A New Assessment of an Old Measure: Utilizing Latent Class Analysis to Examine the Strange Situation

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Abstract

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This work examined the Strange Situation coding system, utilizing Latent Class Analysis (LCA) to assess the number of latent categories underlying this measurement. In addition, the four behavioral dimensions of attachment behavior employed in Strange Situation coding (proximity & contact seeking (PCS), contact maintaining (CM), avoidance, and resistance) were evaluated with the LCA methodology to determine if simplifications (dichotomous vs. multi-level coding) or modifications (continuous vs. nominal/ordinal coding) were achievable. Participants were 1,191 children from the NICHD Study of Early Child Care and Youth Development (SECCYD) who were assessed using the Strange Situation procedure conducted at 15-months of age. Analysis 1 of the current work treated PCS and CM as 7-level nominal variables, and avoidance and resistance as 2-level variables (e.g., none vs. some avoidance). Analysis 2 was identical to

Analysis 1, except participants classified as Unclassifiable (U) or Disorganized/Unclassifiable (DU) were excluded for comparison purposes. Analysis 3 treated PCS and CM as continuous, while avoidance and resistance remained dichotomous. Analysis 4 returned PCS and CM to their original 7-level state and freed the avoidance and resistance variables to vary by making them 3-level. None of the analyses yielded a clear model of best fit, although both Analysis 1 and 4 returned multiple potentially suitable models. Analysis 3 returned no acceptable models, calling into question the common practice of treating the four behavioral dimensions as continuous variables. No definitive answer was reached as to whether binary coding offered similar discrimination to 3-level coding. The 2-class model of each analysis contained latent classes displaying A- (insecure-avoidant) and B- (secure) type behavior, with participants showing classic C behavior seemingly included in the B class. This is counter to the typical secure vs. insecure comparison conducted in much of the attachment literature. The 3-class model of each analysis contained classes resembling the Strange Situation A and B groups, and the B2 subgroup, which diverges from the expectation of replicating the ABC coding system. Taken together, these findings begin to call into question the classic Strange Situation classification system, although further work is needed to address the many issues encountered with these analyses.

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Psalm 115:1

DEDICATION

Gayle Olsen

&

Corey Martin

CHAPTER 1

INTRODUCTION

It could be argued that the theory of attachment, including its measurement, correlates, and developmental outcomes, is one of the most widely studied areas in the field of developmental psychology. Closely following the creation of John Bowlby's (1958) groundbreaking control-systems theory of attachment, the search for accurate methods of measuring this construct began. The most widely used and well-known of these measurements is Mary D. S. Ainsworth's Strange Situation. This measure was extensively validated by Ainsworth and her colleagues (1978), relying not only on observations made in the laboratory setting, but also on assessments of maternal sensitivity made in the home environment. Based on its extensive validation and its history of outcomes that correlate with predicted variables (e.g., Matas, Arend, and Sroufe, 1978; Renken et al., 1989; Bohlin, Hagekull and Rydell, 2000), the Strange Situation has become somewhat of a "Gold Standard" measure for the theory of attachment. Because of this status, many, if not most, of the subsequent measures of attachment that have been created have been validated against the Strange Situation.

While the Strange Situation has arguably been well-validated, one might point out that this validation has been done in the context of three, and only three, attachment styles existing. In fact, all of the efforts made by Ainsworth and colleagues (1978) to validate this measure were predicated on the well-founded assumption that this was the case. Given this major assumption, it only makes sense that it might be necessary to take a step back and actually test if there are in fact three, and only three, attachment styles, utilizing new statistical techniques that can explore this situation further.

One of these techniques that is relatively new to the area of psychology is Latent Class Analysis (LCA). This analysis seeks to assess the underlying structure of a set of data utilizing nominal, ordinal, or continuous indicators. In the current study, LCA is used to examine the classification system used in the Strange Situation in an attempt to evaluate the number of latent categories that underlie this assessment of attachment. Beyond this, the four dimensions of attachment behavior (proximity & contact seeking, contact maintaining, avoidance, and resistance) that are currently used in category assignment in the Strange Situation coding are examined in an effort to make suggestions for future coding and potentially simplify the coding process.

Bowlby's Theory of Attachment

John Bowlby first began to set forth his theory of attachment in 1958 with the publication of an article examining the mother-child relationship. In subsequent years, he refined this theory and ultimately expanded it to the point of creating a three volume work entitled "Attachment and Loss". The first edition of this trilogy, published in 1969, sparked a major shift in the way the relationship between mother and child was viewed. Until this point in time, most researchers believed that any connection between the mother and child was due to the child getting his[1] needs met in some way by the mother. Which of these needs was primary in the formation of the relationship, whether it be a need for food, physical contact, or some other basic necessity, was hotly debated. Of particular popularity at the time was the idea that the mother-child connection resulted from the mother's provision of food to the child. A mother, being the sole figure with the ability to breastfeed her child, was the perfect candidate for the formation of a unique bond

[1] Throughout this manuscript the child's gender will be referred to as male to aid in the ease of distinguishing between references to mother and references to child.

with her infant because of her ability to meet this need for sustenance. Bowlby's theory challenged this idea, and the larger idea that the mother-child bond was based on a child's needs being met. Relying on evidence from research on non-human primates, Bowlby was able to stand on firm ground in his assertion that the mother-child bond was not in fact due to the mother being the child's source of nourishment (Bowlby, 1982).

The crucial piece of evidence presented by Bowlby in this line of defense was the work of Harlow (1958) on infant macaque monkeys. Harlow separated a group of macaques from their mothers at birth and raised them with the aid of mother substitutes. Each monkey was given 24 hour access to two "mothers". The first mother was created out of a tube of wire mesh, generally the size of an adult female macaque with an object roughly resembling a head at the top of the tube. The second mother was identical in size and shape to the first mother, but this mother was covered in soft cloth. Half of the orphaned monkeys received nourishment from a nipple protruding out of the wire mother, and the other half drank from the cloth mother. In looking at the amount of time the monkeys spent in contact with each mother, both groups showed a clear preference for the cloth mother. In fact, even when a fear inducing stimulus was introduced into the cage, whether or not a mother was the source of food had no bearing on the macaques' preference – the monkeys plainly preferred the cloth mother, even if she had not provided nourishment. Harlow called this the concept of "contact comfort", indicating that monkeys were not solely reliant on a mother figure to provide them food, but looked to a preferred mother figure to offer tactile comfort in times of stress. This clearly showed that in non-human primates, a close relative of humans, the bond between a mother and child was not dependent on the feeding relationship.

Bowlby took Harlow's work as evidence against the idea that the human bond between mother and child was based on the mother providing nourishment, and ultimately suggested an ethological theory of human attachment. He asserted that the primary function of attachment behavior was survival of the species. A child that remains in proximity to his mother, or even on his mother's person, is more likely to be protected from any threats the environment might hold. In our evolutionary history as humans, these threats could include predators that might threaten a child's life, and therefore threaten the chance of that child's genes being passed to the next generation. It was in the child's best interest genetically, and for that matter the mother's best interest as well, to remain close to the mother in order to ensure survival. According to Charles Darwin's (1911) theory of evolution, this behavior of seeking proximity to mother, especially in threatening situations, would surely be maintained according to the process of natural selection. Even in today's world, where wild animals are much less of a threat than they were for our ancient ancestors, a child's survival is still dependent on maintaining proximity to a caregiver who will protect and care for that child (Bowlby, 1982).

Bowlby suggested multiple behaviors that could be seen as contributing to the child's maintaining proximity to the mother, including smiling, crying, babbling, approaching, following, clinging, and sucking. It was suggested that, just as the child put forth effort in these behaviors, the mother herself would also encourage such actions, playing her own part in promoting proximity. Over time, Bowlby believed that these behaviors would go through the process of "monotropy" in which the child would single out the mother as the primary recipient of these bids for proximity. In this way, proximity to mother became the set-goal of what Bowlby came to call his control theory of attachment behavior (Bowlby, 1982).

After much expansion and refinement of his theory of attachment between 1958 and 1969, Bowlby came to base his theory of attachment on control systems theory. According to control systems theory, a machine would have a programmed goal, and this goal would be attained by taking action, and then constantly refining this action based on environmental feedback to bring the machine closer to the goal. The classic example of such a system, offered by Bowlby (1982), is that of a thermostat. The thermostat's goal is to maintain a pre-set temperature, and the machine responds to changes in the environmental temperature by taking action (e.g. triggering a heating system to introduce more heat into the area). Bowlby felt that the attachment relationship could be viewed in the context of this type of control system. A child has a set-goal of maintaining proximity to his mother, and responds to changes in the environment (e.g., mother leaving the room, mother picking him up, etc.) by refining his behavioral strategy (e.g., crawling after mother, clinging to mother, etc.) in order to bring him closer to his goal. At the same time, the child is interested in exploring the environment around him, so he must strike some balance between maintaining proximity and exploration. Bowlby termed the process of refining one's actions to meet the needs of the current environmental situation "goal-corrected behavior". He believed that, early on, a child might make a bid for proximity, for example by crying, but this action is not goal-corrected because the child himself has no means of maintaining proximity to his mother – he simply must wait for his mother's response. As the child's repertoire of behaviors expands, however, he will begin to have the means for true goal-corrected behavior, changing his own actions in response to his mother's actions.

With the type of control systems theory of attachment that Bowlby (1982) depicted, the set-goal of every child would be consistent (proximity to mother), while the techniques and behaviors used for actually attaining this goal would be flexible and varied, both among children and within an individual child. Even though, based on this, it would be impossible for Bowlby to describe a set behavioral sequence that every child progressed through over the course of development, he was able to outline a sequence of four general phases of attachment the he believed children followed. The phases as Bowlby labeled them were:

Phase 1: Orientation and Signals with Limited Discrimination of Figure

Phase 2: Orientation and Signals Directed towards One (or More) Discriminated Figure(s)

Phase 3: Maintenance of Proximity to a Discriminated Figure by means of Locomotion as well as Signals

Phase 4: Formation of a Goal-corrected Partnership

In the first phase, lasting from birth to around 12 weeks of age, the baby is responsive to people in the environment, but has difficulty discriminating among these people. In the second phase, ranging from 12 weeks to around 6 months, the baby becomes better at discrimination and begins to focus more positive attention on the mother. The third phase sees the baby gaining new skills in the ability to maintain proximity to his mother, with the mother maintaining primary importance to the child and some signs of stranger anxiety heightening the difference between mother and other. In addition, children are seen as showing some goal-corrected behavior in this phase, more flexibly adjusting their actions to reach their set-goal. Bowlby felt children were in this third phase from around 6 months until at least their second birthday. During the fourth and final phase of attachment development, a more complex relationship develops. A child begins to understand that his mother has her own set-goals, and is able to anticipate them and adjust his own actions accordingly. This partnership, as Bowlby saw it, could be seen at the earliest in children around 2 ½ years of age.

It is important to note that children are so primed to form this attachment bond that they will follow this progression, even if the mother actively works counter to the forming of this relationship. A mother's behavior in response to her child and his bids for proximity can vary immensely, from responsive and sensitive caregiving, to complete rejection. It is clear, based on the fact that attachment is a relationship, that the mother's behavior would also have a bearing on the nature of the mother-child bond. For this reason, it is known that not all attachment relationships are created equal (Bowlby, 1982).

Unfortunately, even though it is clear that attachment relationships differ, it is impossible to arrange those relationships on a continuum of intensity. The problem lies in the fact that the behaviors and strategies that lead to the set-goal of proximity are so incredibly varied. Even within a given child, the methods he might use to reach his set-goal will change based on the environment. There is no way to indicate if one behavior is "better" than another, because supreme importance is given to attaining the goal, not the exact method of attainment. Because of this, it was clear to Bowlby that seeking to create a scaled measure of the intensity of an attachment relationship was not a feasible goal or even a worthy goal. The only possibility would be to look at the quality of the attachment relationship, seeking patterns and profiles that could give researchers insight into the mother-child relationship. Mary D. Salter Ainsworth, colleague and mentee of Bowlby's, developed a measure that sought to do just that (Bowlby, 1982).

Ainsworth's Strange Situation Assessment

The foundations of the measure created by Ainsworth came from the work she conducted in Uganda, where she sought to learn about the bond between mother and child, specifically looking at the child's response to separation. Based on this work, Ainsworth (1964) proceeded to create a catalog of behaviors that she believed were indicative of attachment. These behaviors sparked an interest in further exploration of the attachment phenomenon, and were used in Ainsworth's subsequent work, ultimately helping to create a new measure of attachment.

In the years that followed her time in Uganda, Ainsworth was involved in the collection of data on four samples of a total of 106 mother-child pairs in the Baltimore area. The children in these samples were all approximately one year of age. Much information that was later useful for validation of her new measure was collected, but of primary importance was the fact that Ainsworth and colleagues tested all of these mother-child pairs with a new measurement procedure called the "Strange Situation". The Strange Situation consisted of a series of 8 episodes that the mother and child participated in, with the ultimate goal of creating a mildly stressful situation for the child that might activate the display of attachment behavior (Ainsworth et al., 1978). (Table 1 presents a description of each episode and its' participants, but they will also be described further presently.)

In the first episode of the Strange Situation, the mother and child were introduced to the testing room. In the middle of one end of the room was a pile of toys attractive to children of this age. On the opposite wall from the pile of toys sat two chairs, one at either end of the wall. The purpose of this episode was simply to introduce the pair to the room.

The second episode consisted of the mother and child alone in the room for three minutes, with the mother sitting on a chair and the child playing with the toys. The mother was instructed to read a magazine and not to initiate interaction with the child, but to relate normally if the child were the one to initiate interaction. This phase was intended to allow the child to become comfortable in the room and explore the toys available.

After three minutes, the third episode began in which an adult female stranger entered the room. For the first minute of this episode, the stranger sat in the chair opposite the mother and remained silent, not interacting with the mother or child. After this first minute, the stranger proceeded to engage the mother in pleasant conversation for one minute. Finally, the stranger addressed the child, spending a third minute attempting to interact with the child and engage him in playing with the toys. At the end of this three minute episode, the mother discreetly left the room.

The fourth episode consisted of the stranger and child remaining in the room, constituting the first episode involving a separation of child from mother. The stranger continued to interact with the child as before, gradually reducing this interaction with the goal of moving to the chair and allowing the child to explore on his own. If the child grew upset upon recognizing his mother's absence, the stranger attempted to comfort the child. This episode lasted three minutes, unless the child grew extremely distressed, in which case this fourth episode was terminated early and the fifth episode began.

The fifth episode involved the first reunion, with the mother returning to the room and the stranger unobtrusively leaving. The mother was asked to greet her child as she normally would, and then to seek to re-engage the child with the toys. This episode lasted three minutes, allowing the mother a chance to calm the child if necessary and for the researchers to observe reunion behavior. At the end of this three minute episode, the mother said, "bye-bye" to the child and then left the room again.

After the mother had exited the room, the sixth episode began in which the child was left alone in the room. This second separation episode lasted for three minutes. If the child was extremely distressed, however, this episode was terminated and testing proceeded to the seventh episode.

The seventh episode began with the stranger returning to the room. The stranger responded to the child as necessary, attempting to comfort the child if he were distressed. The goal of the stranger was the same as in the fourth episode – to gradually reduce interaction and encourage the child to engage with the toys on his own. If, however, the child remained highly distressed, this episode was terminated before its typical three minute duration was over and the eighth episode was initiated.

The eighth and final episode involved the mother returning to the room and the stranger discreetly exiting. For this second reunion, the mother was asked to enter the room, greet the baby, and then proceed to pick him up, regardless of his actions at the time. The mother was then free to respond to her child as she normally would, and their reunion behavior was observed. At the end of this three minute episode the testing was completed and the pair was finished with the Strange Situation testing (Ainsworth et. al., 1978).

During the entire Strange Situation, two observers watched the interactions in the testing room through a one-way mirror. They each narrated an account of the behavior they witnessed, which was later transcribed and divided into 15 second intervals of narration for coding purposes. These sessions were not videotaped (due to lack of equipment being available) but some still photographs were taken.

Without a specific coding agenda in mind, Ainsworth and colleagues (1978) began by attempting to classify children according to similarity of behaviors. As a preliminary step in this process, they looked at the first 13 mother-child pairs that had been tested with the Strange Situation assessment. They assumed that the children's level of distress upon separation would be useful in delineating different groups, and were able to identify three groups looking at these separation episodes. To be clear that they were not assigning levels or values to these groups, they labeled them A, B, and C.

After they had collected a total of 23 mother-child pairs, they attempted to separate these participants into groups based on a broader spectrum of behavior, examining all episodes instead of simply the separation episodes. In so doing, they identified seven different sets of children that were demonstrating similar behavioral patterns throughout the assessment procedure. From there, the researchers compared these sets of children in an attempt to group them more broadly. They found three larger groups that they again labeled A, B, and C, even though these three groups differed in many ways from the previously defined groups that were based solely on separation episodes. Even after identifying these three larger groups, however, they retained the original seven sets of children and called them subgroups of the overall ABC classifications. In this way, they identified group A, which had two subgroups, group B with three subgroups, and group C with two subgroups[2] (Ainsworth et. al., 1978).

After defining these three groups, Ainsworth and colleagues (1978) set out to develop criteria that could be used to assign children to these groups. They realized that the behaviors that were most indicative of group membership were found in the reunion episodes, not in the separation episodes as they had originally hypothesized. For this reason, they focused their coding efforts on the reunion episodes. Within those reunion episodes, four dimensions of behavior were identified that appeared to clearly delineate the three groups. These dimensions

[2] Bell (1970) later discovered an additional subgroup in group B that was included into the final coding system (Ainsworth et. al., 1978)

were: proximity & contact seeking (PCS), contact maintaining (CM), resistance, and avoidance. After identifying these dimensions, Ainsworth and her team proceeded to write out a description of any behavior they had witnessed in their first 56 participants that seemed to relate to one of these four dimensions. These descriptions were then arranged on a 7-point continuum for each dimension in an effort to create scales based on actual behaviors that had been witnessed. The intention was not that these exemplars be exhaustive, but provide a detailed example of how a researcher might classify children along each of these four dimensions. From these dimensions, classification into the A, B, and C groups could then easily be performed.

Tying all of these behaviors and dimensions together led to the formation of profiles of each of the three groups. The A group was most recognizable for their avoidance of the mother in the reunion episodes. When mother returned to the room, the typical response was for the baby not to greet her or even for him to actively avoid interaction with her. While group A babies did not show much resistance toward the mother, they also did not actively seek proximity to or contact with her. These babies are often called “insecure-avoidant”. In contrast, the children in group B were active in greeting their mothers upon her return, and typically sought proximity to and contact with her. They showed little resistance and avoidance behavior directed toward the mother. If they were upset by mother’s absence, they seemed to be easily soothed by her upon her return. Group B children are typically termed “secure”. Finally, the babies in group C were conspicuous for their resistance behaviors directed toward the mother. Interestingly, these children often sought proximity and contact with mother, but would then show acts of resistance – pushing the mother away or kicking at her. They rarely showed any avoidance, but were actively engaged in a struggle between contact and resistance. Children in group C are often called “insecure-ambivalent” (Ainsworth et. al., 1978).

The discovery of these individual differences in attachment behavior led Ainsworth and colleagues (1978) to conduct a Multiple Discriminant Function Analysis (MDFA) in order to further analyze the reliability of their three category system. There were two main objectives for this analysis. The first was to see if the three categories that the researchers discovered were in fact statistically disparate. The second was to examine the dimensions of behavior that were being used in classification to see if they were the most useful behaviors for identifying these disparities. The MDFA was performed on the data from the four samples of Strange Situation data previously mentioned[3].

Ainsworth and colleagues (1978) found two highly significant discriminant functions that separated the data into the three groups that had been previously defined. In this way, the Strange Situation classification system was supported by the MDFA. In addition, they looked at 22 different types of behavior that had proven statistically to distinguish one group from another in the ABC system. By looking at a variety of indices, including the correlation of each behavior with the discriminant functions, the researchers were able to determine which variables were offering the "best" discrimination among the three groups. These variables would, in turn, be important measures to include in any future usage of the Strange Situation. The variables that seemed to be best at discrimination were what Ainsworth and colleagues termed the "interactive behaviors" with the mother: proximity & contact seeking, contact maintaining, avoidance, and resistance, all in the reunion episodes. The researchers' earlier hypothesis that these four dimensions of behavior would be most indicative of group membership was statistically supported by the MDFA.

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[3] Only 105 participants were included in the MDFA – one subject was dropped due to equipment failure which led to an incomplete record for this child.

With the information from the MDFA, Ainsworth and colleagues (1978) were able to confidently put forth the final version of the Strange Situation assessment. This assessment required trained coders to rate participants on the four dimensions of interactive behavior witnessed in the two reunion episodes. These ratings were then utilized to assign an overall category to each child. With this finalized version of the assessment, the researchers were prepared to pursue further inquiries using the new measure and to encourage others to do the same.

Of importance to Ainsworth and colleagues (1978) before widely endorsing this new measure, however, was ensuring that the behaviors displayed by infants in the Strange Situation procedure were not unique to the laboratory environment, but represented a child’s typical behavioral pattern. In order to assess this, the researchers examined the data from the original 23 infants that had participated in the Strange Situation procedure. These infants had also participated in a year-long examination of their behavior in the home environment, focused in particular on mother-infant interaction, in which an observer visited the home once every three weeks for the entire first year of life. Ainsworth and colleagues were able to examine the behavior of both the infant and the mother in the home, focusing on the first and fourth quarters of the first year, in order to look for connections and correlations with the child’s later behavior in the Strange Situation assessment. Of particular interest was looking for group differences based on the infant’s assignment to the A, B, or C group.

