for Measurement Invariance Across Native and Transfer Students

Model	χ^2_{SB}	*df*	$\Delta\chi^2_{SB}$	Δdf	$\Delta\chi^2$ *p*-value	RMSEA	90% CI	CFI	ΔCFI
Step 1: Configural Invariance	657.24*	181	--	--	--	.059	.054-.064	.9850	--
Step 2: Metric Invariance	679.82*	195	19.15	14	.16	.057	.053-.062	.9848	.0002
Step 3: Scalar Invariance	743.70*	209	70.73	14	< .001	.058	.054-.063	.9832	.0016

Note: RMSEA = root mean square error of approximation, CI = confidence interval, CFI = comparative fit index. $\Delta\chi^2$ and ΔCFI tests were conducted for each subsequent model tested.

*$p < .01$

Table 13

Parameter Estimates from Configural One-Factor Model Sample 3 (Transfer Sample)

Item	Unstandardized Factor Pattern Coefficients	Standardized Factor Pattern Coefficients	R^2	Error Variance
1	1.00 (1.00)	.66 (.66)	.43 (.43)	.57 (.57)
4	.97 (.92)	.57 (.58)	.33 (.33)	.67 (.67)
10	1.19 (1.19)	.66 (.68)	.44 (.46)	.56 (.54)
11	.97 (.87)	.62 (.57)	.39 (.33)	.61 (.67)
13	1.30 (1.25)	.78 (.78)	.61 (.60)	.39 (.40)
14	1.12 (1.20)	.71 (.75)	.50 (.56)	.50 (.44)
16	.87 (1.00)	.61 (.67)	.37 (.45)	.63 (.55)
22	.94 (1.02)	.60 (.68)	.37 (.47)	.63 (.53)
23	.90 (1.02)	.58 (.61)	.34 (.37)	.67 (.63)
24	1.13 (1.10)	.74 (.71)	.55 (.50)	.45 (.50)
25	1.28 (1.16)	.78 (.73)	.61 (.53)	.39 (.47)
29	.97 (.94)	.64 (.63)	.40 (.39)	.60 (.61)
31	1.28 (1.22)	.85 (.81)	.72 (.66)	.28 (.34)
33	1.10 (1.11)	.73 (.71)	.54 (.50)	.46 (.50)
34	.79 (.74)	.38 (.37)	.14 (.14)	.86 (.86)

Note. Unstandarized factor pattern coefficients for item 1 was fixed at 1.00 to serve as referent item. All freely estimated unstandardized factor pattern coefficients were statistically significant.

Table 14

Mean Differences of Observed and Latent University Mattering scores across Transfer and Native Student Samples

Latent Estimates	Estimate
Latent mean difference	-.28*
Transfer factor variance	.44
Native factor variance	.54
Latent mean difference effect size	-.40
Observed Estimates	**Estimate**
Observed mean difference	-.30*
Transfer sample observed mean (*sd*)	4.04 (.81)
Native sample observed mean (*sd*)	4.34 (.74)
Observed mean difference effect size (Cohen's *d*)	.39

Note. Transfer sample n = 696. Native sample n = 817. Unstandardized estimates (latent and observed mean differences, observed means) range from 1 to 6.