What Ainsworth and colleagues (1978) discovered was a clear connection between group assignment in the Strange Situation and both infant and maternal behavior in the home. In terms of infant behavior, babies that were assigned a classification of B in the Strange Situation tended to cry less in the home and be less distressed by their mothers leaving the room. They also tended to have a positive reaction to being held by mother. In contrast, the A infants were more distressed by separation in the home than B infants, although C infants showed the highest level of distress. Interestingly, given their Strange Situation behavior, infants in the A category displayed the most anger at home. Ainsworth and colleagues suggested that the A infants appeared to be displaying an approach-avoidance conflict in which they showed clear signs of distress at separation from the mother in the home, but at the same time avoided close bodily contact, in some ways displaying signs of fear of the mother. While the behaviors of each group of infants in the home might not identically match the behaviors seen in the laboratory setting of the Strange Situation, clear group differences based on the Strange Situation classifications were seen, lending credence to these distinctions.

Potentially even more important than the infant home behaviors that were observed were the maternal home behaviors. Mothers differed distinctly based on their child's Strange Situation classification, not only in the fourth quarter of the first year, but also as early as the first quarter of the infant's first year of life. Ainsworth and colleagues (1978) found that the most clear and overarching way in which the mothers of the three groups of infants differed was in the mother's sensitive responsiveness. Mothers of B infants were quick to respond to their infants' signals and showed affection while holding their babies. Mothers of C infants clearly showed the opposite pattern, with longer delays before responding to their infants and a lack of affection in holding situations. Mothers of A infants showed subtle but clear signs of aversion to having close physical contact with their babies. While more research needed to be conducted in order to make suggestions about a causal relationship between maternal sensitivity and Strange Situation classification, this was the first piece of evidence suggesting maternal sensitive responsiveness as an important factor in the individual differences seen in attachment statuses.

In the years that have followed the formulation of the Strange Situation assessment, this technique has been used in countless studies. Researchers have delved further into the individual groups, continuing to speculate on what aspects of the mother-child relationship might have led to the individual differences found in the Strange Situation. For example, in a review of work that had been done on the insecure-ambivalent (C) group of children, Cassidy and Berlin (1994) suggested that mothers of children in the C group were inconsistently available for caregiving. In this way, these mothers encouraged (consciously or unconsciously) their children to engage in heightened attachment behavior and discouraged exploration of the environment. In contrast, Main and Weston (1982) found that the insecure-avoidant (A) group had mothers that consistently rejected physical contact. These mothers, when examining multiple samples, also proved to show lower levels of affect across multiple situations. These simple correlations between mother's behavior and Strange Situation classification led to further work in the area, and the propositions suggested by Cassidy and Berlin, and Main and Weston are still held to be true today.

Another line of research that has been taken up as a result of the Strange Situation assessment is the link between attachment classification and various outcome variables. This was a logical next step, given the fact that Bowlby (1982) suggested that, through the process of developing through the phases of attachment with his mother, a child would form a sort of internal working model of close relationships. This model would then serve as a model for all future relationships. In this way, the child's first attachment relationship with his mother would have far-reaching effects, clearly justifying an exploration of the link between attachment status with the mother and later development.

A host of outcome variables has been examined over the years following the development of the Strange Situation. Matas, Arend, and Sroufe (1978) found that children that had been classified as secure (B) at 18 months of age engaged in more symbolic play in a free-play task at 24 months than did children that had been classified as A or C at 18 months. In addition, the B children were more compliant with requests made by mother in a problem-solving task.

Shifting focus to the insecure groups (A and C), Renken and colleagues (1989) found strong links between attachment classification at 18 months of age and teacher ratings of behavior in first through third grade, although this link was only significant for their male participants. They found that a larger than average portion of the boys that were rated as aggressive by their teachers had been classified as avoidant (A) as toddlers. On the other hand, a larger than average portion of the boys showing signs of passive-withdrawal in elementary school had been classified as resistant (C) at 18 months of age. These significant findings highlighted the particular problem of long-lasting links between early insecure attachment and later school adjustment.

More recently, Bohlin, Hagekull and Rydell (2000) found links between early attachment classification and popularity. Children that had been classified as securely attached at 15 months of age were rated as more popular when assessed at 8 and 9 years of age. The preceding examples are merely a few of the multitude of studies that have investigated the links between early attachment status and later outcomes. In this area, the Strange Situation assessment has certainly opened the door for a thriving body of research.

In addition to investigating the links between Strange Situation attachment classification and various precursors and outcomes, researchers have attempted to create new measures of attachment. One of the more popular methods is the Attachment Q-Sort developed by Waters and Deane (1985). This method involves a coder sorting a set of 100 cards that each have a description of a specific attachment-related behavior into a set normal distribution. Based on careful observation of the child in the home, the coder creates this distribution that spans from behaviors that are most characteristic of the child to least characteristic of the child. This distribution that is representative of a specific child can then be compared to criterion sorts which have been created to represent a prototypically secure, resistant, or avoidant child, for example. One of the main differences between this method and the Strange Situation is that the Q-sort is conducted in the home, avoiding the unfamiliarity of the laboratory environment. In addition, the attachment Q-sort is appropriate for children from 1 to 5 years old, offering a substantially wider range of participant ages than the Strange Situation, (Posada et. al., 1995). In these ways, the Q-sort method not only offers an alternative method of assessing the attachment relationship, but it also includes major differences from the Strange Situation assessment that could be considered advantageous in certain situations.

As researchers have attempted to develop new methodology for assessing attachment, there has also been a push to create laboratory-based measures that have the ability to test children that are older than the one-year-old age group for which the Strange Situation was originally created. Moss and colleagues (2004) attempted to validate a measure of attachment called The Preschool Attachment Classification System (PACS) for children 3 to 5 years old, which was created by Cassidy and Marvin with the MacArthur Working Group on Attachment. This assessment consisted of a series of four episodes, similar to those in the Strange Situation in that they consisted of a series of separations and reunions between mother and child[4]. In the

[4] Solomon and George (2008) note that it is also acceptable to the authors of this system to use the entire 8 episode procedure from the Strange Situation assessment.

PACS, however, the separations were longer (up to 5 minutes) and the separations always involved the child being alone. While the coding for this system differed from that of the Strange Situation because the researchers were looking for behaviors that would be indicative of attachment in children at this particular age, children were ultimately assigned to the same categories utilized in the Strange Situation assessment. It could easily be suggested that the PACS system is the adjustment most closely similar to the Strange Situation, modified only slightly to be appropriate for children of this older age.

Patricia Crittenden, on the other hand, designed a system called the Preschool Assessment of Attachment (PAA) that included variations in coding as compared to the Strange Situation. Not only did she conceptualize the groups that were comparable to the original Strange Situation classifications differently, but she also included additional categories that are not found in Ainsworth's original system. In fact, Crittenden specifically predicted that developmental change would affect the categorization of children, and that it is entirely possible, if not likely, that a child's attachment status might change over time. While the PAA significantly diverges theoretically from the PACS (and the Strange Situation), it is entirely the same methodologically. The PAA is aimed at children ages 2 to 4, and the coding is based on the child's behavior in either the original episodes of the Strange Situation, or the modified four episode version used in the PACS. While this assessment is more disparate from the original work of Ainsworth, it is clearly rooted in this tradition stemming from the Strange Situation (Solomon and George, 1999 & 2008).

As should be clearly evident, the Strange Situation assessment has spurred an enormous body of work. Researchers have explored countless precursors to Strange Situation attachment classifications and outcome variables that are correlated with attachment categories. In addition, many new attachment assessment techniques have been developed in an attempt to classify children similarly to the Strange Situation using new methodologies and demographics. The majority of these new assessments have been validated using the Strange Situation, further indicating Ainsworth and colleagues' assessment strategy as the root of this vast body of work. Clearly, in the short span of only a few decades, the Strange Situation has become a major instigator in terms of research on attachment. In fact, this measure appears to be regarded as something of a "gold standard" in the assessment of attachment. Solely based on the plethora of research that is linked to this measure, and the way that most new measures of attachment are based on or validated against the Strange Situation, this gold standard label appears to be accurate.

There are many difficulties, however, with this measure being relied upon as the gold standard. Main and Solomon (1986) suggested that there could easily be more groups than the three classifications discovered by Ainsworth and colleagues (1978). While Main and Solomon reported that they did not discover a new category as such, they did find a group of children that were demonstrating what they termed disorganized or disoriented behavior (D behavior). The most striking characteristic of this group of children was that they appeared to lack a coherent or organized strategy to deal with the stressors presented in the Strange Situation procedure. They speculated that this group of infants had experienced fear associated with an attachment figure and, for this reason, experienced a conflict in situations that induced attachment behavior. When the attachment system was aroused, the child would be drawn to move toward the attachment figure for safety and comfort, but because the child also associated fear with this figure, the child was left in an irresolvable conflict. These children did not show a singular distinct pattern in terms of the four dimensions of behavior utilized by the Strange Situation to classify children, but they did all demonstrate some form of disorganized behavior that Main and Solomon (1990) were able to convert into a distinct scale of D behavior. While the researchers did not find a new classification based on the Strange Situation dimensions of behavior, the discovery of this group of children showing distinct behaviors that were not captured by the original Strange Situation coding system should certainly give us pause, as this alone might suggest that there is the potential for other groups to exist that are not currently addressed by the Strange Situation coding in its present form.

Another potential issue with the Strange Situation being considered a gold standard measure is that it has not been confirmed using the full extent of our current statistical knowledge. Ainsworth and colleagues (1978) utilized statistical procedures, namely MDFA, that were well-known and popular at the time they were creating the Strange Situation. Statistical knowledge has advanced since then, however, and new methods have become accessible to the point that new research can be conducted on "old" measures, such as the Strange Situation. It should be noted that the implication here is not that the Strange Situation should not be considered a gold standard measure, but that there is ample reason to review the treatment of this single assessment to ensure that, as a field, it is justified to continue in this vein.

Latent Class Analysis

In recent years, Latent Class Analysis (LCA) has become increasingly popular in social science research. This analysis can be used for a variety of purposes, one of which is assessing the underlying structure of data (in this case, whether or not there are three underlying attachment styles). Using nominal, ordinal, or continuous indicators, or a mixture of these three, LCA looks for latent classes in the data <u>without</u> the requirement of the data being previously classified (unlike MDFA). In the particular case of the Strange Situation, LCA could be utilized in two specific ways. One would be to use the four dimensions of behavior that are assessed in the Strange Situation (proximity & contact seeking, contact maintaining, avoidance, and resistance) as indicators in an analysis of latent classes. Multiple models could be compared to assess how many latent groups were suggested by the best-fitting model. If the best model indicated three latent classes, this would most likely support the current ABC classification scheme used in the Strange Situation[5]. If the best model indicated a number other than three classes, the profiles of these classes would need to be explored to assess their theoretical validity and make suggestions for future measurement.

An additional way that LCA could be utilized would be in assessing the four dimensions previously mentioned. Because a variety of indicator types (nominal, ordinal, or continuous) can be used with this type of analysis, the data can be coded in different ways in order to facilitate important comparisons. For example, it is common in the field of attachment to treat the four dimensions of behavior as continuous variables, even though they are truly based on an ordinal scale. Given that LCA can handle both continuous and ordinal indicator variables, it allows the possibility of running separate analyses, coding the indicator variables in each of these two ways, and comparing the results. If the results were identical, then this would indicate that the field is somewhat justified in treating these dimensions continuously, but if the results were widely different, a further evaluation of current practice would be suggested. In addition, it might even be the case that the full 7-level ordinal scale that is used for each dimension of behavior is not necessary. There is a possibility that one or more of the dimensions of behavior used as indicator

[5] It is not necessarily true that a 3-class model would match Ainsworth's model and not some other completely different model that happened to have three classes. In order to confirm that a 3-class model aligns with Ainsworth's, one must examine the conditional response probabilities (described in detail later) of a three class model in order to compare them to Ainsworth's ABC profiles.

variables in these analyses could be reduced from a 7-level ordinal scale down to a dichotomous variable (e.g., no avoidance behavior vs. any avoidance behavior). If this were the case, then suggestions could be made to simplify future coding efforts. Again, LCA is ideal for handling this type of question in that it allows the data to be coded in these two different ways and for the analyses to be compared in order to draw conclusions. These applications of LCA (both examining the number of attachment categories present and evaluating the dimensions of behavior used in the Strange Situation) could make a substantial contribution to the confidence we have in the Strange Situation as it is currently utilized.

Using LCA is very different from the way in which Ainsworth and her colleagues (1978) used MDFA, even though these two analyses might appear to be producing similar results. In the case of MDFA, Ainsworth used a variety of different dimensions of behavior that had been measured to determine if combinations of these dimensions might create discriminant functions that would discriminate among the three categories (A, B, and C) that she had discovered. She then went on to determine which of the aforementioned dimensions of behavior was most strongly correlated with these discriminant functions, indicating which dimensions were best at making the discriminations among categories.

An LCA would be approaching the problem from a different angle. It would not be looking to find ways to discriminate among the three suggested categories, but would be comparing models in an attempt to test if these three categories did in fact exist, or even if there are more categories that the field is not currently measuring. Along with this, an LCA would not be trying to determine which dimensions of behavior are best at discriminating pre-assigned category membership, but would be assessing if the four dimensions in their current forms (or in the current way that they are utilized in the field) are “accurate” in making such distinctions.

While the differences might appear subtle, they are actually remarkable, and make the application of LCA to the measurement of attachment a worthwhile and important step for the field.

One of the most important reasons that LCA has not previously been utilized in the area of attachment research, beyond its fairly recent appearance in the field, is the fact that application of this method requires a large number of participants. Attachment studies utilizing the Strange Situation method are notoriously small, and even Ainsworth and her colleagues (1978) only had 105 participants with which to implement MDFA (and this number was only reached by combining multiple samples). Finding a suitably large source of Strange Situation data that was consistently collected has proven to be daunting, and until this point, the application of LCA to the measurement of attachment has never been suggested.

NICHD Study of Early Child Care and Youth Development

In 1989, a project was initiated by the NICHD to investigate the role that various forms of child care play in developmental outcomes in children. Data collection began in 1991 for what is now called the NICHD's Study of Early Child Care and Youth Development (SECCYD). In the first phase of data collection, which followed the children from 0-3 years of age, 1,364 children and their families were participants, gathered from 10 sites across the United States. While the focus of this project was on child care, a host of variables was investigated that could be studied in their own right. One such measure was the Strange Situation, which was administered to all children at 15 months of age. Given that this is one of the largest samples of Strange Situation data in existence, and that it is substantially larger than Ainsworth and colleagues' (1978) original validation sample, this database provides the perfect sample for applying the techniques of LCA.

Categorical vs. Dimensional

It must be acknowledged before proceeding any further that there is still a debate in the field over whether attachment is truly categorical, like the measurement of the Strange Situation suggests, or if a dimensional model actually underlies this concept. This must be mentioned because LCA would be treating attachment patterns as categories, as is done in the Strange Situation. Fraley and Spieker (2003a) argued that attachment styles were in fact continuously distributed. They used a taxometric analysis (which involves examining conditional covariances to determine if a construct – for example security – is in fact a discrete group or "taxon") to support their point that the categorical system that Ainsworth proposed did not fit the data from the Strange Situation as well as a dimensional model with two latent dimensions. A convivial debate ensued, with top researchers in the field of attachment commenting on this position. There are many points, some of them stemming from this debate, that support conducting a confirmatory analysis of Ainsworth's categorical assignment of attachment patterns, even when Fraley and Spieker have presented evidence of these patterns possibly being continuous.

First and foremost, it was suggested that abandoning the categorical system in favor of a dimensional approach is not warranted on the basis of one single study (Cassidy, 2003; Waters & Beauchaine, 2003). Although Fraley and Spieker (2003a, b) did not appear to advocate eliminating the use of the categorical system altogether, they made many arguments in support of moving toward a dimensional model. While these arguments were quite strong, more work in a similar vein needs to be completed before treating the categorical attachment patterns as relics of the past. This is especially true given that a dimensional model was simply suggested by their findings and not in any way definitively proven. In fact, it was suggested by Cummings (2003), and seemingly supported by Fraley and Spieker (at least until a dimensional approach was perfected), that using both a categorical and a dimensional approach might be best in individual research endeavors. If this is true, then there is ample reason to continue perfecting the categorical measurement of the Strange Situation utilizing new statistical techniques.

Fraley and Spieker (2003a) suggested that if researchers were to create a measurement system based on their dimensional model that it should still be capable of representing the ABC attachment patterns created by Ainsworth and colleagues (1978). In fact, they demonstrated how the two dimensions that they discovered could be used to create a 2-dimensional space that effectively differentiated among these three categories. If this is the case, and if a new dimensional system is going to be so closely tied to Ainsworth's model, then it is imperative that Ainsworth's three category model is evaluated and perfected to the best of our statistical ability.

Finally, as Cassidy (2003) pointed out, a variety of other measures have been created for assessing attachment based on Ainsworth's original categorical system. If the field is to continue creating and perfecting such measures, and possibly even move them toward a dimensional approach, then the original measure that they were based upon needs to be strengthened in any way possible. Research must be conducted to determine if the categories used in the original system are actually comprehensive in assessing a child's attachment pattern.

General Aims and Hypotheses

The overarching goal of the current research is to examine the category system of the Strange Situation in order to assess the number of latent categories underlying this measurement.

It is important to note that, while the Strange Situation is under examination in the current work, Bowlby's theory of attachment will be accepted as it stands, allowing for the Strange Situation measure to be evaluated for its usefulness in quantifying the concept of attachment as put forth by Bowlby. It is hypothesized that a three category system that lines up with Ainsworth's three categories will be confirmed, based on the extensive research and validation process undergone by Ainsworth and colleagues (1978). If a more complicated model with a larger number of categories is the best-fitting model, it is hypothesized that these categories will appear similar to the sub-categories suggested in Ainsworth's original work, and that truly new categories will not emerge.

Another goal of the current research will be to examine the four dimensions of behavior used as indicators in this model (proximity & contact seeking, contact maintaining, avoidance, and resistance). The goal of this process will be to make suggestions for potentially making the data coding process simpler and more efficient, and to evaluate the way in which these indicators are currently utilized in attachment related research. It is hypothesized that one or more dimensions might potentially be reduced to binary variables to aid in the ease of data coding (e.g., no resistance behavior vs. some resistance behavior). Potential candidates for this binary reduction include avoidance in episodes 5 and 8, and resistance in episodes 5 and 8. It is also hypothesized that a continuous treatment of the indicator variables, as is commonly applied in current literature, might not be an appropriate utilization of these scales, and that treating them as 7-level ordinal variables may be more appropriate.

CHAPTER 2

METHODS

Participants

Participants were 1,191 children from the NICHD SECCYD for whom classification information was available for the Strange Situation measure. Eight of these participants did not participate in episode 8 of the Strange Situation, but were included in the sample because enough data was collected to assign each of them a Strange Situation classification. Of these eight children, six were classified in the C group while two were classified in the B group. Given the behavioral profile of a child receiving a classification of C, it is not surprising that the C's are overrepresented in this small group that did not complete testing.

Age at Strange Situation testing was 15 months. Participants were 50.5% male (*n*=602) and 49.5% female (*n*=589). In terms of ethnicity, mothers reported their children to be American Indian, Eskimo, Aleut (.4%); Asian or Pacific Islander (1.6%); Black or Afro-American (11.7%); White (81.7%); or Other (4.6%). In addition, 5.9% of participants identified as Hispanic, while 94.1% are non-Hispanic. At the time of testing, 16.2% of included families were below the poverty line, while 82.9% were above the poverty line (information was not available for .9% of the sample). (For further information on recruitment procedures and overall sample characteristics, the reader is referred to Friedman and Boyle, 2008.)

Measures

The measure of interest in this study will be the Strange Situation. In the SECCYD, the Strange Situation was conducted in the same manner as it was used by Ainsworth and colleagues (1978), its creator. In this laboratory based task, a child and his or her mother participate in a series of eight episodes, the ultimate goal of which is to create a mildly stressful situation for the child in order to activate the attachment system. A chart of these episodes and their duration can be found in Table 1.

Trained coders watch a videotaped record of each session, paying particular attention to Episodes 5 and 8, where reunions occur between the child and mother. For each reunion episode, coders assigned a score on a scale of 1 to 7 for each of the following dimensions of behavior: proximity & contact seeking, contact maintaining, resistance, and avoidance. It is on the basis of these scores that coders went on to assign each child to a category of A, B, or C. If a child was unable to be classified according to this system, they received a classification of Unclassifiable or U, or if they displayed a high level of disorganized/disoriented behavior (discussed in detail later) then they were assigned a primary category of D. For this five category system of ABCDU, coder pairs had 86% agreement pre-conferencing, $\kappa = .70$ (Friedman & Boyle, 2008). For each subject that was assigned a classification of D or U, a secondary forced-choice classification of A, B, or C was also made. A list of the number of children assigned each category, and the forced choice classifications for the D and U children is found in Table 2. (For a detailed account of the exact scales used and the behavioral examples associated with them, the reader is referred to Appendix III of Ainsworth and colleagues' (1978) *Patterns of Attachment*. What follows is a condensed summary of these scales.)

Before further explaining the behavioral dimensions used in the Strange Situation coding, it should first be noted that four things were taken into consideration when creating these scales and their anchoring points. Ainsworth and colleagues (1978) noted, "(1) the degree of activity and initiative of the behavior; (2) promptness of the behavior; (3) frequency of the behavior; and (4) duration of the behavior." These considerations helped them to determine what made a behavior stronger or weaker than another behavior, and how to go about assigning scores to these behaviors. For example, a child that clung to an adult for the entire three minute episode would receive a higher score on contact maintaining than a child that clung for only a minute before returning to play. Another example would be that a child that demonstrated repeated acts of resistance toward the adult would receive a higher resistance score than a child that showed one clear act of resistance of a similar intensity.

In addition, for each of these scales the coders were directed to code the behavior of the child, but they must also take into account the behavior of the adult as well. For example, a child whose mother picks him up immediately, even though he is showing no signs of a bid for proximity, would receive a lower score than a child who reaches out toward his mother until she picks him up, even though the end result (i.e., proximity to the mother) is the same. Understanding these general rules of the coding system is imperative for understanding the following individual scales and their anchoring points.

Proximity and contact seeking refers to behaviors produced by the child in an effort to be near to, or in physical contact with, another person. These can include active locomotion on the part of the child to approach the adult, or bids by the child for the adult to draw near to the child. Examples include, moving to the adult, raising both arms to reach for the adult, or partial approaches with some intervening behavior that interrupts a complete or successful approach. A score of 7 on this scale indicates that a child has shown, “Very active effort and initiative in achieving physical contact.” The middle value of 4 indicates a child that shows, “Obvious desire to achieve physical contact, but with ineffective effort or lack of initiative OR Active effort to gain proximity without persisting toward contact.” A child that receives a score of 1 has shown, “No effort to achieve physical contact or proximity” (Ainsworth et. al., 1978).

Contact maintaining implies that contact has already been made between the child and adult and refers to the lengths the child goes to, and the measures used, in order to remain in contact with the adult. This behavior might involve clinging to the adult, returning to the adult for more contact upon being set down, or the child hiding his face in the adult. A child scoring at the highest end of this scale would show, “Very active and persistent effort to maintain physical contact.” A middle score of 4 indicates, “Obvious desire to maintain physical contact but relatively little active effort to do so.” At the lowest end of this scale are children exhibiting, “Either no physical contact or no effort to maintain it” (Ainsworth et. al., 1978).

Resistant behavior is typified by a child demonstrating resistance toward the adult, or an object that the adult has offered. Anger is the predominant emotion associated with high levels of resistance. A child might kick, hit, push, or squirm away from the adult, demonstrating active lashing out in frustration or anger. At lower levels, a child might simply appear cranky or fussy. A score of 7 is reserved for children showing, “Very intense and persistent resistance.” At a medium level of 4 a child demonstrates, “Isolated but definite instances of resistance in the absence of a pervasive angry mood.” A child at the low end of this scale with a score of 1 demonstrates no resistant behavior (Ainsworth et. al., 1978).

Avoidant behavior is displayed through a child evading either proximity to the adult, or even basic interaction with the adult. An avoidant child might actively ignore the adult, avoid eye contact with her, or make efforts to increase the distance between himself and the adult. In terms of visible affect, the child tends to display a cool neutrality toward the adult. One of the most important instances in the Strange Situation for coders to focus on avoidance is when the mother first returns to the room after the separation episodes. In these instances, a highly avoidant child will completely ignore the mother upon her return, even if the mother goes so far as to initiate contact with the child. This behavior would fall into the category of, “Very marked and persistent avoidance,” and would receive a score of 7 on the avoidance scale. A middle score of 4 is associated with, “Brief but clear-cut avoidance OR Persistent low-keyed avoidance.” Similar to the resistance scale, a score of 1 on the avoidance scale indicates no avoidant behavior (Ainsworth et. al., 1978).

It must be noted that coders of the SECCYD database also assigned scores for children on their distress (specifically crying) in episodes 4, 6, and 7. It was decided that these scores would not be included in the current analyses for multiple reasons. In their original MDFA, Ainsworth and colleagues (1978) found that crying in these episodes was not reliably related to group membership. When correlating the individual crying variables from each episode with each of their two discriminant functions, they found mixed results. With discriminant function 1, Ainsworth and colleagues suggested that crying did not offer much information above and beyond the information obtained from the 4 typical dimensions of behavior measured in each of the reunion episodes. Beyond this, crying in episode 6 displayed the opposite pattern as would be expected. When examining discriminant function 2, crying in episodes 2 and 6 appeared significantly correlated to this function, but the discriminant coefficient for episode 6 was quite small. With such mixed results, it is difficult to justify including distress scores.

More recently, Richters, Waters, and Vaughan (1988) attempted to use a variety of coded indicators of behavior to statistically assign participants to attachment categories. In their system, they used crying scores, but only from the two reunion episodes (5 and 8). This was because they found that the crying scores from all other episodes were not aiding in classification. With evidence from both the original creator of the Strange Situation assessment and subsequent researchers that crying scores in episodes 4, 6, and 7 do not seem to be overwhelmingly helpful in terms of classification, it does not seem necessary to include these variables in the current analyses, even though they are readily available. Depending on the results of these analyses, crying variables could potentially be considered for future research, but do not appear justified for this early work in the area.

In addition, each child received a score for disorganized/disoriented behavior on the D behavior rating scale (Main and Solomon, 1990). This includes behaviors in the reunion episodes such as the infant freezing with a face devoid of affect, moving distinctly away from the parent upon her return after being distressed by her absence, the child displaying stereotypies when held by the parent, or showing clear signs of fear or distress directed toward the parent. This score will not, however, be included in the current research. This scale is traditionally treated somewhat separately from the four dimensions of behavior that *will* be included in this project, given that the D score is not used to aid in primary A, B, or C classification. In fact, a child that receives a classification of D is still assigned a forced choice A, B, or C classification, which is often used in analyses, keeping the D scale fairly separate from the overall Strange Situation coding scheme. For simplicity in this first foray into Latent Class Analysis for the field of attachment, the current research only aims to evaluate the original Strange Situation coding scheme, not including D behavior. If in the course of these analyses a class emerges that seems to be highly influenced by what appears to be D behavior, then suggestions can be made for future research to include this rating scale (See Table 2 for the number of participants in the SECCYD assigned a classification of D and their forced choice ABC classifications).

Profiles Under the Strange Situation Coding Scheme

The latent class profiles that are obtained in each model will be compared to the existing Strange Situation coding scheme to check for overlap (and in some cases to compare for theoretical soundness). For this reason, it is important to detail the coding that would be done to assign children to categories and subcategories if the above scales were utilized under the Ainsworth coding scheme. These assignments are available in the SECCYD database, but are not utilized as variables in the current analyses. The typical profiles however, outlined in what follows, will be crucial for comparison to the obtained latent class profiles for each model.

Based on these four scales (proximity & contact seeking, contact maintaining, avoidance, and resistance), attending to the child’s behavior toward the mother in the reunion episodes, coders ultimately assign each child to a category of A, B, or C. Children assigned to group A are most noticeable because of their high levels of avoidant behavior. They tend to receive low scores on all three of the remaining scales, indicating that they do not appear interested in proximity or contact, they make little effort to maintain contact if it is achieved, and they rarely demonstrate any resistant behavior. Due to the fact that avoidance is the hallmark of this group, children in group A are often labeled “insecure-avoidant” (Ainsworth et. al., 1978).

The profile of a child assigned to group B is strikingly different from that of a child assigned to group A. A child in group B tends to score at the higher end of the proximity & contact seeking scale, demonstrating a clear desire for proximity to the mother in the reunion episodes. He also tends to have higher scores for contact maintaining, although it would not be out of the question for a B child to recover quickly and return to playing without persistent contact with the mother. Importantly, a child in this B category has very low scores on both the avoidance and resistance scales. He seems to desire contact with his mother, but also to be easily soothed by her. For these reasons, the B group is also referred to as the “secure” group (Ainsworth et. al., 1978).

Children assigned to group C are also uniquely different from groups A and B. The hallmark of a child in group C is his high levels of resistant behavior. Somewhat paradoxically, a child in this group also tends to score at the middle to high range on both the proximity & contact seeking, and the contact maintaining scales. In this way, there is an intricate push and pull of behavior directed toward the mother, with the child seeking proximity and then pushing away once contact is gained. Children in this group demonstrate almost no avoidant behavior. This unique pattern involving such seemingly conflicting feelings and behaviors has served to earn children in this group the label of “insecure-ambivalent” (Ainsworth et. al., 1978).

These three patterns represent the prototypical groups that Ainsworth and colleagues (1978) defined in their early work in the field (See Table 2 for a chart of the group assignments made to the children in the SECCYD database using the Strange Situation coding scheme). Beyond this, they further delineated 8 subgroups that were apparent in their early studies which distinguished children even further. In the current work, it was considered a distinct possibility that an LCA might “discover” some or all of these subgroups as opposed to simply the three main classes, so it is important to become somewhat familiar with the distinct characteristics of each of these groups. (The reader is directed to Ainsworth and colleagues (1978) *Patterns of Attachment* for a table of means and standard deviations for the scores on each of the four dimensions of behavior for each of the eight subgroups, based on their original samples, to supplement the subgroup descriptions that follow.)

Ainsworth and colleagues (1978) found that the insecure-avoidant (A) group could be divided into two subgroups: A1 and A2. A hallmark of the A1 subgroup is a stronger display of true avoidant behavior – not greeting or approaching the mother upon reunion, avoiding contact with the mother, etc. While the A2 subgroup also clearly shows avoidant behaviors that are apparent on the scale measuring the dimension of avoidance, these children show more frequent displays of mixed feelings – showing some interest in mother and then avoiding her or seeking and then quickly avoiding contact or proximity. While these displays of mixed feelings are enough to place the child in the A2 subgroup as opposed to the A1 group, it is clear that the predominant behavior is avoidance, indicating a marked difference from a child showing mixed feelings that earns him placement in the insecure-ambivalent (C) category.

The secure (B) group of children can be divided into four distinct subgroups: B1, B2, B3, and B4. Children in the B1 subgroup tend to be less outgoing in their responses to reuniting with mother. They will greet her, but not make any large efforts to move closer to her or maintain any contact she has initiated. Children in this subgroup might even display higher scores on the avoidance scale than their fellow secure children in other subgroups, but clearly have lower levels of avoidance than children assigned a status of insecure-avoidant. Children in the B2 subgroup show many similar behaviors to B1 children, but they tend to show more proximity & contact seeking behavior and contact maintaining behavior, especially during the second reunion with mother. In fact, a unique feature of the B2 subgroup is that their behavior in the two reunion episodes is often quite different. In the first reunion, B2 children show higher levels of avoidance than others that are securely classified and might even appear to belong to the A2 subgroup. Behavior in the second reunion, however, shows much lower levels of avoidance and high levels of proximity & contact seeking and contact maintaining. This clear morphing of behavior places a child firmly within the B2 subgroup. A child in the B3 subgroup, in contrast to the B1 or B2 groups, shows high levels of proximity & contact seeking and contact maintaining in both reunion episodes of the Strange Situation. They display much lower levels of avoidance in both reunions and very low levels of resistance. In short, the characteristics of this subgroup line up the most clearly with the overarching description of the B group as a whole. Finally, children in the B4 subgroup are similar to those in the B3 subgroup, but they show higher levels of distress throughout the Strange Situation. They are highly upset by mother leaving and immediately want contact with her upon her return. On average, they show higher levels of resistance behavior than the other three B subgroups, but certainly not enough to classify them in the insecure-ambivalent category.

Finally, Ainsworth and her colleagues (1978) delineated two subgroups within the insecure-ambivalent (C) category: C1 and C2. The C1 subgroup displays many of the typical “C” behaviors already discussed – strong proximity & contact seeking and contact maintaining behaviors, while at the same time showing distinct acts of resistance, giving a marked impression of mixed emotions and often anger toward the mother. While the C2 subgroup displays these same patterns of behavior, they are much more passive throughout the Strange Situation, making them distinctly less emotional than the C1 subgroup.

The Strange Situation behavior of a small percentage of children in any given sample will understandably not fit into any of the subgroups or even major categories listed above. Main and Weston (1981) were the first to propose that these children should not be forced into one of the existing categories, but could be labeled as “Unclassifiable”, forming a new classification of “U” (although in many studies, these children are also assigned a forced choice classification of A, B, or C). These children do not show a clearly definable pattern of behavior according to the original classification scheme of Ainsworth and her colleagues. Behaviorally, Main and Weston suggested that examples of this Unclassifiable behavior could include children displaying odd combinations of behavior in the Strange Situation (e.g. a high level of distress and avoidance shown by the same child) or even behavior patterns that seem to be conflicting from one reunion to the next (e.g. a child appears to fit into the B category in the first reunion and the A category in the second reunion). This U category has come to be used in most current Strange Situation coding, representing a unique group of children that does not seem to fit into any of the established categories of behavior represented by the Strange Situation coding scheme, but also not presenting a clear pattern of behavior that earns them a classification as a group in its own rite. Including this U category, which is done in the SECCYD database, allows for a fuller spectrum of behavior to be encompassed than the original Strange Situation coding scheme permitted (See Table 2 for the number of participants in the SECCYD assigned a classification of U and their forced choice ABC classifications).

Analyses

Researchers in the Social Sciences frequently attempt to quantify concepts such as love, religiosity, attachment, or grief that are truly unable to be measured directly. Our best efforts involve measuring concrete behaviors that might provide a window into these underlying variables. It may be claimed that the actual concept is being measured, but at best we are attempting to describe these latent variables utilizing measures that are merely indicators of the latent concept. Latent Class Analysis, however, gives researchers a method of using indicator variables to clearly define the latent concepts we are painstakingly seeking to quantify.

The simplest way to describe this method is to begin by imagining a 2x2 matrix on which a chi-squared test of independence will be performed. Suppose at this basic level, the two variables in question (we will call them J and K) are found to be not independent of one another

– they are in some way related. Now suppose a third 2-level variable (L) is introduced into the equation. When L is introduced, J and K are now found to be independent of one another at each separate level of L. In this way, L is responsible for the entire relationship between J and K – any variance is explained by the overarching variable L.

If each of these three hypothetical variables were directly measurable, then this would be an interesting finding, but the important application of this method to quantifying latent variables comes when L is a latent variable that we are unable to measure directly. Using concrete indicator variables (J and K) that are hypothesized to relate to a specific latent concept, researchers can see if a latent variable, L, exists that accounts for the relationship between J and K. Expanding this example to allow L to include any number of levels, each containing different proportions of the subjects, researchers could use this method to learn many things about the latent variable (McCutcheon, 1987).

The preceding example can be expanded to fit numerous research situations. Multiple indicator variables can be utilized, each with any number of levels (Latent Class Analysis), continuous indicator variables can be used (Latent Profile Analysis), or even a mixture of these types of indicators (Mixture Modeling). In each of these cases, the goal remains the same of discovering a categorical latent variable that accounts for any relationship among the indicator variables. This leads to the most important assumption (and one of the few assumptions) of LCA – that of conditional independence. This assumption states that there is no relationship among the indicator variables beyond that which is explained by the latent variable (McCutcheon, 1987; Flaherty, 2002).

In the current research, eight indicator variables were utilized (proximity & contact seeking, contact maintaining, avoidance, and resistance, in each of the two reunion episodes) in an effort to explore the latent variable of attachment. In order to meet the criteria of conditional independence, these eight variables must have no relationship beyond that which is related to the latent variable of attachment. It could be argued that there is the potential for some of these variables to be related to one another beyond this attachment variable, given that these eight indicators are actually made up of four separate variables that are each measured twice – in episode 5 and again in episode 8. Perhaps contact maintaining in episode 5 is related to contact maintaining in episode 8, beyond the variance that is explained by the latent variable of attachment. At the same time, it would not be out of the realm of normal behavior for a child to increase, decrease, or remain constant in his level of this variable across the two episodes, and for this pattern to not be consistent across all children in the sample. Based on this final logical approach to the variables, the current analyses were approached assuming that the conditional independence assumption had been met and no further action was taken to account for extraneous relationships. If the current analyses do not return clear or interpretable results, it could be important in future research in this area to address the conditional independence assumption further, but for this first venture into utilizing LCA to evaluate the Strange Situation, the assumption was treated as if it were met.

The latent class model has two different types of parameters, both of which are probabilities. The first type of parameter is the latent class probabilities. These represent the probability that any given participant is a member of a specific latent class. Regardless of the number of latent classes being examined, these latent class probabilities will always sum to 1 within a specific model, due to the nature of probabilities. The second type of parameter is the conditional response probabilities. This is the probability of a particular score on a given scale or item, conditional on membership in a specific latent class (e.g., the probability of a score of 6 on the avoidance scale in episode 5, given that the participant is a member of latent class 1). Again, given the nature of probabilities, these conditional response probabilities will sum to 1 for the various scores of any one specific scale or item within one specific latent class (McCutcheon, 1987; Flaherty, 2002). Examining these two types of parameters for a given model provides an opportunity to understand the nature of the latent classes within that model. For example, if the Strange Situation measure as it stands is doing a good job of representing the latent construct, then we might expect to find a latent class in a 3-class model that has a high probability of a high score on both episodes of the resistance scale, a high probability of a low score on both episodes of the avoidance scale, and a high probability of a medium to high score on both episodes of the proximity & contact seeking and contact maintaining scales. We might also expect that the probability of a subject falling into this latent class would be around .10. This would clearly represent a prototypical C classification, with the expected 10% of participants in American samples falling into this category (van Ijzendoorn & Kroonenberg, 1988). In this way, it is clear how the results of an LCA can be examined to provide an understanding of the meaning behind a given model.

The preceding discussion of parameters holds true for an LCA where all of the indicator variables are discrete. When continuous indicators are utilized (in a Mixture Model or Latent Profile Analysis), however, it is logically impossible for the model to return conditional response probabilities, given that the number of possible responses is technically infinite. In this case, the model produces means for each indicator, conditional on membership in a specific class (e.g., the mean avoidance score in episode 5 for members of latent class 2). These means can then be used in a similar fashion to the conditional response probabilities to interpret each model. In the case of continuous indicators, the model also includes residual variances.

In total, a series of four analyses were conducted – three LCAs and one Mixture Model (MM). Each analysis will be outlined and discussed in its corresponding chapter, but there were several details that remained the same across all four analyses. All data were analyzed using the Mplus 6.11 statistical software (Muthén & Muthén, 2010). By default, this program treats missing data as Missing at Random (MAR), and this setting was maintained for all analyses, allowing the 8 incomplete cases previously discussed to remain included in the data sets.

Given that the goal of the latent class model is to define a latent variable that maximally accounts for the relationship between indicator variables, it is the parameter value estimates for this latent variable that are sought to provide this definition. If some information is known a priori about these parameters, then a researcher's estimates of the parameter values can be entered into the analyzing software to provide a starting point for the iterative process that will return the best parameter estimates for a given model. In the current exploratory analyses, there was no sound reason to suggest one set of parameter estimates as start values over another, so random starts were utilized to begin the analysis process for each model. In an attempt to avoid arriving at a local solution, which can be a large problem in LCA, it was decided that multiple sets of random start values should be initiated (Nylund, Asparouhov, & Muthén, 2007). The default setting for Mplus 6.11 involves initially using 10 sets of start values and then carrying the 2 best results of those to completion. This number of sets was deemed to be too small to comfortably assume a non-local solution had been reached, so for all models 10,000 sets of start values were initially used with the 1,000 best being carried to completion. In addition, by default, Mplus 6.11 allows a maximum of 10 iterations to be completed for the initial sets of start values. This default setting was altered to allow up to 1,000 iterations for all models tested.

Utilizing multiple sets of random start values is an important step in assessing empirical identification, which is aiming to determine whether a global maximum has been reached or if the best-fitting model in a given analysis is actually a local solution. The number of different final solutions (or log likelihood values) returned, also known as modes, can be telling of whether or not identification problems have been encountered. If only one mode is returned, then clearly all of the sets of start values lead to the same solution. With a large number of modes, however, there is a higher likelihood that multiple solutions have been returned that may have distinctly different parameter estimates from one another. For this reason, a table with the number of modes for each model of each analysis of the current work is provided (see Table 3) and is referenced in the Results section of each analysis as a first step toward assessing empirical identification.

Beyond exploring the number of modes, empirical identification was further assessed by examining the parameter estimates associated with various final solutions. In the current work, the five highest log likelihood values (or fewer if there were fewer than five modes for a given model) were examined for each model that was considered substantively meaningful within an analysis. The conditional response probabilities (and means for the Mixture Model) were gathered for each latent class of each of these five best solutions, and the five sets of probabilities were then compared graphically. If the conditional response probabilities (and means) represented the same patterning across all five solutions, it was considered that they were all pointing to the same solution and that a global maximum had most likely been reached.

As an initial starting point, it was decided that for each analysis, models containing 2 through 9 classes should be examined. Nine latent classes was originally selected as the largest model because, if current attachment coding were accurate and there are truly 8 subcategories of attachment, then an 8 class model might potentially fit the data and a 9 class model would not offer any significant improvement in classification. Testing 9 classes allowed for this comparison without continuing to test larger models unnecessarily. Because the idea in this set of analyses was not, however, to assume that the current coding classifications were accurate, it was never the case that 9 classes was the set maximum. If 9 classes provided a better-fitting model than the 8 class solution, it was in the research plan to continue increasing the number of classes until the best-fitting model was reached. In all analyses, however, the substantive makeup of the classes had deteriorated beyond coherence by the time 9 classes was reached, so it was never necessary to test a model with more than 9 classes.

Model Selection Criteria

It is clear in the literature that there is no one definitive method for selecting a best-fitting model from among many in latent class analysis (Nylund, Asparouhov, & Muthen, 2007; Tofighi & Enders, 2008). A broad range of model selection criteria have been suggested, however, each attempting to inform the decision as to the best-fitting model in a given situation. In fact, new model selection criteria are continually being created and tested. With so many to choose from, and each performing differently in unique circumstances, the most common approach is to examine multiple criteria in the hopes that they will all point the researcher in a similar direction, making the ultimate model selection decision as clear as possible. For this reason, the current research will involve examining a number of model selection criteria, the details of which are outlined below.

<u>Likelihood Ratio Statistic - *G^2*:</u> The G^2 likelihood ratio statistic is a test of model fit. At a basic level, it examines how well the model being tested represents the observed data. The G^2 value which is returned can then be compared to the degrees of freedom (df) for this test. Because the goal is to find a model that fits the data well, the desired outcome is that the G^2 test would be non-significant, and the G^2 value would be close to or less than the df, indicating that the expected values of the model and the observed data are similar. While this test is a good measure of whether or not the model under examination is a good fit for the observed data, nested model testing is not possible with LCA. This means that, while a G^2 value can be compared to the df to gain insight into whether or not the model is a good fit, G^2 values cannot be used in nested comparisons (comparing a k class model to a k-1 class model) in order to make decisions about which model is best (Flaherty, 2002; McCutcheon, 1987).