* $p < .001$

Figure 1. One-Factor Model

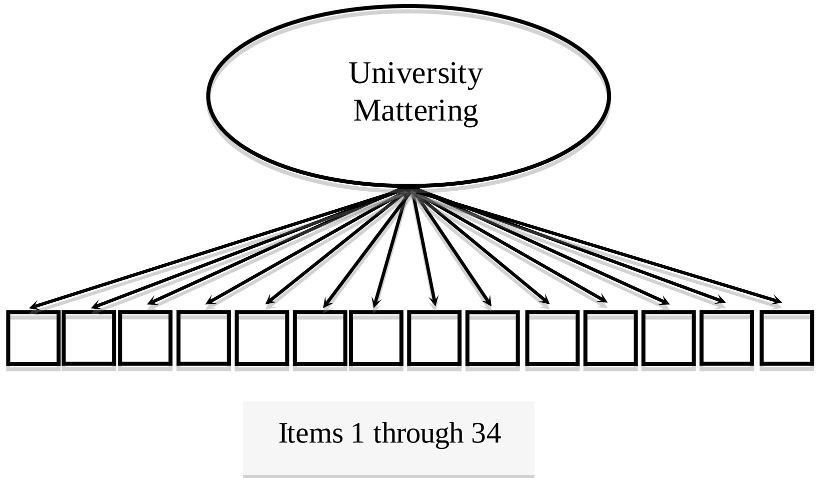


Figure 2. Correlated Four-Factor Model

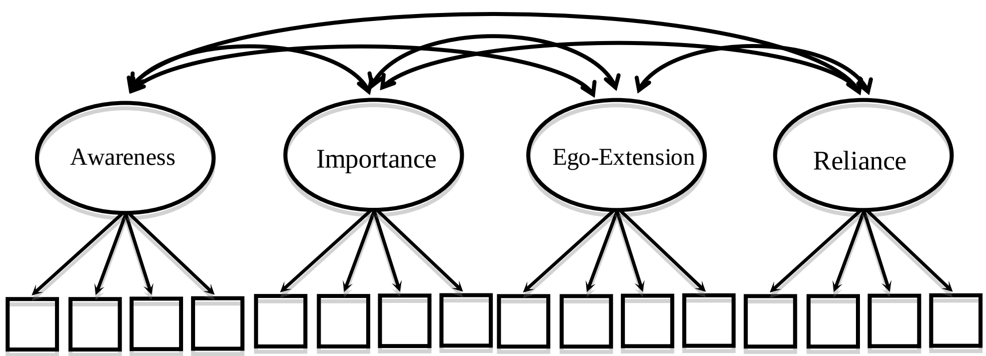


Figure 3. Higher-Order Model

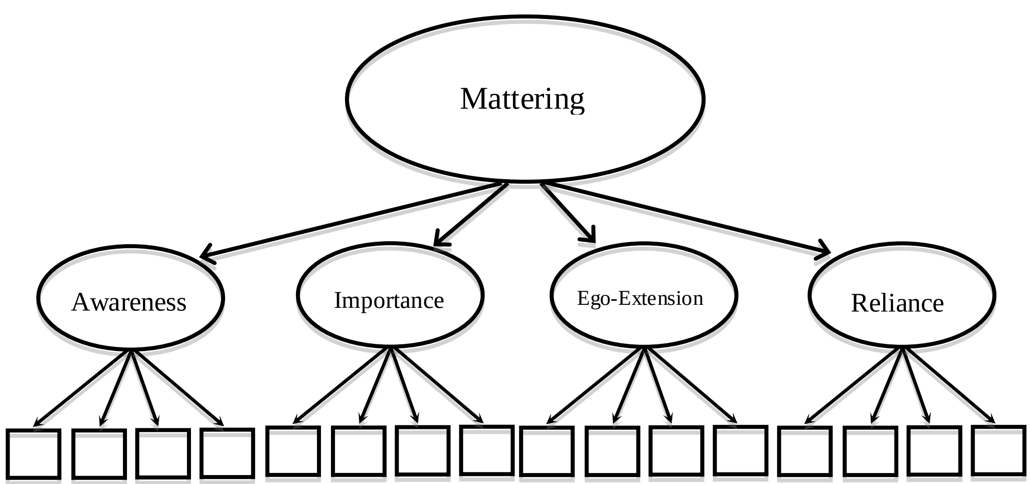


Figure 4. Bifactor Model

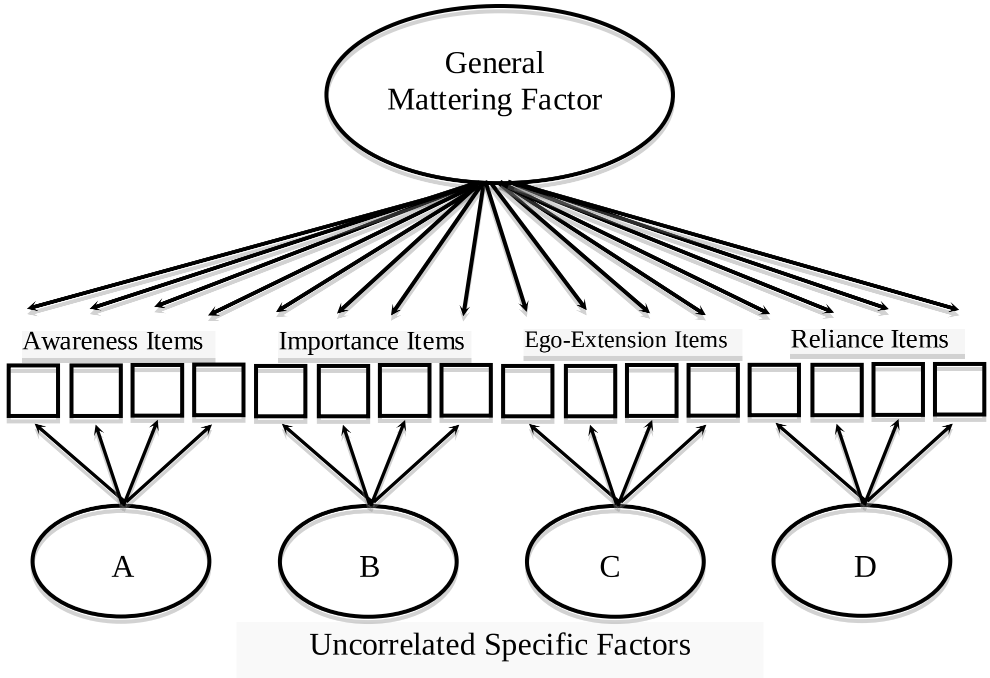


Figure 5. Incomplete Bifactor Model

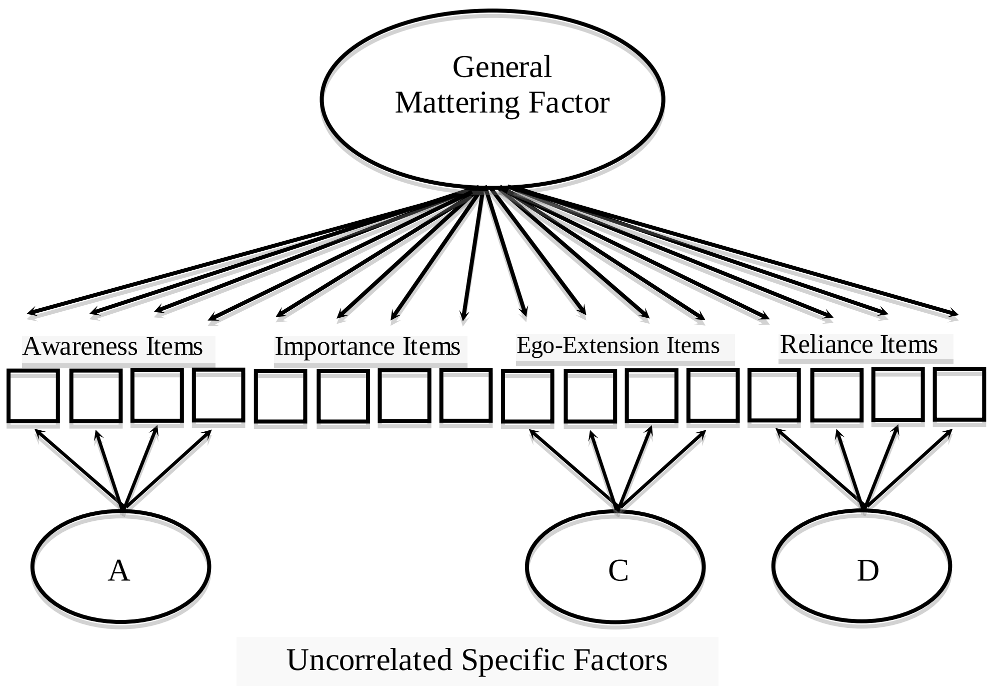


Figure 6. Conceptualizing University Mattering as Four Correlated Factors

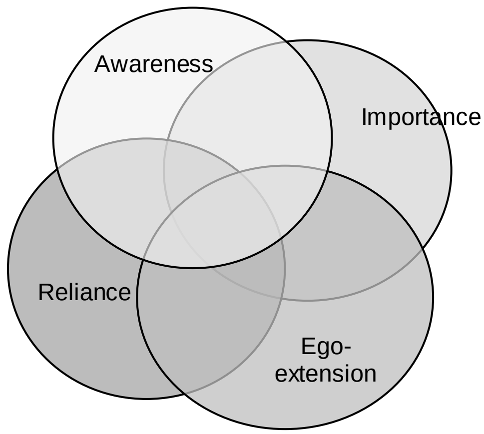
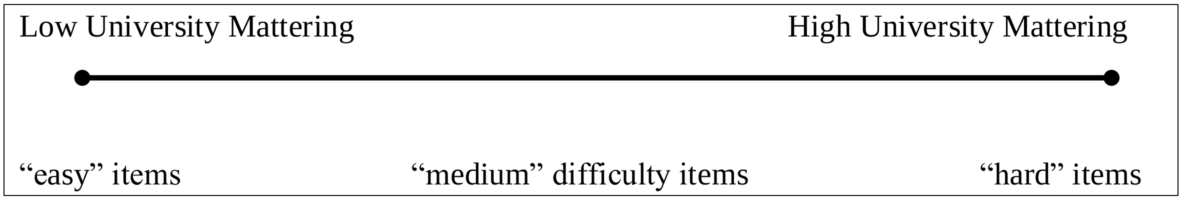


Figure 7. Conceptualizing University Mattering as a Continuum



Appendix A

Comparison of UMS to Revised UMS

Item	Revised UMS		UMS
2	When people at JMU need help, they come to me.	No revision	2
*21.	Sometimes at JMU, I feel as if I were invisible.	No revision	4
32	The people of the JMU community tend to rely on me for support.	No revision	5
4	My successes are a source of pride to the people of the JMU community.	No revision	6
24	The people of the JMU community are usually aware of my presence.	No revision	9
*19.	I am not someone the people of the JMU community would turn to when they need something.	No revision	10
14	Often, the people of the JMU community trust me with things that are important to them.	No revision	12
*17.	It is hard for me to get attention from people of the JMU community.	No revision	16