<u>Information Criteria:</u> Information criteria are a group of tests that were designed to find the best-fitting model from a group of models by seeking the most parsimonious model among them. This parsimony is achieved by maximizing the likelihood of a model, while penalizing for increasing numbers of parameters (Muthen & Muthen, 2000). In each case, the information criterion reaches its lowest value, indicating the best-fitting model, when this balance has been maximally achieved. In the current analyses, three information criteria will be examined. The first of these is Akaike's Information Criterion (AIC), which was introduced by Hirotugu Akaike (1974) with relatively narrow applications in mind, and then realized to be useful in multiple model selection settings (Akaike, 1987). The second is the Bayesian Information Criterion (BIC), introduced by Gideon Schwarz (1978) in an effort to provide an alternative to AIC. Schwarz asserted that AIC and BIC are extremely similar, but that the BIC trends toward

selecting a model with fewer dimensions (indicating a stricter penalty for more complicated models). The final information criteria that will be examined in the current research is actually a simple adjustment to one of the information criterion already discussed – that is the Sample Size Adjusted BIC (BIC*), suggested by Stanley L. Sclove (1987). Yang (2006) pointed out that this adjustment is made by simply replacing the sample size in the original BIC equation with an adjusted sample size, which ultimately reduces the penalty assigned in the original BIC, leading to more accurate results in situations involving a small sample or a large number of parameters.

Likelihood-Based Tests: There are two main tests that fall into this category, one of which will be examined in the following analyses.[6] Lo, Mendell, and Rubin (2001) put forward an adjustment to a likelihood ratio test procedure originally proposed by Vuong which compares two given models (one of which is a k class model, the other of which includes k-1 classes). This test (referred to in this document as the LMR) looks to see if there is a statistically significant difference between the larger and smaller model. If the p-value of this test is significant, then it is considered that the k class model is a better fit to the data. If the p-value is not significant, the k-1 class model is retained, indicating that there is no improvement to model fit gained by adding another class. The unadjusted test, suggested by Vuong, tends to produce significant p-values for larger models than the LMR adjusted test, so the LMR is considered to be a more conservative approach to model selection.

Log Likelihood Plots: Although not a typical approach, Nylund, Asparouhov, and Muthén (2007) suggest looking at plots of the likelihood values for each number of classes as another

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[6] It was impossible to perform the Bootstrap Likelihood Ratio Test (BLRT) on these data as Mplus was unable to converge on a solution.

helpful indicator of the best-fitting model. In their experience using simulation studies, these plots tend to level off at the correct number of classes. While not a convincing argument alone, these plots could potentially add weight to the other criteria considered, especially in a situation where the results are not extremely clear-cut. For this reason, these plots will be examined in the current analyses.

Substantive Meaning: Beyond the statistical criteria discussed above, it is also imperative to examine the substantive meaning behind each model considered. For this reason, in the following analyses, an examination of the latent class profiles will be carried out, checking to make sure that a model that fits well statistically also makes sense at a theoretical level. Included in this will be an examination of the final class proportions, ensuring that a model that includes one or more extremely small classes has a theoretical justification.

Much research has been conducted and presented as to which of the preceding criteria is best at determining the correct model or should be given the most attention when seeking the best-fitting model. Nylund, Asparouhov, and Muthén (2007) ran a simulation study that indicated that, overall, AIC did a fairly poor job of detecting the correct model, and that as a given sample size increased, the accuracy actually decreased. When a mistake was made, the AIC tended to err on the side of choosing a larger model. Their results indicated that both the BIC and BIC* are more accurate than the AIC at model selection, with the BIC* slightly out-performing the BIC for categorical latent class analyses. When it did return an incorrect result, the BIC* also tended to err on the side of a larger model.

Yang (2006) had found a similar pattern of results to Nylund and colleagues (2007), but made stronger conclusions based on his simulation studies. In fact, he found AIC to perform so poorly that he suggested against using it in applied research settings. He also found that the BIC* consistently outperformed the BIC until sample size reached at least 1,000, at which point both reached a level of almost complete accuracy at detecting the true model in the simulation. When BIC did make an error, it tended to favor smaller models. Even though Yang strongly recommended BIC* as the best of the information criteria that he tested, he was careful to stipulate that the accuracy of the BIC* was reduced in the case of latent classes containing a small number of subjects. The BIC* needed at least 50 subjects per class to maintain its high levels of accuracy. The other information criteria suffered even more, however, when there were small class sizes to contend with, so ultimately the BIC* was still considered the best criterion.

Burnham and Anderson (2004) take issue with these types of clear-cut suggestions based on simulation studies when comparing AIC and BIC. They suggested that AIC and BIC performed differently depending on the actual context given by the data being used. They indicate that one should look at the type of scenario expected in a given data set, compare that to studies of the performance of the AIC and BIC, and choose which is best based on that comparison. In short, they seem to feel that the AIC has been misrepresented in the literature and that it actually could be expected to out-perform the BIC in particular situations. A researcher must take the time to examine the unique context of each data set to make a choice about which criterion to utilize.

Given that there are differing opinions among the top researchers in this area, the current research will not take a strong stand and rely on one specific information criterion while ignoring the others. If large discrepancies are found, the BIC* will be favored over the AIC, but all available information criteria will be examined in order to gain the best chance at choosing the best-fitting model, keeping in mind which direction each criterion tends to favor when incorrect.

CHAPTER 3

ANALYSIS 1

(PCS and CM: 7-level; Avoidance and Resistance: 2-level; All Subjects Included)

Analysis 1 was designed as a "baseline" analysis. It is the simplest analysis in this work, allowing further analyses to become gradually more complicated and be compared back to this analysis. In this first analysis, all eight indicators were utilized. They were not, however, all left in their typical 7-level format. As can be seen in Figure 1, not all of the indicators are distributed normally, or even equally, among the seven potential scores. In fact, some of the indicators are highly skewed, and could even suggest a dichotomy of answers. For example, resistance behavior in episode 5 is highly positively skewed, and might be better represented by a binary variable that included scores of "No Resistance Behavior" versus "Some Resistance Behavior" (a score of 1 vs. the combined scores of 2-7). Based on this idea, the first analysis includes indicators that were reduced in a data driven manner. The set of variables that were reduced to binary variables consists of avoidance in episodes 5 and 8, and resistance in episodes 5 and 8[7]. The intention was to use this exercise for comparison purposes – if this analysis where the variables were treated as binary variables performed at a level similar to an analysis where these variables were afforded more variability, this could potentially inform future coding efforts.

The remaining four indicators (contact maintaining in episodes 5 and 8 and proximity & contact seeking in episodes 5 and 8) were coded as seven-level variables. They were not treated as continuous variables as they frequently are in the attachment literature. This is because, as can be seen in Figure 1, these variables also do not appear to be normally distributed. In fact, by

[7] Contact maintaining in episode 5 does show a similar pattern to the other variables that were reduced to binary variables. Due to the fact that contact maintaining in episode 8 does not show a similar pattern, it was decided that the best course of action would be to treat both episodes 5 and 8 consistently in order to further explore this change from episode 5 to episode 8.

examining the graphs, it is unclear exactly how to treat these variables (i.e., continuous vs. ordinal vs. nominal). For this reason, these four indicators were treated as seven-level nominal variables so that this first analysis could be used to determine how these variables should be treated in future analyses.

Results

As can be seen in Table 4, no clear consensus is indicated by the fit indices considered in this analysis. According to the G^2 likelihood ratio statistic, all tested models are a good fit for the data (although this might be somewhat artificial, given the number of empty cells in the analysis – this will be discussed in detail in the General Discussion section). The AIC technically indicates a 9-class model, although there is always the possibility that this index might have continued to decrease if larger models were tested. A 9-class model did not make theoretical sense (which will be discussed further), however, so no further models were tested. Both the BIC and BIC* suggest a 5-class model, which appears to be somewhat supported by the log likelihood plot for this analysis, found in Figure 2. Although it is not a distinct turning point, the plot does appear to begin to level out, or at least decrease in slope, at the 5-class model. Finally, the LMR points toward a 3-class model, with the 4-class model being the first that does not have a significantly better fit than the k-1 class model.

The conditional response probabilities that make up the latent class profiles (see the Appendix) can be examined to begin to determine if the substantive meaning behind the classes gives a better indication of which model is the best fit for these data. The 3-class model, suggested by the LMR, contains three classes that each fairly clearly line up with one of Ainsworth's categories or subgroups (although they are noticeably not the A, B, and C groups that might be expected). The class labeled LC #1 appears to represent a prototypical A group (i.e., this class has a high probability of lower scores on CM and PCS for both episodes, of no resistance, and of some avoidance), while LC #2 represents a prototypical B group (i.e., this class has a high probability of a medium to high score on CM and PCS for both episodes, and of no avoidance or resistance), but LC #3 can be best defined by the subgroup B2 (i.e., this class has a high probability of a low score on CM and PCS, of no resistance, and of some avoidance, all for episode 5. For episode 8, there is a high probability of a medium to high score on CM and PCS, and of no avoidance or resistance). Each of these classes holds a substantial portion of the subjects, and overall, this 3-class model appears reasonable substantively.

The 5-class model, suggested by the BIC, BIC*, and potentially the log likelihood plot, also appears to be reasonable according to attachment theory. Classes from previous models have been retained (LC #1 = A, LC #2 = B, LC #3 = B2, and LC #4 = C) and each class continues to hold a strong portion of the subjects. Although it is somewhat difficult to assign a subgroup to LC #5 according to the Ainsworth system, it appears to most closely resemble the A2 subgroup (i.e., this class shows the somewhat mixed feelings of the A2 subgroup in that there is a high probability of medium scores on CM and PCS, of higher avoidance, and of no resistance). Beyond that, even if this class is not clearly represented by the Ainsworth coding system, it appears to be a reasonable profile of behavior according to attachment theory in general, and the intention of this analysis is to not assume the Ainsworth categories will be a perfect match. For all of these reasons, the 5-class model also appears to be theoretically reasonable.

The 6-class model is similar to the 5-class model in that, even if the classes do not clearly line up with one of Ainsworth and colleagues' categories or subgroups, they all appear to be profiles of behavior that a child might reasonably display according to attachment theory. Once the 7-class model is reached, however, the substantive meaning behind the classes begins to break down. The class labeled LC #5 is difficult to conceptualize. According to the Ainsworth system, there is the potential that these children might be showing A/C behavior – most closely matching the A group on the first reunion, but the C group on the second reunion. There are still contradictions within this profile, however, that one might not expect to see, including fairly high levels of proximity & contact seeking in episode 5, combined with high levels of avoidance in that same episode. Even if this class could be accepted as potentially explainable according to attachment theory, LC #7 seems to be quite divergent from any behavior pattern a child might be expected to display in the Strange Situation. Numerically, this class displays a split on the indicator variable of contact maintaining in episode 5 – close to half of the participants have a high probability of a score of 2 or 3 on this variable, while another half have a high probability of a score of 5 or 6. In addition, this class seems to be displaying medium to high levels of proximity & contact seeking while also showing high levels of avoidance, which does not make sense according to typical patterns of behavior. This class also only contains about 3% of the participants, making it suspicious as an actual class that would be consistently found in new data sets, especially given its odd profile. Combining all of this information, the 7-class model appears to be where one begins to see a substantive breakdown. The class profiles were still examined for the 8- and 9-class models, but a similar pattern of classes that did not line up with attachment theory was found. For this reason, any model larger than the 6-class model in this analysis was considered unreasonable substantively.

All of the models that were considered substantively meaningful in this analysis were evaluated for empirical identification (see Table 3 for the number of modes returned for each model). In all cases, an examination of the parameter estimates for each mode indicated that the same pattern of results was returned for the top five modes in each model. For this reason, these models were considered identified.

Discussion

While it is fairly common with LCA studies for the fit indices to point to slightly different solutions, it is an odd predicament to have fit indices that suggest everything from a 3-class model to a 9-class model. In addition, this study is unique in that the goal is to not simply rely on previous coding theory to make decisions about which model is best. In fact, the goal is to do quite the opposite, exploring whether or not these coding categories are actually legitimate and remaining open to the possibility of new classes being discovered that line up with overall attachment theory, but not necessarily the Strange Situation coding system. For all of these reasons, it was decided that instead of simply settling on a model based on one fit index and a reasonable substantive explanation, that this best-fitting model decision would be postponed until further analyses were conducted and the possible explanations for these discrepancies in fit indices were explored.

This begs the question, why were the fit indices so varied in their recommendations? With one in particular – the AIC – the answer might be quite simple. In multiple simulation studies it was found that the AIC often performed poorly, and when it did return a “wrong” answer, it often erred on the side of choosing a model that was too large (Nylund et. al., 2007; Yang, 2006). The fact that the AIC, in this case, suggested a 9-class model that could not be justified with a substantive explanation suggests that maybe this exact problem is occurring here.

The other fit indices that are often found to be quite reliable, however, still returned varying decisions. In these cases, the substantive meaning behind the two different suggested models (3-class and 5-class) was reasonable and explicable in both cases, leaving an impossible decision between the two. One possible explanation for this lack of a clear model decision is that a small group of children with data that do not fit into this coding scheme are skewing the results. In this first analysis, all children from the SECCYD database that had been assessed using the Strange Situation measure were included. This included a small group of children that did not fit neatly into the ABC or even clearly into the D category. Under the Strange Situation coding guidelines, these children were given a classification of “Unclassifiable” or U (other children of concern are the DU’s – children whose major classification was Disorganized, but had a secondary classification of Unclassifiable). It is possible that including these U and DU children, that do not seem to fit into the Strange Situation coding scheme, made it impossible for an LCA to clearly assign classes. They were left in the database for Analysis 1 because the goal was to not assume that the Strange Situation coding system was in fact accurate, but there is the possibility that this led to the model selection problem of this first analysis. For this reason, Analysis 2 was conducted, in which the U and DU children were removed from the data set and the data were reanalyzed.

Another potential problem that could have been affecting the results of this analysis lies in the way the data were coded. In this first analysis, four of the indicators were reduced to dichotomous variables. This was done for clear, data-driven reasons, but there is a possibility that the simple presence versus absence of these behaviors was not enough information to distinguish between groups of children. For this reason, Analysis 4 was conducted, in which these four restricted variables were slightly freed to vary, allowing comparisons to be made to address whether or not this restriction was in fact causing the problems with model selection.

The clear conclusion here is that, it is inappropriate to select one best-fitting model until these issues are addressed. After conducting these subsequent analyses, it might be possible to look at this larger set of analyses as a whole and determine which model seems to be best at fitting this data set. This will hopefully offer the most accurate answer as to whether or not the Strange Situation coding system is accurately portraying the patterns found in the actual data, or if adjustments need to be made.

While this is the clear conclusion in terms of model selection, there are still many interesting results to discuss. For instance, even though none of the fit indices suggested it as the best fitting model, it is still extremely interesting to examine the 2-class model arrived upon in Analysis 1. When examining the probability profiles for the classes of this model (see the Appendix), the two classes seem to line up fairly clearly with classic insecure-avoidant (A) behavior and classic secure (B) behavior from the Strange Situation coding scheme. If anything, in this 2 class model, any children that would have been classified as C seem to be grouped with the B children (due to the slightly higher level of resistance behavior found in this second group in episode 8).

This model is of particular interest because of the enormous number of studies in the field of attachment that reduce their data to a 2 group treatment, typically analyzing a secure (B) group versus an insecure (combined A and C) group (e.g., Brinich, Drotar, and Brinich, 1989; Juffer and Rosenboom, 1997; Levendosky et al., 2011). This dichotomy is utilized by many in the field of attachment because it often provides the clearest results, especially with small data sets or when there are a very small number of C classifications (as is very typical). It is also used because, theoretically, it seems to make the most logical sense – combining children that are showing some variety of insecure behavior and comparing them to children exhibiting secure behavior would seem the natural choice. What is so interesting about the 2-class model in Analysis 1, however, is that this is not the combination that occurs. In fact, it seems to represent either an A vs. B dichotomy, with C not even entering the picture, or an A vs. B and C combined dichotomy. Although this result is not what would be expected according to standard practice and even, to some degree, logic (that the insecure groups would easily combine), this is not necessarily divergent from what one might expect a priori if only observing the patterns these groups represent. Merely examining the patterns of behavior represented by the eight indicator variables of the current study, the B and C groups appear quite similar, only differing greatly on their levels of resistance in episodes 5 and 8. The A and C groups, however, would be expected to be almost opposite on their levels of every indicator variable. For this reason, one might expect that an analysis which groups participants based on response patterns would return the result obtained in this analysis. The problem, however, is that the standard treatment for these variables in the field does not line up with these results. Although this is only the first analysis in this set, if this pattern continues in further analyses, it could have serious implications for how the field of attachment treats these groups. According to these latent classes, it would be inappropriate to combine A and C into one group for comparison purposes, because the groups do not naturally hang together. This would seriously call into question the overwhelmingly common practice of analyzing a secure versus insecure dichotomy.

Another model of interest in this first analysis is the 3-class model. The LMR suggested that this might be the best-fitting model, and the classes did line up with attachment theory. What one might expect if the Strange Situation coding system were able to detect and assign children to their “true” latent classes is that this 3-class model would line up fairly closely with the A, B, and C groups of the Strange Situation. Looking at the probability profiles found in the Appendix, however, this is clearly not the case. Two of the classes in this 3-class model match what was seen in the 2-class model – a group that strongly resembles a prototypical A group (LC #1) and a prototypical B group (LC #2). So far, this also lines up with what one might expect to see in a 3-class model if the Strange Situation coding system detected latent classes well. The third group (LC #3), however, is where one finds the divergence from expectation. This third group, if compared to the Strange Situation system, seems to match most clearly the B2 subgroup, and holding around 29% of the cases, this is certainly not a group to ignore. Hallmarks of this B2 subgroup, according to Ainsworth and colleagues (1978) include low levels of proximity & contact seeking and contact maintaining in episode 5, giving way to higher levels in episode 8, but more importantly include higher levels of avoidance in episode 5 giving way to much lower levels in episode 8. The B2 child begins the Strange Situation appearing aloof or avoidant, but by the last reunion, the stress level has become high enough that this behavior disappears in favor of more secure attachment behaviors being produced, earning this child a classification of B2. Interestingly, this B2 group remains large and clearly evident in every model tested in this analysis (in all models of Analysis 1 this B2 group is labeled LC #3), encompassing around 25% of the cases even in the 9-class model.

There are two points that are important to note in relation to this somewhat surprising result. One is that the 3-class model in this analysis being so different from the model assumed by the Strange Situation coding system is certainly somewhat of a concern and something to explore further. If other analyses continue to find that the 3-class model does not match the ABC groups of the Strange Situation, then this would certainly raise questions about the gold standard status of the current system and would warrant further investigation. Along with this, the other important point to make is that the B2 group seems to represent a large class that the LCA is clearly indicating is its own group. The fact that this analysis separated the B2 group from the rest of the B's (with whom they are usually grouped) as early as the 3-class model could indicate that the B2 group is truly a category in its own right. By continuing to combine them with the rest of the secure children, important distinctions between these two groups might be missed in the plentiful research being conducted in the field of attachment. Again, if this trend of a strong and separate B2 group continues to be evident in future analyses, a re-evaluation of the coding system as it stands may be called for, with special attention being paid to subgroups that might be better treated as full categories of attachment behavior.

It is apparent that, even though it is necessary to leave this analysis for the moment without a clear decision as to which model is best, there are many interesting conclusions to be drawn here. Each of these conclusions points to further investigation, some of which will be taken up in the next three analyses, and some of which will be left for future research. In any case, the hope is that, even though this model is being left fairly open for the moment, the full set of analyses presented here will combine to paint a clearer picture as to which model might be best for the data, and what implications this has for the Strange Situation in particular and the field of attachment in general.

CHAPTER 4

ANALYSIS 2

(PCS and CM: 7-level; Avoidance and Resistance: 2-level; U and DU Subjects Excluded)

In this second analysis, all indicator variables were coded in the same manner as in Analysis 1. Any child that received a primary classification of Unclassifiable (U) or Disorganized with a secondary Unclassifiable status (DU) according to the original Strange Situation coding classifications assigned to participants in the SECCYD database, however, was excluded from Analysis 2. (DU's were excluded here given that the D category is not addressed in the current work, so these children would be assigned a primary classification of U). It could be speculated that a classification of U in the original coding system indicates that the child's behavior is not fully captured by the 4 behavioral dimensions of the Strange Situation coding system, which are used in the present latent class analyses as indicator variables. If these children are truly "unclassifiable" under the current system, it could be argued that their data has the potential to greatly impact any LCA that might be conducted on the overall dataset. In order to address this concern, Analysis 2 was conducted, excluding children that received a U or DU classification in order to enable a comparison to Analysis 1.

A total of 67 participants that received a classification of U (n=42) or DU (n=25) were removed from the original sample to create the sub-sample of 1124 children utilized in this analysis. The demographics of this new sub-sample are nearly identical to those of the entire sample, with 50.7% male (n=570) and 49.3% female (n=554). Mothers reported .4% of participants to be American Indian, Eskimo, or Aleut, 1.7% Asian or Pacific Islander, 11.7% Black or Afro-American, 81.8% White, and 4.4% Other. In addition, 5.6% of participants were identified as Hispanic, while 94.4% are non-Hispanic. Percentages of participants above and below the poverty line were identical to the larger sample from Analysis 1 (16.2% below, 82.9% above, .9% information not available).

Results

The fit indices for Analysis 2 (see Table 5) point to nearly identical conclusions as they did in Analysis 1. The G^2 likelihood ratio statistic suggests that all of the tested models are a good fit for the observed data. The AIC suggests a 9-class model although, again, this might not be the true minimum of the AIC. Substantively a breakdown occurred at the same point as in Analysis 1, so no larger models were tested. Similarly to Analysis 1, both the BIC and BIC* indicated the best-fitting model to contain 5 classes. It could be said that the log likelihood graph (see Figure 2) supported this conclusion, especially because it was fairly similar to the plot from Analysis 1, but the point where the plot leveled off was not nearly as distinct. In fact, the plot for Analysis 2 shows a fairly gradual and continuous decline in slope, so it is difficult to make any conclusions or suggestions based on this plot. The only fit index that supported a conclusion different from that of Analysis 1 was the LMR, which in this case pointed to a 2-class solution.

Examining the latent class profiles for substantive meaning and similarity to Analysis 1, it appears that Analysis 1 and Analysis 2 provide extremely similar profiles of each of the classes in each model up through the 6-class model (see the Appendix). The 2-class model, which in the current Analysis is suggested by the LMR, lines up well with two of the categories from Ainsworth's coding scheme, with LC #1 appearing to represent the prototypical A category and LC #2 representing the prototypical B category. This is reasonable according to attachment theory and also matches the profiles found in Analysis 1. The 5-class model, suggested by the BIC and BIC* in this Analysis (and also in Analysis 1) contains class profiles that are nearly identical to those in the 5-class model of Analysis 1, so as before, they appear to be substantively reasonable.

Interestingly, given that the 7-class model of Analysis 1 appeared to be where a breakdown began in substantive meaning, the 7-class model of Analysis 2 is the first point that the class profiles slightly diverge from those found in Analysis 1. Even though it is in a somewhat different manner, a substantive breakdown also seems to begin with the 7-class model of Analysis 2. The class labeled LC #4 in this model contains the odd pairing of behavior of high levels of proximity & contact seeking with high levels of avoidance. Although this strange pattern was a reason for concern with LC #7 in the 7-class model of Analysis 1, these two class profiles are not as similar as might be expected, especially given that in Analysis 2 this class contains a much larger proportion of the participants at 11%. The important point here is that the substantive breakdown found in Analysis 1 at the 7-class model is also repeated in Analysis 2 at the same point, even though the class profiles are slightly different and it could be suggested that this breakdown happens in a slightly different manner. This might not be all that unexpected, however, given that the suggestion here is that anything over a 6-class model loses its substantive value. It may not be as important to know exactly how this breakdown occurs as it is noteworthy that it happens at exactly the same point in each analysis.

Similarly to Analysis 1, an examination was conducted of the top five modes for each model that was considered substantively meaningful in Analysis 2 in order to assess empirical identification (see Table 3 for the number of modes returned for each model). In all cases, the parameter estimates for each mode in a given model displayed the same pattern of results. This led to the same conclusion reached in Analysis 1, that these models were considered identified.

Discussion

The main conclusion to be drawn from Analysis 2 is that the U and DU subjects do not appear to be making an appreciable difference in the outcome of the LCA. The overall results of Analysis 1 and Analysis 2 are nearly identical, regardless of whether or not these subjects are included. Based on this conclusion, and because the intent of this set of analyses is to examine the Strange Situation coding scheme without assuming that its categories and subgroups are "real" and exclusive, the U and DU subjects will be included in all further analyses.

One interesting point to note, however, stems from the origins of the "Unclassifiable" category. In their 1981 article introducing the classification of Unclassifiable to the Strange Situation coding system, Main and Weston made an interesting discovery. In their sample there were 13 children that were classified as U but would have received a forced classification of B in the traditional coding scheme. Of these 13, 10 would have been placed in the B2 subgroup. Based on this large proportion being classified as B2, one might suggest that children in the U group are actually showing a cohesive pattern of behavior which lines up most closely with the B2 profile, instead of being a group that does not show any consistent pattern of behavior. After reviewing Analysis 1 of the current work, it might even appear that this conclusion was supported, based on the fact that the B2 subgroup appeared so early among the latent classes, showing up in the 3-class model and remaining a strong class containing a large proportion of the participants throughout subsequent models. This could potentially mean that many of the U subjects included in that first database were being included in this B2 group. If this pattern were continued in future studies, this could potentially lead to the suggestion that many subjects formerly classified as U should be re-examined to see if B2 is a more appropriate classification. Upon examination of Analysis 2, however, where all of the Unclassifiable subjects have been removed, it becomes clear that this is most likely not the case. The B2 subgroup emerges at the same point in this analysis as it did in Analysis 1, and remains a strong presence, containing a large proportion of the subjects throughout this analysis.

CHAPTER 5

ANALYSIS 3

(PCS and CM: Continuous; Avoidance and Resistance: 2-level; All Subjects Included)

In this analysis, the four variables that were reduced to binary variables in Analyses 1 and 2 (resistance in episodes 5 and 8, and avoidance in episodes 5 and 8) remained coded as binary variables. The four variables that were coded as 7-level nominal variables, however, were now treated as continuous variables. Given that the field of attachment frequently treats these measures as continuous, it was important to examine the validity of this assumption. In Analysis 1, there was no indication upon examination of the conditional response probabilities that these variables did not at least adhere to an ordinal pattern, so an analysis with these variables treated continuously appeared justified. The intent of this analysis was to then compare it to Analysis 1 to see if this continuous treatment provided similar results to the instance where the variables were maintained as 7-level variables. Participants receiving a primary classification of U or DU in the original SECCYD database were restored to the data set for this analysis, returning the demographics for this analysis to the original demographics found in the Methods section.

Results

This analysis provided the most consistent results in terms of the fit indices alone (see Table 6).[8] The LMR suggested an 8-class model as the model of best fit. The remaining fit indices – AIC, BIC, and BIC* - all pointed to a 9-class model. Unfortunately with these three, it is again unclear as to whether a true minimum was reached, or if these indices would suggest larger models if only they had been tested. Due to a substantial breakdown in the substantive

[8] It should be noted that the G^2 likelihood ratio statistic cannot be performed when continuous indicators are utilized, and is therefore not reported in Table 6.

meaning of the classes well before a 9-class model, however, no further models were tested. The log likelihood plot does not seem to shed any light on the issue as well. In this case, the plot (see Figure 2) appears to begin to level off around 5 classes, but then makes a significant increase in slope, leveling off again at 7 classes, adding no substantial clarity to the portrait painted by the fit indices.

Unfortunately, the substantive meaning behind the latent class profiles does not in any way support the conclusions drawn by the fit indices. Examining the smaller models that were tested in this analysis, they appear somewhat similar to those found in Analysis 1. In the 2-class model there appear to be two classes that line up fairly well with the Strange Situation A (LC #1) and B (LC #2) groups (see the Appendix). When moving to the 3-class model, a group that lines up with the B2 subgroup appears to be added (LC #3). This pattern continues until around the 5-class model of the current analysis, where it begins to become difficult to assign the class profiles to categories or subgroups found in the Strange Situation. While this is divergent from the results found in Analysis 1 (where the classes seemed to fit the Strange Situation coding scheme with relative ease) this is not necessarily a reason to question the theoretical validity of the results. The classes may not line up directly with the Strange Situation coding scheme, but they still make sense according to attachment theory. In the 5-class model there do not appear to be any odd profiles of behavior that one would be unlikely to see. Upon examination of the 6-class model, however, two major problems appear that point toward a substantive breakdown.

The first major problem is that profiles appear that represent patterns of behavior that one might not expect to find given what we know of attachment. For example, the group labeled LC #2 in the 6-class model of this analysis shows the odd pairing of a relatively high level of proximity & contact seeking in episode 5 with a medium to high level of avoidance found in this same episode, and contains around 17% of the subjects. While this one instance of seemingly discrepant behavior would not be enough to signal a substantive breakdown, this is the first instance where this type of conflict appears in a considerably large class, and the number of odd behavior patterns like this only increases in the larger models of this analysis.

Of more concern than these seemingly odd behavior patterns, however, is the complete lack of a class that appears to contain classically secure children when examining the 6-class model. It could be said that this problem arises even earlier, given that many of the smaller models have a profile that seems to represent secure children, but still contains much higher levels of resistance than might be expected. Certainly by the time a 5- or 6-class model is reached, however, it is clear that there is not a class that lines up with what one might expect to be a classic B or secure profile. Setting the Strange Situation coding scheme aside for a moment and focusing specifically on the idea of attachment in general, we would expect to find a large, if not substantial, group of children that showed a behavior pattern indicating they had formed a secure attachment bond with their mothers. In terms of the dimensions of behavior examined in this study, we would expect these children to seek proximity and contact with their mothers after a mildly stressful separation, and most likely to also seek to maintain that contact once achieved. These behaviors might not be extreme, but we would expect to see them. In terms of avoidance or resistance of the mother, we would expect to see low or nonexistent levels of these behaviors. This profile of behavior would appear to represent a child that was fairly classically attached to his mother, regardless of what label this profile was given. The fact that this profile is seemingly nonexistent in any of the models of this analysis, and that by the 5- or 6-class model it is strikingly absent, leads to the conclusion that these models might be untrustworthy.

Of the models that were considered substantively meaningful in Analysis 3, only the 5-class model returned more than one mode (see Table 3 for the number of modes for each model). The top five modes were examined for this model to assess empirical identification and indicated that each solution held a similar pattern of parameter estimates, so this model was considered identified. Although the 7-, 8-, and 9-class models of this analysis were not evaluated, due to the substantive breakdown that occurred before these larger models, it should be noted that the Mplus statistical software returned an error message for these three models, indicating that identification problems were experienced. For this reason, these models, and the tables representing the parameter estimates for these models (see the Appendix), should be interpreted with caution, acknowledging that identification was certainly a problem in these cases.

Discussion

Unfortunately, this analysis in which the indicator variables of proximity & contact seeking and contact maintaining were treated continuously, did not lead to any satisfactory conclusions in terms of a model of best fit. In fact, none of the models were truly acceptable in terms of substantive meaning, but certainly not the large models suggested by the fit indices. Unlike Analysis 1 where there were multiple models that could be reasonably chosen and the problem was finding a solid justification for choosing just one, this analysis offered not even one model that could be rationally selected. Given that the only difference between Analysis 1 and Analysis 3 is found in the treatment of four of the indicator variables (7-level vs. continuous), this treatment is what must be examined.

When the coding scales for the indicator variables used in this study (proximity & contact seeking, contact maintaining, avoidance, and resistance) were originally conceptualized, Ainsworth and colleagues (1978) set out to create an ordinal scale of behaviors. They created a

7-point scale for each that ranged from none of the given behavior to a high level of the given behavior. In creating this scale, they provided a large number of exemplar behaviors for each point on the scale, realizing that this list of behaviors would not be exhaustive but would aid a coder in placing observed behavior within the confines of this scale. They never suggested, however, that this scale could be considered continuous, with equal intervals between each anchor on the scale. In fact, when examining these types of behaviors, especially with such clear examples offered, it would be unreasonable to imply that a truly continuous scale had been, or could be, created. For this reason, based on the original conceptualization of the Strange Situation coding scale, it would seem inappropriate to treat these dimensions continuously.

Treating the dimensions continuously, however, is exactly what has been done in countless attachment studies, and the validity of this treatment is rarely, if ever, questioned (e.g., Lyons-Ruth et al., 1987; Bridges, Connell, and Belsky, 1988; Leerkes, Parade, and Gudmundson, 2011). The nature of the scales, however, and the results of this analysis begin to seriously call this practice into question. Not only do the scales not appear continuous on paper, but strikingly different results are found in these analyses when the only difference in practice is the treatment of the indicator variables. When treated continuously, the fit indices suggest a much different model than when the scales are treated as 7-level variables. This result could be blamed on the analysis itself – LCA studies that include continuous indicator variables tend to trend toward larger models as those of best fit than do analyses that include only categorical indicators. The bigger problem is the substantive breakdown that occurs when some of the indicators are treated continuously. One might expect to find a larger model with continuous indicators, but the meaning behind the class profiles of this model and smaller models within the same analysis should still be valid. It is quite concerning that this is not the case in the current analysis, and seems to indicate that the problem lies not in the analysis itself but in the treatment of the variables. Clearly more work needs to be done to examine this issue and determine if it is ever appropriate to treat the dimensions of behavior from the Strange Situation continuously, or if this practice should be discontinued in light of the fact that it might be providing incorrect, or at the very least different results than what would be found if the dimensions were simply treated ordinally as the scales were originally created.

CHAPTER 6

ANALYSIS 4

(PCS and CM: 7-level; Avoidance and Resistance: 3-level; All Subjects Included)

In this analysis, the variables that were treated continuously in Analysis 3 (contact maintaining in episodes 5 and 8, and proximity & contact seeking in episodes 5 and 8) were returned to being treated as 7-level variables as they were in Analyses 1 and 2. With the breakdown in theoretically meaningful conclusions that occurred in Analysis 3 when these variables were treated continuously, it became clear that it was inappropriate to handle these variables continuously in future analyses. For this reason, they were returned to their original state.

The four variables that had been reduced to binary coding in the previous three analyses (resistance in episodes 5 and 8, and avoidance in episodes 5 and 8) were afforded more freedom to vary in this analysis. Due to the miniscule amount of data available at the extreme high scores on all four of these variables, it was impossible to treat them as 7-level variables (as they are in the original coding scheme). There was, quite simply, not enough information available at these high scores to make this feasible. For this reason, they were transformed into 3-level variables. Groupings were created in a data-driven fashion, combining ratings of 1 and 2, ratings of 3 and 4, and ratings of 5, 6, and 7. The combination of a larger group of ratings at the upper end of the scale created a sufficiently large category, even in the face of such skewed data.

This analysis ultimately allowed for a comparison to be made to Analysis 1, seeking information on whether or not the binary reduction still allowed for sufficient discrimination among the latent classes. If it were found that, once freed to vary, these indicators in Analysis 4 were no better at discrimination than their dichotomously coded counterparts, then suggestions could be made about future coding efforts.

Results

Of all of the analyses, the fit indices paint the most inconsistent picture in this final analysis (see Table 7). The G^2 likelihood ratio statistic in this case is similar to those in Analyses 1 and 2 in that it suggests that all tested models are a good fit for the observed data. The AIC suggests 9 classes yet, again, it is unclear if this is the true minimum value. For the first time the BIC and BIC* point to different models, and in this case, they point to vastly different models. The BIC suggests that the 4-class model is the best fit for the data, while the BIC* indicates a 7-class model is best. The LMR first becomes non-significant when comparing a 4-class model to a 3-class model, indicating that the 3-class model fits the data best. In examining the log likelihood plot (see Figure 2), the slope increases somewhat sharply at first and then at 3 classes levels out slightly. This could possibly lend some support to the LMR indicating that the 3-class model is best.

Examination of the latent class profiles in the Appendix does not lead to any clear conclusions in terms of model selection. The 3-class model suggested by the LMR and potentially by the log likelihood plot appears to make sense substantively. In fact it quite clearly mimics the 3-class model found in Analysis 1, with the three classes representing the A, B, and B2 groups of the Strange Situation coding system (LC #1, LC #2, and LC #3, respectively). Even the distribution of participants in each of these three classes is nearly identical in the 3-class models of both Analysis 1 and Analysis 4.

The 4-class model, suggested by the BIC, also appears to make sense substantively. Although one of the classes (LC #4) does not clearly map onto the Strange Situation coding system (representing what could potentially be either the B4 or C2 subgroup), it is a profile of behavior that is not divergent from what could be expected according to attachment theory. This is slightly different from Analysis 1, in which each of the classes in the 4-class model clearly aligned with a category or subgroup of the Strange Situation coding system, but it does not in any way discount this model's substantive meaning.

The 7-class model, suggested by the BIC*, contains two classes that are difficult to align with the Strange Situation subgroups: LC #5 and LC #6. They appear to represent the B1 and A2 subgroups, respectively, but in this model are difficult to decisively distinguish in terms of the Strange Situation coding system. This difficulty in clearly aligning the classes with subgroups from the Strange Situation does not, however, indicate a substantive breakdown. All of the classes appear reasonable in terms of attachment theory.

It could be argued that even the 9-class model, suggested by the AIC, continues to include classes that are indicative of behavior that would not be in any way surprising or unlikely according to attachment theory. At this point, many of the classes are difficult to align with the Strange Situation coding system, but the goal of not assuming that this coding system is "accurate" must be maintained. The problem that occurs with this large model, however, is that the practical differences between some classes become negligible. Statistically, the LCA is finding classes that are distinct from one another, but the actual applicable value of these differences becomes almost nonexistent. For this reason, even though the classes of this model appear reasonable substantively, and the AIC might not have reached a true minimum, it was decided that the 9-class model would be the largest model examined. It was assumed that larger models would include classes that were either not divergent enough substantively from other classes to justify their inclusion, or that were so small that replication in other samples would become a major concern.

In Analysis 4, all models were assessed for empirical identification. In all cases, an examination of the parameter estimates for each mode indicated that the same pattern of results was returned for the top five modes in each model. While this is true even for the largest models in this analysis, the fact that these largest models returned hundreds of modes (and many sets of start values did not converge) does indicate that identification may have been an issue (see Table 3 for the number of modes returned for each model).

Discussion

Unfortunately, Analysis 4 presents another situation in which it is nearly impossible to select a best-fitting model. The fit statistics are much too varied to justify making a decision. In fact, almost any one of the models suggested by each fit statistic could be selected and defended as the best-fitting model, given that substantively each appeared reasonable, making a choice among them impossible.

This analysis does, however, allow for a comparison to be made to Analysis 1 in an effort to determine if the variables that were reduced to dichotomous coding are as effective in distinguishing among classes as the 3-level coding of these same variables. At a very basic level, it is clear that allowing these variables more room to vary did not improve the ability to select one best-fitting model among those tested. In fact, the increase in variance led to an analysis in which the fit statistics were extraordinarily disparate in their recommendations. Given the fact that it was also difficult to make a decision as to the model of best fit in Analysis 1, however, this does not necessarily indicate that the dichotomously coded variables are best. In fact, because Analysis 4 included more possible levels for four of the indicator variables, this greatly increased the size of the grid of potential responses. Without adding any additional participants in this analysis, this resulted in the data being spread out among even more cells than they were in Analysis 1. This is another reason that the results of Analysis 4 might not necessarily indicate that dichotomously coded variables are best. Analysis 4 could simply be suffering from the problem of sparse data.

The greatest difficulty in deciding which coding of the variables was best at distinguishing among classes lies in the fact that each coding method led to different strengths within a given analysis. In Analysis 1, where four of the variables were reduced to a dichotomy, the resulting classes of the various models appeared to line up fairly well with the categories and subgroups of the Strange Situation coding system (that is, up until the point of the substantive break-down). This would seem to indicate that the variables that were reduced to “some” of a behavior versus “none” of a behavior were somewhat effective at distinguishing the boundaries suggested by the Strange Situation coding system. Analysis 4, on the other hand, in which these same variables were allowed more variance, had many classes that were difficult to match with categories or subgroups of Ainsworth’s coding system. They were reasonable according to attachment theory, but not decisively Strange Situation groups. In terms of the goals of this research, this leads to a dilemma, because the aim is to remain as impartial as possible, not assuming that the Strange Situation coding system is the best method of classifying these data. It is unclear which coding of the variables is best because it is unclear if the resulting model should closely mimic the Strange Situation or if a different grouping of the data is more accurate. Given that neither analysis resulted in a clear-cut model selection, it is inappropriate to expect that these analyses alone would provide an answer as to whether or not binary coding is as effective as 3-level coding with these variables. The fact that both coding methods led to successful analyses in which many reasonable models were presented, however, indicates that this issue has the potential to be resolved in future analyses. If so, important suggestions could be made as to how to treat these data in the future, potentially leading to a simplification of the data coding process.

CHAPTER 7

GENERAL DISCUSSION

With the goal of examining the category system of the Strange Situation in order to assess the number of latent categories underlying this measurement, the current set of analyses unfortunately leads to more questions for future research than answers. Nevertheless, several important discoveries were made that will not only inform this future research, but hopefully encourage those in the field of attachment to examine coding practices and systems that have been taken for granted since their inception. In addition, the presentation of this research should encourage the field to explore new approaches to analyzing attachment data, utilizing methods that have been hitherto ignored, in the hopes that broadening research horizons in this manner will lead to a general strengthening of the field.

Examination of the Combined Set of Analyses

Given the fact that none of the individual analyses in this set of work arrived at a clearly suggested model of best fit, the implications of the combined set of analyses do not shed any more light on the subject. In fact, Analysis 1 appeared to have the narrowest suggestion for a model of best fit, most likely implying that the best model would include somewhere between three and five classes. The hope was that subsequent analyses would narrow this even further to one specific model, but this was not the case. Analysis 2 seemed to echo the conclusions of Analysis 1, although it did indicate that a two class model could be a possible contender. Analysis 3 did not aid in the decision making process given the substantial breakdown in substantive meaning that occurred, effectively eliminating Analysis 3 from any discussions of the overall implications of these analyses. Finally, Analysis 4 had the unexpected effect of broadening the list of potential models of best fit as opposed to narrowing the field, most likely due to the issue of sparse data. Looking at this set of analyses as a whole seems to lead to the conclusion that Analysis 1 was actually the best attempt toward finding a model of best fit, and the conclusions drawn from this analysis are about as strong as is possible with this set of analyses. This begs a reexamination of the conclusions drawn from Analysis 1, given that the hope was that subsequent analyses would allow for a clearer decision to be made and that this result did not occur. Unfortunately, one is left with the same conclusion as before – that Analysis 1 suggests either a 3-class or a 5-class model, and that there is no clear evidence to recommend one over the other. Given that the Strange Situation coding system is so clearly based around a 3-class model, it would be easy to suggest that this lends support toward the 3-class model being selected as that of best fit, but the goal of the current research was to not assume that the Strange Situation coding system was accurate (not to mention the fact that the 3-class model from Analysis 1 did not mirror the 3-class model that might be expected according to the Strange Situation coding scheme). The class profiles of the 3-class and 5-class models are easily justifiable according to attachment theory, and so neither should be given more weight based on the coding system that is under evaluation. With this set of analyses alone, it is impossible to clearly assess the exact number of latent categories underlying this measurement. An important step has been taken in the right direction, however, given that future research efforts in this area might be able to focus on the models including between three and five latent classes, and will hopefully lead to stronger conclusions in this area.