26	Quite a few people of the JMU community look to me for advice on issues of importance.	No revision	17
10	There are people of the JMU community who react to what happens to me in the same way they would if it happened to them.	No revision	20
30	The people of the JMU community generally know when I am around.	No revision	21
*11.	When I have a problem, people of the JMU community usually don't want to hear about it.	No revision	22
9	People of the JMU community count on me to be there in times of need.	No revision	24
1	The people of the JMU community pay attention to me.	1-revised	The people of the JMU community do not ignore me
27	People of the JMU community tend to remember my name.	13-revised	People of the JMU community tend not to remember my name.
6	People of the JMU community are concerned about my needs.	14-revised	People of the JMU community do not care what happens to me.
12	Most people of the JMU community seem to notice when I come or go.	18-revised	Most people of the JMU community do not seem to notice when I come or go.
3	I have noticed that people at JMU will take the time to help me.	19-revised	I have noticed that people at JMU will sometimes inconvenience themselves to help me.
16	There are people at JMU who give me advice me when I need it.	23-revised	There are people at JMU who care enough about me to criticize me when I need it.
*23.	No one in the JMU community depends on me.	3-revised	No one at JMU really needs me.
5	The majority of people in the JMU community recognize me.	7-revised	At JMU social gatherings, no one recognizes me.
*7.	There is no one at JMU who would share in my excitement about my accomplishments.	New item	
8	Most people of the JMU community seem to notice me.	New item	
13	I know people in the JMU community are sincerely interested in me.	New item	
*15.	If I had a set back, there would be no one at JMU who would share in my feelings of unhappiness.	New item	
18	There are people of the JMU community who would be sad if they knew I was sad.	New item	

20	Some people at JMU would feel as enthusiastic as I would, if I were to achieve an important goal.	New item	
22	There are people in the JMU community who would also experience my disappointment if I didn’t reach my full potential.	New item	
25	People of the JMU community are invested in my life.	New item	
*28.	People of the JMU community don’t care about my personal welfare.	New item	
29	My contributions to JMU benefit the JMU community.	New item	
33	People at JMU would be upset if I were mistreated.	New item	
34	If I were not a JMU student, the JMU community would suffer.	New item	
31	People of the JMU community care what happens to me.	New item	