The fact that none of the analyses conducted in this work pointed to a clear model of best fit warrants an examination of why this result occurred. There are many potential answers to this question, and the remedy might even lie in a combination of several of these possibilities. One source of this problem, that has already been discussed, is the issue of sparse data. Even though the number of participants included in the current work is enormous compared to the typical Strange Situation study, the sample was actually fairly small in LCA terms. These models require incredibly large samples, especially as the models become more complicated. To illustrate this point, in Analysis 1, the simplest of the current work, there were a total of 38,416 possible response patterns. The participants included in this analysis represented only 825 different response patterns, meaning there were thousands of empty cells in this data table. This indicates that even in this simplest analysis of those included in this work, sparse data was an issue, and the problem only compounded as the analyses became more complicated and therefore included more potential response patterns.

This might present a particular problem when examining the G^2 likelihood ratio statistic, which is compared to the df for that test in order to assess if the tested model is a good fit for the observed data. If the statistic is close to or smaller than the df, this indicates that the model is a good fit. The df for this test is calculated by subtracting the number of parameters plus one from the number of possible response patterns. With so many of these response patterns not representing any actual responses from participants, the df for these tests were most likely artificially inflated. For this reason, the G^2 likelihood ratio statistic might have indicated that the models were all a good fit for the data, but this could be inaccurate because the statistic is being compared to an artificially large df. This problem with the G^2 likelihood ratio statistic represents just one of the many issues related to sparse data. Future efforts in this area should strive to obtain larger samples for use with LCA. This could be very difficult, owing to the labor and resource intensive process of collecting Strange Situation data, so creative solutions including combining multiple samples from various data sets will most likely need to be utilized in order to obtain a suitably large sample.

Another potential problem could be assuming conditional independence in this data set. The point was raised that there could be relationships between indicator variables, above and beyond what is explained by the latent variable, especially between the sets of indicators that represent the same dimension of behavior being measured in each of two different episodes. While the results (or lack of clear results) do not specifically indicate that the conditional independence assumption has been violated, this could certainly be contributing to the issues found in this set of analyses. The best way to address this concern would be to repeat these analyses, introducing residual dependencies to see if the quality of the results improved. If so, this would indicate that relationships between indicator variables might have played a role in the problems found in this set of analyses.

One final possible explanation for the lack of clear results could be related to the D category of disorganized/disoriented behavior that was not included in this research. Inclusion of the D behavior rating scale would have vastly increased the complexity of this work, and it was deemed too complicated for this first attempt at utilizing LCA with Strange Situation data. This decision must be examined, however, in light of the results that were obtained. Main and Solomon (1990), in creating the D behavior scale, indicated that they did not find distinct patterns on the Strange Situation’s four dimensions of behavior that encompassed children that they had identified as belonging to the D group. In fact, one of the reasons for creating the D scale was to create a method that could be used to distinguish a child that was displaying a disorganized pattern of attachment, because the dimensions of behavior from the Strange Situation were not differentiating these children as distinct from children displaying organized patterns. Included in this D behavior scale that they created, Main and Solomon delineated seven main groupings of disorganized/disoriented behavior. Two of these groupings were "Sequential Display of Contradictory Behavior Patterns" and "Simultaneous Display of Contradictory Behavior Patterns." These involved displaying contradictory behaviors such as strong proximity seeking followed by strong avoidance or even stilling within one reunion episode (sequential), or approaching the parent with head averted or by walking backward toward the parent (simultaneous). Even though these are only two of the seven major groupings of D behavior, in light of the results of the current study, they are noteworthy. Perhaps some of the latent classes that were dismissed in the current research as "odd" in terms of attachment theory, and were taken as indications of substantive breakdown in the analyses, were actually groups of children that would have been classified as D using the D behavior scale. The fact that these "odd" groups often involved high scores on both proximity seeking and avoidance in the same episode seems to support this conclusion. Even though, as a whole, children given a D classification cannot be distinguished based on the Strange Situation's four dimensions of behavior alone, perhaps there are subgroups of the D category that can be differentiated using only these four dimensions, and perhaps these subgroups were appearing as distinct latent classes in the current analyses.

It is not a new idea to suggest that there may be subgroups of D behavior. Lyons-Ruth and colleagues (1991) found that the D group could be divided into two subgroups based on the forced choice ABC class assignment given to these children: D forced-secure and D forced-insecure. They found that these two subgroups differed significantly in terms of their mothers' histories. Children who had a mother that had experienced loss of one of her own parents were more likely than other children to be classified as disorganized/disoriented, but specifically in the

D forced-secure subgroup. On the other hand, they found that the severity of a mother's psychosocial problems was positively associated with D group assignment, but only for the D forced-insecure subgroup. In addition, they found that the forced-secure subgroup was associated with lower maternal involvement, while the forced-insecure subgroup was associated with higher maternal involvement and hostility. Lyons-Ruth, Bronfman, and Parsons (1999) furthered this research, finding that mothers of D forced-insecure infants displayed more atypical behaviors, including role confusion and negative-intrusive behaviors, while mothers of D forced-secure infants displayed higher levels of fearfulness in relation to their infants. Their most intriguing finding in relation to the current work is that infants in the D forced-insecure subgroup of their sample were recognizable for their conflicting behaviors, often displayed in the form of distress, followed by avoidance or resistance at reunion. This might suggest that the analyses of the current work, even without the D score included, were distinguishing latent classes made up of children that would typically be assigned a category of D, and further, might best fit into the D forced-insecure subgroup. At the very least, the work detailed here on D subgroups suggests that the D category might be divided into subgroups that are meaningfully related to maternal behavior, and potentially child outcomes. This opens the door to the possibility that an LCA performed on Strange Situation data, even if the D scale is not included, might include classes that represent what is typically considered D category behavior, albeit at a subgroup level, not including all types of D classifications. In the future, it could be telling to re-examine the classes of the current work that at first appeared "odd" or atypical in terms of attachment theory. One could look at a given class in which the infants appeared to be displaying conflicting behavior patterns and examine the classification that was assigned to each of these infants under the Strange Situation coding scheme, including the D category for these purposes. This process could be extremely informative, especially if it were the case that the majority of these infants were classified as D, and even more interesting if their forced choice assignment was A or C.

While the exploration of D subgroups was an unexpected and potentially fruitful area of research to come out of the current work, it still must be acknowledged that not including the D behavior scale might have resulted in, or contributed to, the problem of not finding a clear model of best fit in these analyses. It might be the case that, even though the Strange Situation's four dimensions of behavior appear to potentially be distinguishing a subgroup or subgroups of D behavior, that these four dimensions are simply not sufficient to classify all children that should be given a D classification. This was the conclusion made previously, and the reason that it was assumed that latent classes representing a D group or groups would not be found, but there is a chance that infants that should be assigned a classification of D do differ from typical A, B, or C children in subtle ways on the Strange Situation's four dimensions of behavior. If this were true, and the differences were only subtle, then an LCA might have difficulty producing a model that fits the data well without the inclusion of a direct measure of D behavior. There is a chance that if the D behavior scale were included, this might contribute to classification in a meaningful way. On the other hand, if there were truly no differences on the Strange Situation dimensions of behavior between a typical A, B, or C infant (or whatever the "true" categories may be) and a D infant, then including the D scale would not serve to add any information to a model beyond what the D scale could provide on its own. In future work, analyses should be performed with and without inclusion of the D behavior scale in order to provide a basis for comparison. This comparison will be crucial for determining if the D scale should be included in further LCA endeavors or if it should be excluded as was the case in the current work.

Overarching Conclusions and Implications

Although a clear conclusion was not derived as to the model of best fit, an inspection and comparison of the many models examined in these four analyses leads to many interesting conclusions and implications for the field of attachment and the Strange Situation coding system. To begin with, the 2-class models of each analysis can be examined. In each analysis, the 2-class model's latent class profiles appear quite similar, with a nearly equal number of participants falling into each group. These classes resemble the A and B categories of the Strange Situation coding system. The idea that these two classes would line up in such a way would not be at all surprising to an attachment researcher familiar with the Strange Situation coding system, especially given the fact that many researchers reduce their data to a secure versus insecure comparison when analyzing data. What is unclear is where the insecure-ambivalent or C group is placed in the 2-class coding schemes of the current analyses. An attachment researcher utilizing the Strange Situation would assume that the C group would be included in the latent class that most closely resembles the A group, given that this would represent the combining of the two insecure groups of children. Upon examination of the latent class profiles of each of these 2-class models, however, it is evident that, if anything, the children that would typically be classified as C are most likely included in the latent class that resembles the B category. This is evidenced by the fact that, in each of the four analyses, the B class shows a higher level of resistance than the A class (which seems to show almost no resistance) in the 2-class models. This indicates that the LCA is suggesting that the natural groupings might be an A versus B and C combined comparison. This is absolutely contrary to the manner in which these types of data are handled in the field of attachment. It has long been assumed that the two categories of insecure attachment are substantively similar enough to one another to warrant being paired together in comparison to the secure category. The current analyses indicate that, statistically, the insecure-ambivalent category may be more similar to the secure group than to the insecure-avoidant category. While further research must be conducted in the area, the fact that all four of the current analyses repeated this result suggests that it may be inappropriate to reduce attachment data to an insecure versus secure comparison when utilizing the Strange Situation coding method. With the wealth of problems encountered in these analyses, strong conclusions are not justified, but these analyses would seem to suggest that, if the data in an attachment study do need to be reduced owing to an insufficient number of subjects in each group, the appropriate comparison might be between the A and B categories, setting aside the C category for a particular analysis.

The 3-class model of each of the analyses in the current work can also be examined. Similar to the 2-class models, the 3-class models of each analysis are strikingly similar to one another. In each case, the three classes are easily identified as most closely resembling the A, B, and B2 groups of the Strange Situation coding system, with the B group containing around half of the participants, and the other two groups containing roughly 25 to 30 percent of the participants. What is fascinating here is that the models do not match the assumption that an attachment researcher might have after examining the 2-class models. That assumption would be that, in the 2-class models, the children displaying a C behavior profile were simply combined with one of the other classes, but that in the 3-class model the C group would distinguish itself as a class in its own right. Given that attachment coding has focused on the three groups of A, B, and C, the natural hypothesis, even with no knowledge of the 2-class model profiles, would be that these A, B, and C groups would be represented in the latent class profiles of the 3-class model. In fact, this hypothesis is so natural given the state of attachment research today that it was the hypothesis of the current work that this result would be obtained. The C category does not appear as expected, however, in any of the 3-class models examined in these analyses. In fact, in each case, a class that displays a profile of C-type behavior does not appear until at least the 4-class model. There are two aspects of this surprising result in terms of the 3-class models that must be examined. The first of these is the fact that the C category is surprisingly absent from the 3-class models, and the second of these is the fact that the B2 subgroup was included and represented such a large proportion of the participants. Each of these will be considered in turn.

First, the unexpected lack of a C group in the 3-class models. Given the vast amount of research that went into the creation of the Strange Situation and that has resulted from it, one would expect that the ABC category system would be clearly represented in any 3-class model derived by an LCA. The conspicuous lack of a C group in any of the 3-class models in this work is, therefore, surprising. One could easily argue, however, that the C category is typically representative of the smallest number of participants in any attachment study of infants born in the United States. In fact, many researchers have difficulty obtaining enough participants in the C category to support the statistical analyses they had planned, leading to the aforementioned practice of reducing attachment data to a secure versus insecure comparison. It could be argued that perhaps there was simply not a large enough group of children displaying clear insecure-ambivalent behaviors for the LCA to be able to identify it as a unique group as early as the 3-class model (although any clear and distinct group, regardless of size, should be delineated as a separate class by the LCA). The problem with this line of logic in the current work, however, is that the SECCYD database contained a larger than average number of children assigned a classification of C as their attachment status. In fact, 15% of the participants were assigned a classification of insecure-ambivalent, as compared to the more standard 10% that is seen as the typical proportion when averaged across American samples (van Ijzendoorn & Kroonenberg, 1988). Even if the participants that would have received a primary classification of D or U with a forced choice classification of C are removed from this number, acknowledging the claim that this particular sub-population might not be showing clear or typical C behavior, there still remain 9% of the participants that received a primary classification of C. Clearly there were ample insecure-ambivalent subjects according to the Strange Situation classification system in order to represent a latent class if such a class truly exists, so the question remains: Why is the C category conspicuously absent from any of the 3-class models? One conclusion could be that the C category does not truly exist as a latent category underlying this grouping of behaviors that has come to be known as insecure-ambivalent according to the Strange Situation coding system. If the 3-class model including the A, B, and B2 groups had been strongly implicated as a model of best fit, this argument might have more footing, but without a decisive argument for the 3-class model, this suggestion appears premature. This is especially true given the fact that, in each of the 4-class models, a latent class profile that appears to line up with C-type behaviors is included and contains around 25% of the participants in each case. More work is needed addressing the many issues mentioned previously (sparse data, conditional independence, etc.), which will hopefully lead to a clear model of best fit. This model will give researchers a better understanding of the latent structure underlying attachment styles and whether or not the C category is a true latent class.

On the same token, the conspicuous absence of a C category in the 3-class models examined in this work left open the possibility of a third category being defined that was outside of the typical three category model presented by the Strange Situation coding system. Although it could have been that a truly “new” category was discovered, this does not appear to be the case. The third group in all four 3-class models closely resembles the B2 subgroup of the Strange Situation. This group contained around 25% of the participants in the 3-class models of all analyses, and maintained a strong presence in all models that were substantively meaningful. The fact that this class was so consistent from such an early point seems to suggest that it is an important class, and could potentially be considered a category in its own right as opposed to merely a subgroup of the B category. In fact, the B2 class was considered distinct from the overall B class in each of the 3-class models. Perhaps the behavior representative of a B2 classification, including displaying some avoidance behaviors in the first reunion of the Strange Situation procedure which give way to displays of secure attachment behavior in the second reunion, are more common than was originally thought when the Strange Situation coding scheme was created. The clearest way to approach this problem would be to analyze various outcome measures for children originally assigned a classification of B2 in comparison to those assigned to the other B subgroups. If the outcomes are statistically disparate, this could lend support to the idea presented in this set of LCAs that the B2 subgroup might be a classification in its own right, as opposed to a subgroup of general secure behavior. On the other hand, it could simply be that the subgroups presented by Ainsworth and colleagues have always represented distinct groups, but that the field of attachment has never obtained large enough samples to truly compare these groups. Perhaps the current research is simply the first example of a sample large enough to make such comparisons, and the LCA is merely picking up on this distinct B2 subgroup that has been unique all along. The best method of resolving this debate is to conduct further research in this area, focusing on utilizing LCAs and outcome measures in concert in order to obtain a clear picture of the true groupings of participants using the Strange Situation method.

The bottom line is that the 3-class models presented in each of the analyses of this work do not line up with the expectation of a clear A, B, and C group. While this does not decisively discredit the entire ABC coding system, especially given the wealth of problems encountered in this work, it does begin to call into question the gold standard status with which the Strange Situation coding has been credited. It seems to have been taken for granted that this 3-class system is the true nature of attachment statuses, and represents a latent structure that supports this system. Given the results of this work, tenuous as they may be, this confidence in the Strange Situation coding system may require evaluation. For this reason, it is imperative that more work be conducted in this area, especially given the vast body of work that is still being conducted every year which utilizes the Strange Situation. This future work must include further LCAs, hopefully analyzing even larger databases, with a focus on comparing outcome measures for any groups that are suggested by a model of best fit found in an LCA. It is only in this way that the Strange Situation coding system can truly be evaluated and the latent structure underlying attachment statuses can be further explored.

While the primary aim of the current work was to evaluate the Strange Situation coding system in order to assess the number of latent categories underlying the system, the secondary aim was to evaluate the scales themselves, looking for possible simplifications or adjustments to the four dimensions of behavior typically employed. Two areas that held the potential for adjustments were explored: Making certain dimensions binary as opposed to 7-level (as they were originally created), and treating certain dimensions continuously as opposed to categorically or ordinally. In terms of a binary treatment of certain variables (avoidance and resistance in both reunion episodes) versus a multi-level treatment of these same variables, which was explored in the comparison of Analysis 1 to Analysis 4, no clear conclusion can be drawn. The major issue with this comparison is the fact that a final model was not chosen in either analysis, making it impossible to truly compare the two. In Analysis 1 with the dichotomously coded variables, the results aligned well with the Strange Situation coding system as it stands. Analysis 4, however, which allowed more freedom for these same variables to vary, seemed to veer away from the pure Strange Situation coding. Without one distinct model from each analysis to compare, and given that the point of the current research was to evaluate the Strange Situation and not assume its validity, this coding issue was not resolved. In the future, if a larger data set were obtained, hopefully diminishing the issues found here with sparse data, it seems a true comparison could be conducted and a suggestion could be made about future coding efforts. In addition, if future efforts using LCA found that the Strange Situation category system was viable as it currently stands, then it would seem that a reduction of these particular variables to dichotomous coding might be effective. This is given the fact that the dichotomously coded variables appeared to be successful at distinguishing the various latent classes that mimicked the categories and subgroups of the Strange Situation coding system. The final check in this case would be to take the final model of best fit and use it to assign classes to each of the participants. These assignments could then be compared to the classification each subject received using the Strange Situation coding. If there were general agreement in both of these methods, then a strong argument could be made for dichotomous coding, especially given the fact that this would greatly reduce the burden on the coders. In terms of coder effort and even training and reliability, this would be a sizeable improvement to the scale.

The second area with the potential for adjustments to the scales used in the Strange Situation coding was the treatment of the variables of proximity & contact seeking, and contact maintaining. The current research compared treating these variables ordinally versus continuously. Countless studies in the area of attachment have analyzed data using a continuous treatment of these scales without ever examining this comparison (e.g., Lyons-Ruth et al., 1987; Bridges, Connell, and Belsky, 1988; Leerkes, Parade, and Gudmundson, 2011). Given the manner in which these scales were created, it appears inaccurate to conceptualize these variables as continuous, but the comparison was made in the current work in order to examine a common practice in the field. What was found fell in line with the idea that assuming equal intervals in these scales, as is the case if a scale is truly continuous, is completely unjustified – the continuous coding of these data fell apart upon analysis. Not only was it impossible to select a model of best fit in Analysis 3, where proximity & contact seeking and contact maintaining were treated continuously, but none of the models suggested by the fit indices were even candidates for selection given the substantive breakdown in this analysis. The fact that the only difference between Analysis 1, in which there were multiple candidates for a model of best fit, and Analysis 3 was in the coding of these variables leads to the clear suggestion that continuous treatment of these variables is inappropriate. As always, more research should be done in this area before decisive changes are made to the way in which the field treats these measures. Specifically, increasing the number of participants in an LCA treating these dimensions continuously could only serve to help clarify the situation given the fact that models with continuous data tend to be so large. Even with more work ahead, however, the current work should result in a serious questioning of the automatic assumption that a continuous treatment of Strange Situation coding is appropriate. At the very least, this work shows that the continuous coding provided very different answers than the ordinal coding, so the field would be wise to pursue further evaluation of the scales in this area.

Future Directions

Although many suggestions have already been made for future directions with this work, there are a few exciting paths that this research could lead to once an LCA has been executed that is able to arrive at a clear model of best fit. First and foremost, once an official model has been settled upon, it would be possible to compare the class assignments of this model to the assignments made by the original Strange Situation coding system. This simple comparison would be incredibly indicative of whether or not the Strange Situation coding system is truly picking up on the underlying latent structure of the data. Obtaining these results should clearly be the goal of future research given the potential statements it could make about the effectiveness of the Strange Situation coding system as it currently stands.

Another line of inquiry that could be pursued if an LCA is conducted that clearly indicates a model of best fit is examining the indicators to see if they are all contributing significantly to class assignment. It is possible that one of the four dimensions of behavior coded in the Strange Situation is not actually contributing to class assignment and could therefore be dropped from the data collection. This seems unlikely, but this could be examined if a final model were obtained. Another related possibility is that the coding of the four dimensions of behavior in one of the episodes is unnecessary to achieve class assignment. For example, perhaps only the coding from episode 8 is needed to assign children to classes and the information from episode 5 is redundant. This is a distinct possibility, as Ainsworth and colleagues (1978) noted that episode 8 appeared to be the most important for discriminating individual differences, but a clear model of best fit must be obtained before this can be explored.[9] Once obtained, a model of best fit could be compared to one in which only the dimensions of behavior coded in episode 8 were used as indicators to see if the same results were obtained.

Finally, once a best-fitting model is found, it could be used as the baseline to which best-fitting models from other analyses could be compared. For example, an analysis could be conducted that included the variable of infant crying in various episodes of the Strange Situation. The best-fitting model from this analysis could then be compared to the baseline best-fitting model in order to assess if the inclusion of other indicator variables might improve classification. There are countless ways in which LCA can be used in the future in this area, and once an analysis is conducted which is able to suggest a best-fitting model, the floodgates will truly be opened.