Appendix B

The Revised University Mattering Scale (RUMS)

Below are a series of statements that represent feelings toward JMU. Think about your relationships with the people in the JMU community and indicate the degree to which each statement is in line with your relationships. When you respond to these statements, do not think of specific others at JMU, rather, try to focus on JMU in general as an entity or whole community. By "community" we mean JMU students, faculty, administrators, and staff. Think of all these people as a whole when responding to these items. There are no right or wrong answers. Just answer as honestly as possible. Not all students feel the same way or are expected to feel the same way.

1	2	3	4	5	6
Strongly Disagree	Disagree	Disagree slightly	Agree slightly	Agree	Strongly Agree

1. The people of the JMU community pay attention to me.
2. When people at JMU need help, they come to me.
3. I have noticed that people at JMU will take the time to help me.
4. My successes are a source of pride to the people of the JMU community.
5. The majority of people in the JMU community recognize me.
6. People of the JMU community are concerned about my needs.
7. There is no one at JMU who would share in my excitement about my accomplishments.
8. Most people of the JMU community seem to notice me.
9. People of the JMU community count on me to be there in times of need.
10. There are people of the JMU community who react to what happens to me in the same way they would if it happened to them.
11. When I have a problem, people of the JMU community usually don't want to hear about it.
12. Most people of the JMU community seem to notice when I come or go.
13. I know people in the JMU community are sincerely interested in me.
14. Often, the people of the JMU community trust me with things that are important to them.
15. If I had a set back, there would be no one at JMU who would share in my feelings of unhappiness.
16. There are people at JMU who give me advice when I need it.

17. It is hard for me to get attention from people of the JMU community.

18. There are people of the JMU community who would be sad if they knew I was sad.

19. I am not someone the people of the JMU community would turn to when they need something.

20. Some people at JMU would feel as enthusiastic as I would, if I were to achieve an important goal.

21. Sometimes at JMU, I feel as if I were invisible.

22. There are people in the JMU community who would also experience my disappointment if I didn't reach my full potential.

23. No one in the JMU community depends on me.

24. The people of the JMU community are usually aware of my presence.

25. People of the JMU community are invested in my life.

26. Quite a few people of the JMU community look to me for advice on issues of importance.

27. People of the JMU community tend to remember my name.

28. People of the JMU community don't care about my personal welfare.

29. My contributions to JMU benefit the JMU community.

30. The people of the JMU community generally know when I am around.

31. People of the JMU community care what happens to me.

32. The people of the JMU community tend to rely on me for support.

33. People at JMU would be upset if I were mistreated.

34. If I were not a JMU student, the JMU community would suffer.

Scoring Key:

<u>Awareness</u>
1, 5, 8, 12, 17*, 21*, 24, 27, 30

<u>Reliance</u>
2, 9, 14, 19*, 23*, 26, 29, 32, 34

<u>Ego-Extension</u>
4, 7*, 10, 15*, 18, 20, 22, 33

<u>Importance</u>
3, 6, 11*, 13, 16, 25, 28*, 31

*Indicates reverse scored items

Appendix C

The Unified Measure of University Mattering- 15 (UMUM-15)

Number*	Item
1	The people of the JMU community pay attention to me.
4	My successes are a source of pride to the people of the JMU community.
10	There are people of the JMU community who react to what happens to me in the same way they would if it happened to them.
11	When I have a problem, people of the JMU community usually don't want to hear about it.
13	I know people in the JMU community are sincerely interested in me.
14	Often, the people of the JMU community trust me with things that are important to them.
16	There are people at JMU who give me advice when I need it.
22	There are people in the JMU community who would also experience my disappointment if I didn't reach my full potential.
23	No one in the JMU community depends on me.
24	The people of the JMU community are usually aware of my presence.
25	People of the JMU community are invested in my life.
29	My contributions to JMU benefit the JMU community.
31	People of the JMU community care what happens to me.
33	People at JMU would be upset if I were mistreated.
34	If I were not a JMU student, the JMU community would suffer.

*Original numbering was retained from the RUMS to facilitate comparisons.

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