While all of these suggested future analyses appear multiple steps ahead of the current state of this new body of work utilizing LCA to evaluate the Strange Situation, especially given that a best-fitting model was never found in the current work, it is still important to acknowledge the vast amount of potential work ahead. This first foray into this area opens doors to an entire body of work that has the potential to improve and perfect attachment research as we know it. Utilizing a relatively new statistical procedure to evaluate a measure that is so well accepted that it is often taken for granted may be the key to approaching this measurement with a new perspective, possibly offering new insights and a new lens through which to view it. Latent

[9] While it is not possible to examine this line of inquiry here, given that a model of best fit was not found, it is important to note that the current work points toward both episodes 5 and 8 being important in class assignment. This is due to the fact that the class that appeared most similar to the B2 subgroup of the Strange Situation was so large and such a strong presence in all analyses. This particular group showed one profile of behavior in episode 5 (fairly avoidant) and a different profile in episode 8 (clearly secure), meaning the data from both episodes were imperative in class assignment for this group.

Class Analysis truly has the potential to revolutionize the Strange Situation coding procedure (and attachment coding in general) and this research is just the first tiny step in that direction.

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Table 1

Description of the Episodes of the Strange Situation Assessment

Episode	Participants / Actions	Duration
Episode 1	Mother & Child introduced to playroom	30 seconds
Episode 2	Mother & Child alone in playroom – Child engages w/ toys, Mother sits in chair	3 minutes
Episode 3	Stranger enters – sits silently in chair	1 minute
	Stranger speaks with Mother	1 minute
	Stranger attempts to interact w/ Child and toys	1 minute
Episode 4	Mother leaves room. Stranger comforts child if needed	3 minutes[a]
Episode 5	Mother returns – reunites w/ Child. Stranger slips out of room.	3 minutes
Episode 6	Mother leaves room. Child is alone w/ toys	3 minutes[a]
Episode 7	Stranger returns – comforts child if needed	3 minutes[a]
Episode 8	Mother returns – reunites w/ Child	3 minutes

[a]Episode shortened if the Child is in extreme distress

Table 2

Class Assignments in the SECCYD Database

5-Category Class Assignments

	All Subjects	No U or DU
A	160	160
B	710	710
C	102	102
D	177	152
U	42	0
Total:	1191	1124

Forced Choice ABC Class Assignments

	Primary D	Primary U
A	33	2
B	97	16
C	47	24
Total:	177	42

Table 3

Number of Modes (Final Solutions) Obtained for Each Model

Number of Latent Classes	Analysis 1	Analysis 2	Analysis 3	Analysis 4
2	2	2	1	1
3	2	2	1	2
4	11[a]	7	1	10
5	21	43[a]	7	48[a]
6	129	186[a]	59	187[a]
7	567[b]	611[b]	153	489[a]
8	708[b]	696[b]	350[a]	604[b]
9	615[b]	608[b]	609[a]	677[b]

[a]Between 2 and 31 sets of start values did not converge. [b]Over 90 sets of start values did not converge.

Table 4

Fit Indices for Analysis 1

Model	G^2	AIC	BIC	BIC*	LMR
2-class	4145.59	20626.33	20916.04	20734.98	2633.77
df	38358				
p-value					0.00
3-class	3596.82	20141.52	20578.62	20305.45	540.19**
df	38329				
p-value					0.00
4-class	3438.85	19883.17	20467.67	20102.38	314.81
df	38300				
p-value					0.20
5-class	3312.33	19710.22	20442.11**	19984.71**	229.83
df	38271				
p-value					0.71
6-class	3301.38	19664.87	20544.15	19994.64	102.86
df	38242				
p-value					0.03
7-class	3283.21	19649.76	20676.44	20034.81	72.75
df	38213				
p-value					0.80
8-class	3263.14	19638.24	20812.31	20078.56	69.19
df	38184				
p-value					0.76
9-class	3247.69	19625.68**	20947.14	20121.29	69.20
df	38155				
p-value					0.78

** Indicates the model of best fit according to each fit index.

Table 5

Fit Indices for Analysis 2

Model	G^2	AIC	BIC	BIC*	LMR
2-class	3958.35	19341.07	19627.47	19446.42	2661.27**
df	38358				
p-value					0.00
3-class	3392.17	18895.12	19327.24	19054.08	501.48
df	38329				
p-value					0.29
4-class	3232.81	18647.76	19225.60	18860.32	303.87
df	38300				
p-value					0.24
5-class	3097.67	18490.21	19213.76**	18756.37**	214.50
df	38271				
p-value					0.00
6-class	3101.56	18440.01	19309.27	18759.78	107.67
df	38242				
p-value					0.77
7-class	3083.74	18420.44	19435.42	18793.81	77.19
df	38213				
p-value					0.82
8-class	3004.27	18404.87	19565.57	18831.85	73.14
df	38184				
p-value					0.83
9-class	2958.86	18391.14**	19697.55	18871.72	70.57
df	38155				
p-value					0.78

** Indicates the model of best fit according to each fit index.

Table 6

Fit Indices for Analysis 3

Model	AIC	BIC	BIC*	LMR
2-class	22594.42	22701.16	22634.45	2818.80
p-value				0.00
3-class	21845.24	21997.72	21902.43	755.33
p-value				0.00
4-class	21359.51	21557.73	21433.85	495.95
p-value				0.00
5-class	21003.15	21247.11	21094.65	368.58
p-value				0.00
6-class	20781.15	21070.86	20889.80	236.29
p-value				0.00
7-class	20006.89	20342.34	20132.70	625.01
p-value				0.00
8-class	19898.62	20279.81	20041.58	124.32**
p-value				0.00
9-class	19739.51**	20166.45**	19899.63**	144.41
p-value				0.23

** Indicates the model of best fit according to each fit index.

Table 7

Fit Indices for Analysis 4

Model	G^2	AIC	BIC	BIC*	LMR
2-class	4231.72	21939.06	22269.43	22062.97	2718.14
df	194415				
p-value					0.00
3-class	3711.19	21379.12	21877.21	21565.93	623.28**
df	194382				
p-value					0.00
4-class	3489.69	21158.57	21824.38**	21408.28	285.33
df	194349				
p-value					0.76
5-class	3440.76	21032.10	21865.64	21344.71	191.65
df	194316				
p-value					0.21
6-class	3320.89	20945.66	21946.92	21321.17	151.79
df	194283				
p-value					0.83
7-class	3313.35	20868.81	22037.79	21307.23**	142.24
df	194250				
p-value					0.82
8-class	3237.07	20840.02	22176.73	21341.34	94.38
df	194217				
p-value					0.79
9-class	3208.07	20819.65**	22324.09	21383.88	86.02
df	194184				
p-value					0.82

** Indicates the model of best fit according to each fit index.

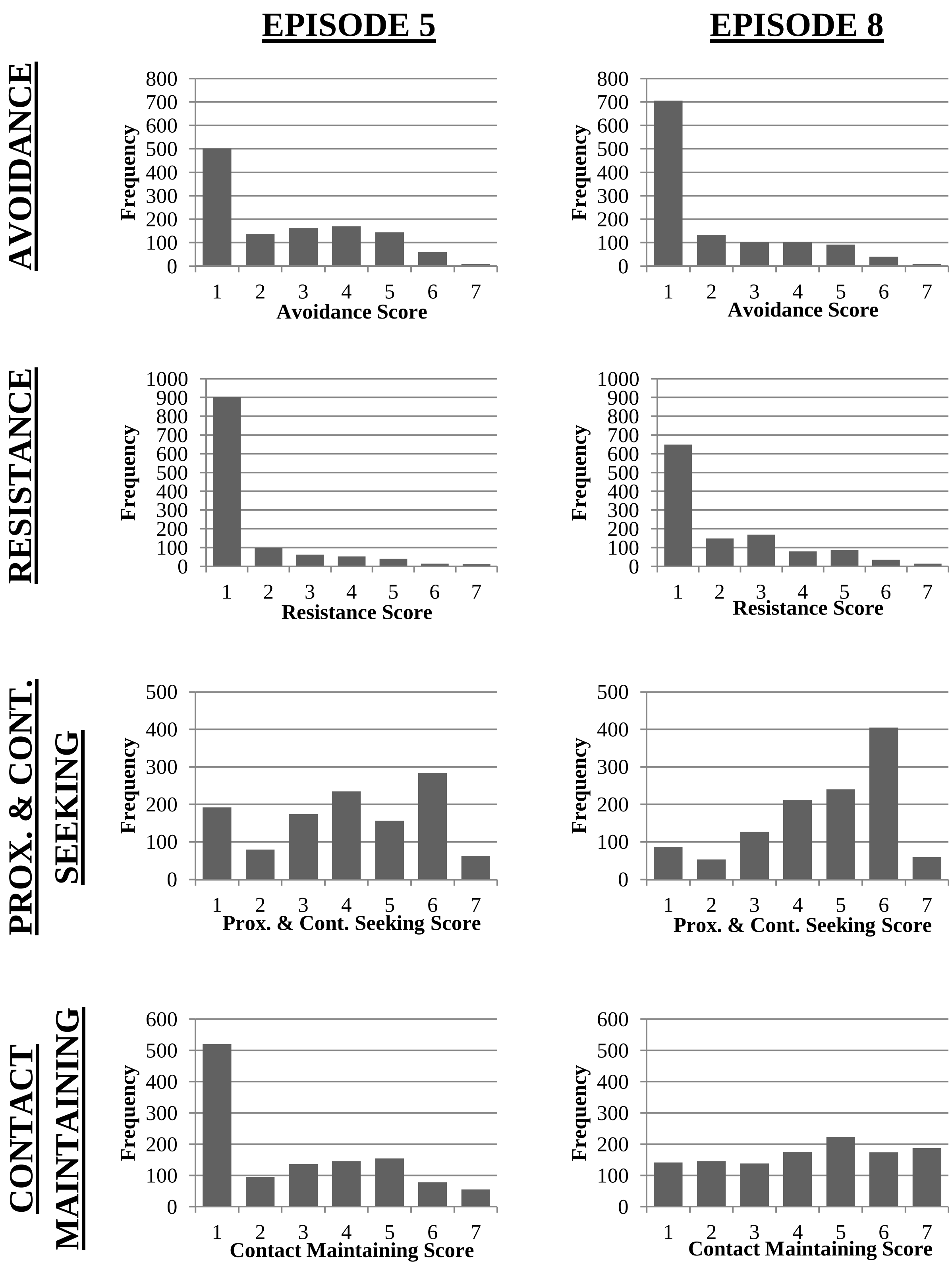

Figure 1. Frequency graphs for each of the 8 indicator variables in the SECCYD database.

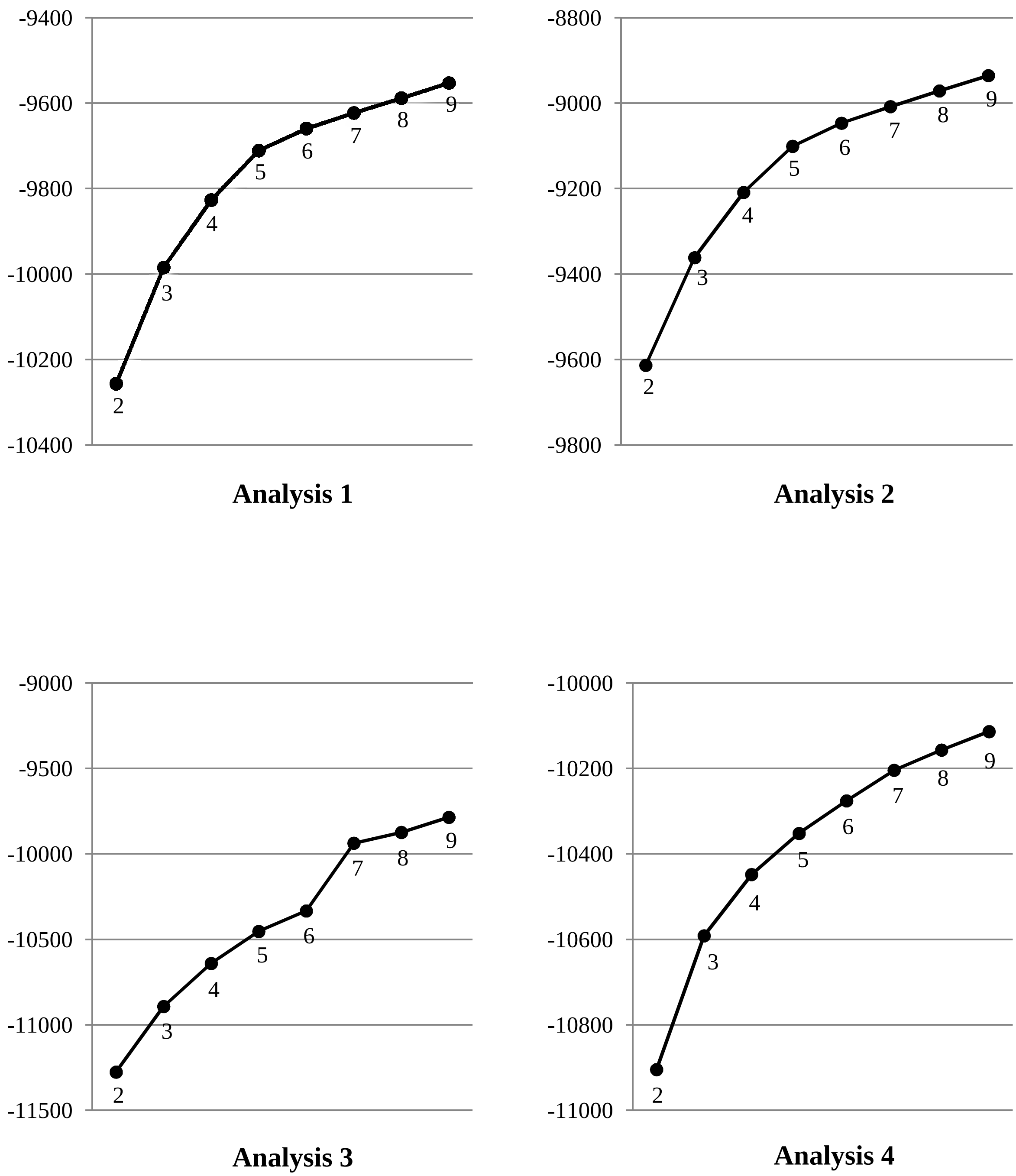

Figure 2. Log likelihood plots for Analyses 1 through 4. Each point on a given line represents the log likelihood value for a specific model within that analysis (e.g., the 5-class model of Analysis 3).

Appendix

Conditional Response Probabilities and Latent Class Probabilities

This Appendix includes the conditional response probabilities and latent class probabilities for each class of each model in a given analysis. What follows is a list of abbreviations used in each table: LC = Latent Class, Ep. = Episode, CM = Contact Maintaining, PCS = Proximity & Contact Seeking, Avoid = Avoidance, Resist = Resistance, Prob. = Probability.

Table A1

Analysis 1: 2-class model

	LC #1	LC #2
CM Ep. 5		
1	0.855	0.003
2	0.082	0.077
3	0.047	0.188
4	0.015	0.234
5	0.000	0.267
6	0.001	0.134
7	0.000	0.097
CM Ep. 8		
1	0.231	0.002
2	0.206	0.035
3	0.155	0.076
4	0.127	0.170
5	0.138	0.242
6	0.088	0.209
7	0.055	0.266
PCS Ep. 5		
1	0.317	0.000
2	0.132	0.001
3	0.260	0.028
4	0.282	0.110
5	0.010	0.260
6	0.000	0.492
7	0.000	0.109
PCS Ep. 8		
1	0.142	0.002
2	0.079	0.009
3	0.172	0.040
4	0.212	0.143
5	0.173	0.234
6	0.208	0.483
7	0.014	0.089
Avoid Ep. 5		
None	0.118	0.746
Some	0.882	0.254
Avoid Ep. 8		
None	0.375	0.828
Some	0.625	0.172
Resist Ep. 5		
None	0.906	0.609
Some	0.094	0.391
Resist Ep. 8		
None	0.642	0.450
Some	0.358	0.550
Latent Class Probability	0.509	0.491

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A2

Analysis 1: 3-class model

	LC #1	LC #2	LC #3
CM Ep. 5			
1	0.876	0.002	0.773
2	0.073	0.065	0.109
3	0.040	0.176	0.082
4	0.010	0.234	0.036
5	0.000	0.280	0.000
6	0.001	0.141	0.000
7	0.000	0.102	0.000
CM Ep. 8			
1	0.487	0.002	0.000
2	0.333	0.031	0.094
3	0.100	0.072	0.201
4	0.012	0.167	0.231
5	0.025	0.243	0.237
6	0.021	0.207	0.157
7	0.022	0.278	0.080
PCS Ep. 5			
1	0.365	0.000	0.252
2	0.149	0.000	0.107
3	0.229	0.025	0.272
4	0.240	0.084	0.344
5	0.011	0.262	0.025
6	0.006	0.513	0.000
7	0.000	0.115	0.000
PCS Ep. 8			
1	0.303	0.000	0.000
2	0.167	0.009	0.000
3	0.319	0.041	0.037
4	0.212	0.139	0.213
5	0.000	0.230	0.328
6	0.000	0.488	0.395
7	0.000	0.092	0.028
Avoid Ep. 5			
None	0.103	0.768	0.143
Some	0.897	0.232	0.857
Avoid Ep. 8			
None	0.092	0.834	0.636
Some	0.908	0.166	0.364
Resist Ep. 5			
None	0.922	0.602	0.880
Some	0.078	0.398	0.120
Resist Ep. 8			
None	0.720	0.447	0.568
Some	0.280	0.553	0.432
Latent Class Probability	0.241	0.469	0.290

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A3

Analysis 1: 4-class model

	LC #1	LC #2	LC #3	LC #4
CM Ep. 5				
1	0.894	0.000	0.914	0.003
2	0.067	0.163	0.074	0.021
3	0.026	0.378	0.012	0.052
4	0.011	0.250	0.000	0.215
5	0.000	0.167	0.000	0.329
6	0.000	0.037	0.000	0.210
7	0.001	0.005	0.000	0.170
CM Ep. 8				
1	0.492	0.007	0.000	0.000
2	0.323	0.085	0.100	0.000
3	0.102	0.167	0.196	0.012
4	0.012	0.243	0.227	0.111
5	0.022	0.292	0.237	0.199
6	0.022	0.164	0.152	0.238
7	0.027	0.044	0.088	0.441
PCS Ep. 5				
1	0.372	0.000	0.298	0.000
2	0.153	0.017	0.110	0.000
3	0.236	0.044	0.300	0.022
4	0.235	0.245	0.289	0.040
5	0.003	0.342	0.004	0.173
6	0.000	0.329	0.000	0.589
7	0.000	0.023	0.000	0.176
PCS Ep. 8				
1	0.303	0.004	0.000	0.000
2	0.165	0.022	0.000	0.000
3	0.323	0.080	0.025	0.016
4	0.209	0.210	0.195	0.107
5	0.000	0.291	0.333	0.184
6	0.000	0.340	0.417	0.580
7	0.000	0.053	0.029	0.113
Avoid Ep. 5				
None	0.092	0.516	0.133	0.899
Some	0.908	0.484	0.867	0.101
Avoid Ep. 8				
None	0.089	0.670	0.653	0.925
Some	0.911	0.330	0.347	0.075
Resist Ep. 5				
None	0.922	0.761	0.896	0.497
Some	0.078	0.239	0.104	0.503
Resist Ep. 8				
None	0.716	0.607	0.567	0.331
Some	0.284	0.393	0.433	0.669
Latent Class Probability	0.238	0.245	0.244	0.274

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A4

Analysis 1: 5-class model

	LC #1	LC #2	LC #3	LC #4	LC #5
CM Ep. 5					
1	0.908	0.000	0.904	0.006	0.000
2	0.064	0.097	0.084	0.022	0.156
3	0.023	0.266	0.013	0.040	0.368
4	0.005	0.246	0.000	0.213	0.250
5	0.000	0.275	0.000	0.299	0.168
6	0.000	0.095	0.000	0.210	0.051
7	0.000	0.021	0.000	0.210	0.007
CM Ep. 8					
1	0.493	0.000	0.000	0.000	0.018
2	0.325	0.013	0.099	0.000	0.124
3	0.103	0.084	0.196	0.010	0.183
4	0.012	0.197	0.226	0.104	0.238
5	0.022	0.315	0.237	0.178	0.250
6	0.023	0.234	0.155	0.213	0.150
7	0.023	0.157	0.087	0.494	0.037
PCS Ep. 5					
1	0.378	0.000	0.295	0.000	0.000
2	0.154	0.002	0.109	0.000	0.024
3	0.236	0.006	0.293	0.034	0.068
4	0.232	0.076	0.299	0.053	0.297
5	0.000	0.239	0.004	0.183	0.363
6	0.000	0.569	0.000	0.572	0.222
7	0.000	0.107	0.000	0.159	0.027
PCS Ep. 8					
1	0.304	0.000	0.000	0.000	0.011
2	0.167	0.000	0.000	0.000	0.035
3	0.323	0.004	0.025	0.026	0.122
4	0.206	0.008	0.191	0.144	0.331
5	0.000	0.216	0.332	0.193	0.303
6	0.000	0.646	0.421	0.522	0.197
7	0.000	0.126	0.031	0.115	0.000
Avoid Ep. 5					
None	0.093	0.873	0.132	0.882	0.343
Some	0.907	0.127	0.868	0.118	0.657
Avoid Ep. 8					
None	0.090	1.000	0.660	0.899	0.461
Some	0.910	0.000	0.340	0.101	0.539
Resist Ep. 5					
None	0.926	0.998	0.895	0.292	0.680
Some	0.074	0.002	0.105	0.708	0.320
Resist Ep. 8					
None	0.720	0.828	0.567	0.135	0.520
Some	0.280	0.172	0.433	0.865	0.480
Latent Class Probability	0.234	0.156	0.247	0.207	0.156

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A5

Analysis 1: 6-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6
CM Ep. 5						
1	0.907	0.000	0.893	0.000	0.000	0.019
2	0.066	0.113	0.094	0.000	0.110	0.079
3	0.023	0.294	0.013	0.000	0.400	0.086
4	0.005	0.291	0.000	0.082	0.240	0.308
5	0.000	0.244	0.000	0.375	0.177	0.227
6	0.000	0.058	0.000	0.318	0.065	0.101
7	0.000	0.000	0.000	0.224	0.008	0.181
CM Ep. 8						
1	0.492	0.000	0.000	0.000	0.022	0.000
2	0.326	0.017	0.097	0.000	0.116	0.032
3	0.103	0.095	0.199	0.000	0.188	0.031
4	0.012	0.237	0.225	0.000	0.226	0.200
5	0.022	0.336	0.238	0.102	0.253	0.236
6	0.023	0.211	0.155	0.301	0.163	0.126
7	0.024	0.103	0.085	0.597	0.032	0.374
PCS Ep. 5						
1	0.378	0.000	0.292	0.000	0.000	0.000
2	0.154	0.003	0.109	0.000	0.026	0.000
3	0.237	0.013	0.288	0.002	0.068	0.070
4	0.232	0.098	0.307	0.007	0.285	0.123
5	0.000	0.279	0.004	0.025	0.356	0.341
6	0.000	0.533	0.000	0.688	0.231	0.418
7	0.000	0.074	0.000	0.277	0.033	0.048
PCS Ep. 8						
1	0.303	0.000	0.000	0.000	0.014	0.000
2	0.167	0.000	0.000	0.000	0.041	0.000
3	0.323	0.008	0.026	0.000	0.125	0.064
4	0.207	0.028	0.187	0.053	0.364	0.226
5	0.000	0.238	0.333	0.094	0.294	0.298
6	0.000	0.607	0.424	0.712	0.161	0.339
7	0.000	0.119	0.030	0.141	0.000	0.073
Avoid Ep. 5						
None	0.095	0.853	0.127	0.905	0.301	0.822
Some	0.905	0.147	0.873	0.095	0.699	0.178
Avoid Ep. 8						
None	0.091	1.000	0.658	0.887	0.367	0.915
Some	0.909	0.000	0.342	0.113	0.633	0.085
Resist Ep. 5						
None	0.926	0.980	0.897	0.494	0.725	0.133
Some	0.074	0.020	0.103	0.506	0.275	0.867
Resist Ep. 8						
None	0.720	0.783	0.568	0.343	0.575	0.000
Some	0.280	0.217	0.432	0.657	0.425	1.000
Latent Class Probability	0.235	0.157	0.248	0.117	0.128	0.115

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A6

Analysis 1: 7-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7
CM Ep. 5							
1	0.905	0.000	0.899	0.000	0.000	0.040	0.000
2	0.067	0.113	0.085	0.000	0.113	0.111	0.152
3	0.023	0.289	0.015	0.037	0.424	0.052	0.290
4	0.005	0.286	0.000	0.164	0.305	0.242	0.000
5	0.000	0.246	0.000	0.328	0.120	0.246	0.412
6	0.000	0.066	0.000	0.276	0.038	0.101	0.115
7	0.000	0.000	0.000	0.195	0.000	0.208	0.031
CM Ep. 8							
1	0.491	0.000	0.000	0.000	0.016	0.000	0.037
2	0.326	0.018	0.097	0.000	0.073	0.056	0.219
3	0.103	0.098	0.200	0.006	0.185	0.027	0.196
4	0.012	0.229	0.227	0.070	0.252	0.158	0.136
5	0.022	0.331	0.238	0.142	0.266	0.210	0.265
6	0.023	0.222	0.153	0.272	0.175	0.118	0.088
7	0.024	0.101	0.085	0.510	0.033	0.430	0.060
PCS Ep. 5							
1	0.377	0.000	0.296	0.000	0.000	0.000	0.000
2	0.154	0.005	0.110	0.000	0.031	0.000	0.000
3	0.237	0.016	0.287	0.000	0.065	0.118	0.000
4	0.232	0.112	0.303	0.000	0.335	0.126	0.181
5	0.000	0.279	0.004	0.049	0.417	0.375	0.161
6	0.000	0.528	0.000	0.673	0.152	0.380	0.504
7	0.000	0.061	0.000	0.277	0.000	0.000	0.155
PCS Ep. 8							
1	0.303	0.000	0.000	0.000	0.008	0.000	0.032
2	0.167	0.000	0.000	0.000	0.041	0.000	0.031
3	0.323	0.013	0.025	0.000	0.079	0.089	0.232
4	0.207	0.047	0.186	0.028	0.307	0.322	0.413
5	0.000	0.243	0.337	0.105	0.280	0.344	0.292
6	0.000	0.587	0.421	0.682	0.285	0.245	0.000
7	0.000	0.110	0.031	0.185	0.000	0.000	0.000
Avoid Ep. 5							
None	0.096	0.849	0.123	0.882	0.202	0.925	0.464
Some	0.904	0.151	0.877	0.118	0.798	0.075	0.536
Avoid Ep. 8							
None	0.092	1.000	0.655	0.905	0.467	0.922	0.000
Some	0.908	0.000	0.345	0.095	0.533	0.078	1.000
Resist Ep. 5							
None	0.926	0.999	0.908	0.432	0.576	0.195	1.000
Some	0.074	0.001	0.092	0.568	0.424	0.805	0.000
Resist Ep. 8							
None	0.719	0.838	0.577	0.275	0.368	0.039	1.000
Some	0.281	0.162	0.423	0.725	0.632	0.961	0.000
Latent Class Probability	0.236	0.151	0.245	0.146	0.106	0.090	0.027

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A7

Analysis 1: 8-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8
CM Ep. 5								
1	0.908	0.000	0.889	0.000	0.013	0.074	0.000	0.016
2	0.065	0.110	0.095	0.003	0.081	0.156	0.183	0.027
3	0.022	0.281	0.017	0.000	0.437	0.000	0.322	0.136
4	0.005	0.297	0.000	0.063	0.316	0.156	0.000	0.467
5	0.000	0.250	0.000	0.353	0.103	0.192	0.395	0.272
6	0.000	0.062	0.000	0.324	0.040	0.144	0.101	0.047
7	0.000	0.000	0.000	0.257	0.009	0.279	0.000	0.037
CM Ep. 8								
1	0.491	0.000	0.000	0.000	0.017	0.000	0.044	0.000
2	0.326	0.018	0.095	0.000	0.070	0.111	0.232	0.000
3	0.103	0.092	0.202	0.007	0.175	0.036	0.222	0.019
4	0.012	0.235	0.227	0.000	0.246	0.176	0.131	0.246
5	0.022	0.332	0.237	0.082	0.268	0.078	0.270	0.397
6	0.023	0.213	0.154	0.267	0.189	0.134	0.046	0.178
7	0.024	0.110	0.084	0.643	0.035	0.465	0.055	0.161
PCS Ep. 5								
1	0.378	0.000	0.296	0.000	0.000	0.000	0.000	0.000
2	0.154	0.004	0.110	0.000	0.033	0.000	0.000	0.000
3	0.238	0.017	0.283	0.000	0.070	0.227	0.000	0.000
4	0.229	0.102	0.311	0.010	0.306	0.167	0.264	0.060
5	0.000	0.281	0.000	0.046	0.426	0.380	0.163	0.274
6	0.000	0.523	0.000	0.681	0.165	0.225	0.435	0.566
7	0.000	0.073	0.000	0.263	0.000	0.000	0.138	0.100
PCS Ep. 8								
1	0.303	0.000	0.000	0.000	0.009	0.000	0.029	0.000
2	0.168	0.000	0.000	0.000	0.054	0.000	0.000	0.000
3	0.322	0.012	0.026	0.000	0.079	0.159	0.235	0.007
4	0.207	0.040	0.181	0.050	0.323	0.558	0.457	0.000
5	0.000	0.243	0.337	0.103	0.282	0.255	0.279	0.346
6	0.000	0.591	0.425	0.713	0.252	0.028	0.000	0.498
7	0.000	0.113	0.031	0.134	0.000	0.000	0.000	0.149
Avoid Ep. 5								
None	0.095	0.857	0.119	0.902	0.180	0.934	0.480	0.781
Some	0.905	0.143	0.881	0.098	0.820	0.066	0.520	0.219
Avoid Ep. 8								
None	0.092	1.000	0.659	0.890	0.404	0.893	0.094	0.945
Some	0.908	0.000	0.341	0.110	0.596	0.107	0.906	0.055
Resist Ep. 5								
None	0.926	0.980	0.906	0.472	0.611	0.174	1.000	0.000
Some	0.074	0.020	0.094	0.528	0.389	0.826	0.000	1.000
Resist Ep. 8								
None	0.718	0.767	0.578	0.310	0.376	0.062	1.000	0.000
Some	0.282	0.233	0.422	0.690	0.624	0.938	0.000	1.000
Latent Class Probability	0.235	0.170	0.245	0.121	0.096	0.049	0.029	0.054

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A8

Analysis 1: 9-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8	LC #9
CM Ep. 5									
1	0.910	0.000	0.876	0.000	0.000	0.077	0.000	0.014	0.831
2	0.061	0.111	0.110	0.000	0.033	0.170	0.177	0.041	0.081
3	0.012	0.279	0.014	0.000	0.492	0.000	0.285	0.126	0.088
4	0.017	0.296	0.000	0.064	0.307	0.157	0.000	0.450	0.000
5	0.000	0.252	0.000	0.350	0.112	0.184	0.425	0.280	0.000
6	0.000	0.062	0.000	0.325	0.046	0.141	0.113	0.053	0.000
7	0.000	0.000	0.000	0.261	0.010	0.270	0.000	0.035	0.000
CM Ep. 8									
1	0.518	0.000	0.000	0.000	0.000	0.000	0.043	0.000	0.301
2	0.299	0.018	0.077	0.000	0.073	0.117	0.229	0.000	0.408
3	0.117	0.091	0.203	0.007	0.189	0.038	0.205	0.021	0.087
4	0.000	0.233	0.232	0.000	0.274	0.176	0.130	0.224	0.068
5	0.019	0.333	0.248	0.081	0.263	0.080	0.282	0.389	0.052
6	0.009	0.211	0.156	0.265	0.202	0.129	0.050	0.185	0.084
7	0.039	0.114	0.085	0.647	0.000	0.461	0.062	0.181	0.000
PCS Ep. 5									
1	0.378	0.000	0.291	0.000	0.000	0.000	0.000	0.000	0.328
2	0.166	0.004	0.114	0.000	0.037	0.000	0.000	0.000	0.082
3	0.223	0.017	0.273	0.000	0.063	0.230	0.000	0.000	0.305
4	0.228	0.104	0.318	0.010	0.265	0.172	0.204	0.090	0.285
5	0.005	0.281	0.004	0.042	0.451	0.379	0.152	0.267	0.000
6	0.000	0.523	0.000	0.680	0.184	0.219	0.480	0.550	0.000
7	0.000	0.072	0.000	0.267	0.000	0.000	0.164	0.093	0.000
PCS Ep. 8									
1	0.311	0.000	0.000	0.000	0.000	0.000	0.034	0.000	0.207
2	0.167	0.000	0.000	0.000	0.059	0.000	0.000	0.000	0.122
3	0.338	0.013	0.020	0.000	0.064	0.159	0.250	0.007	0.245
4	0.184	0.039	0.154	0.051	0.356	0.550	0.432	0.000	0.384
5	0.000	0.242	0.341	0.104	0.312	0.258	0.284	0.326	0.042
6	0.000	0.593	0.454	0.713	0.208	0.033	0.000	0.524	0.000
7	0.000	0.113	0.032	0.132	0.000	0.000	0.000	0.143	0.000
Avoid Ep. 5									
None	0.000	0.853	0.090	0.913	0.190	0.920	0.495	0.734	0.493
Some	1.000	0.147	0.910	0.087	0.810	0.080	0.505	0.266	0.507
Avoid Ep. 8									
None	0.000	1.000	0.650	0.896	0.406	0.885	0.000	0.900	0.522
Some	1.000	0.000	0.350	0.104	0.594	0.115	1.000	0.100	0.478
Resist Ep. 5									
None	0.903	0.981	0.898	0.478	0.642	0.175	1.000	0.000	1.000
Some	0.097	0.019	0.102	0.522	0.358	0.825	0.000	1.000	0.000
Resist Ep. 8									
None	0.686	0.766	0.555	0.314	0.419	0.066	1.000	0.000	0.840
Some	0.314	0.234	0.445	0.686	0.581	0.934	0.000	1.000	0.160
Latent Class Probability	0.189	0.171	0.235	0.119	0.086	0.051	0.025	0.059	0.064

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A9

Analysis 2: 2-class model

	LC #1	LC #2
CM Ep. 5		
1	0.857	0.004
2	0.082	0.079
3	0.045	0.184
4	0.015	0.232
5	0.000	0.267
6	0.001	0.136
7	0.000	0.097
CM Ep. 8		
1	0.252	0.002
2	0.217	0.030
3	0.166	0.078
4	0.125	0.173
5	0.131	0.243
6	0.076	0.207
7	0.034	0.267
PCS Ep. 5		
1	0.310	0.000
2	0.131	0.000
3	0.258	0.027
4	0.290	0.112
5	0.011	0.261
6	0.000	0.491
7	0.000	0.109
PCS Ep. 8		
1	0.153	0.000
2	0.082	0.007
3	0.179	0.038
4	0.217	0.141
5	0.161	0.239
6	0.201	0.482
7	0.008	0.091
Avoid Ep. 5		
None	0.121	0.746
Some	0.879	0.254
Avoid Ep. 8		
None	0.352	0.837
Some	0.648	0.163
Resist Ep. 5		
None	0.910	0.610
Some	0.090	0.390
Resist Ep. 8		
None	0.695	0.453
Some	0.305	0.547
Latent Class Probability	0.488	0.512

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A10

Analysis 2: 3-class model

	LC #1	LC #2	LC #3
CM Ep. 5			
1	0.887	0.002	0.739
2	0.068	0.067	0.115
3	0.035	0.168	0.099
4	0.009	0.231	0.047
5	0.000	0.284	0.000
6	0.002	0.145	0.000
7	0.000	0.103	0.000
CM Ep. 8			
1	0.497	0.002	0.000
2	0.328	0.028	0.099
3	0.102	0.072	0.225
4	0.012	0.167	0.245
5	0.027	0.246	0.234
6	0.018	0.204	0.148
7	0.016	0.282	0.049
PCS Ep. 5			
1	0.365	0.000	0.226
2	0.155	0.000	0.096
3	0.228	0.023	0.267
4	0.246	0.081	0.365
5	0.007	0.258	0.047
6	0.000	0.522	0.000
7	0.000	0.116	0.000
PCS Ep. 8			
1	0.302	0.000	0.000
2	0.161	0.008	0.000
3	0.323	0.041	0.028
4	0.214	0.135	0.222
5	0.000	0.233	0.328
6	0.000	0.489	0.404
7	0.000	0.095	0.018
Avoid Ep. 5			
None	0.096	0.778	0.157
Some	0.904	0.222	0.843
Avoid Ep. 8			
None	0.091	0.844	0.630
Some	0.909	0.156	0.370
Resist Ep. 5			
None	0.918	0.600	0.888
Some	0.082	0.400	0.112
Resist Ep. 8			
None	0.734	0.449	0.640
Some	0.266	0.551	0.360
Latent Class Probability	0.247	0.482	0.270

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A11

Analysis 2: 4-class model

	LC #1	LC #2	LC #3	LC #4
CM Ep. 5				
1	0.893	0.005	0.873	0.000
2	0.068	0.021	0.081	0.152
3	0.028	0.033	0.021	0.372
4	0.010	0.216	0.024	0.234
5	0.000	0.323	0.000	0.195
6	0.000	0.220	0.000	0.043
7	0.000	0.181	0.000	0.004
CM Ep. 8				
1	0.498	0.000	0.000	0.005
2	0.329	0.000	0.096	0.072
3	0.102	0.009	0.225	0.162
4	0.011	0.108	0.248	0.238
5	0.024	0.186	0.232	0.310
6	0.019	0.231	0.145	0.168
7	0.018	0.466	0.054	0.045
PCS Ep. 5				
1	0.368	0.000	0.267	0.000
2	0.156	0.000	0.107	0.005
3	0.231	0.038	0.311	0.007
4	0.241	0.037	0.310	0.227
5	0.005	0.165	0.004	0.359
6	0.000	0.582	0.000	0.370
7	0.000	0.177	0.000	0.032
PCS Ep. 8				
1	0.304	0.000	0.000	0.000
2	0.159	0.000	0.000	0.017
3	0.326	0.029	0.014	0.063
4	0.211	0.117	0.211	0.181
5	0.000	0.179	0.326	0.305
6	0.000	0.563	0.433	0.370
7	0.000	0.112	0.017	0.064
Avoid Ep. 5				
None	0.095	0.894	0.142	0.564
Some	0.905	0.106	0.858	0.436
Avoid Ep. 8				
None	0.091	0.921	0.637	0.720
Some	0.909	0.079	0.363	0.280
Resist Ep. 5				
None	0.920	0.455	0.896	0.792
Some	0.080	0.545	0.104	0.208
Resist Ep. 8				
None	0.734	0.300	0.647	0.629
Some	0.266	0.700	0.353	0.371
Latent Class Probability	0.246	0.269	0.228	0.257

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A12

Analysis 2: 5-class model

	LC #1	LC #2	LC #3	LC #4	LC #5
CM Ep. 5					
1	0.906	0.008	0.856	0.000	0.000
2	0.065	0.024	0.089	0.160	0.096
3	0.024	0.037	0.026	0.374	0.264
4	0.005	0.224	0.029	0.208	0.240
5	0.000	0.291	0.000	0.192	0.278
6	0.000	0.210	0.000	0.058	0.097
7	0.000	0.205	0.000	0.007	0.024
CM Ep. 8					
1	0.497	0.000	0.000	0.021	0.000
2	0.329	0.000	0.095	0.123	0.013
3	0.103	0.011	0.224	0.198	0.082
4	0.012	0.110	0.248	0.234	0.195
5	0.023	0.182	0.231	0.262	0.315
6	0.019	0.205	0.150	0.138	0.236
7	0.018	0.493	0.053	0.024	0.159
PCS Ep. 5					
1	0.373	0.000	0.262	0.000	0.000
2	0.157	0.000	0.108	0.000	0.004
3	0.234	0.049	0.308	0.000	0.005
4	0.236	0.051	0.317	0.318	0.072
5	0.000	0.184	0.005	0.413	0.238
6	0.000	0.564	0.000	0.237	0.570
7	0.000	0.152	0.000	0.031	0.111
PCS Ep. 8					
1	0.304	0.000	0.000	0.007	0.000
2	0.161	0.000	0.000	0.032	0.000
3	0.327	0.036	0.014	0.112	0.004
4	0.208	0.151	0.205	0.324	0.011
5	0.000	0.193	0.324	0.338	0.217
6	0.000	0.507	0.437	0.186	0.640
7	0.000	0.113	0.019	0.000	0.128
Avoid Ep. 5					
None	0.095	0.874	0.143	0.337	0.879
Some	0.905	0.126	0.857	0.663	0.121
Avoid Ep. 8					
None	0.090	0.898	0.645	0.470	1.000
Some	0.910	0.102	0.355	0.530	0.000
Resist Ep. 5					
None	0.924	0.277	0.897	0.696	0.993
Some	0.076	0.723	0.103	0.304	0.007
Resist Ep. 8					
None	0.734	0.134	0.651	0.529	0.818
Some	0.266	0.866	0.349	0.471	0.182
Latent Class Probability	0.243	0.218	0.232	0.140	0.168

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A13

Analysis 2: 6-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6
CM Ep. 5						
1	0.905	0.000	0.855	0.000	0.000	0.021
2	0.066	0.000	0.099	0.106	0.112	0.084
3	0.023	0.000	0.026	0.409	0.289	0.086
4	0.006	0.064	0.020	0.204	0.293	0.323
5	0.000	0.382	0.000	0.203	0.243	0.218
6	0.000	0.319	0.000	0.070	0.063	0.106
7	0.000	0.235	0.000	0.008	0.000	0.163
CM Ep. 8						
1	0.495	0.000	0.000	0.027	0.000	0.000
2	0.329	0.000	0.093	0.111	0.018	0.034
3	0.103	0.000	0.227	0.209	0.094	0.034
4	0.012	0.000	0.246	0.221	0.237	0.203
5	0.023	0.102	0.234	0.271	0.333	0.240
6	0.019	0.280	0.150	0.144	0.216	0.140
7	0.018	0.618	0.051	0.018	0.102	0.349
PCS Ep. 5						
1	0.372	0.000	0.263	0.000	0.000	0.000
2	0.157	0.000	0.105	0.007	0.004	0.000
3	0.234	0.000	0.300	0.000	0.015	0.088
4	0.236	0.000	0.327	0.295	0.100	0.128
5	0.000	0.028	0.005	0.406	0.280	0.335
6	0.000	0.697	0.000	0.252	0.527	0.402
7	0.000	0.275	0.000	0.040	0.074	0.047
PCS Ep. 8						
1	0.303	0.000	0.000	0.008	0.000	0.000
2	0.160	0.000	0.000	0.041	0.000	0.000
3	0.327	0.000	0.014	0.116	0.010	0.075
4	0.210	0.049	0.199	0.355	0.038	0.236
5	0.000	0.098	0.327	0.332	0.237	0.294
6	0.000	0.709	0.441	0.147	0.597	0.324
7	0.000	0.144	0.019	0.000	0.118	0.071
Avoid Ep. 5						
None	0.096	0.904	0.137	0.271	0.858	0.813
Some	0.904	0.096	0.863	0.729	0.142	0.187
Avoid Ep. 8						
None	0.091	0.891	0.645	0.347	1.000	0.912
Some	0.909	0.109	0.355	0.653	0.000	0.088
Resist Ep. 5						
None	0.923	0.485	0.900	0.755	0.983	0.126
Some	0.077	0.515	0.100	0.245	0.017	0.874
Resist Ep. 8						
None	0.734	0.335	0.651	0.589	0.780	0.031
Some	0.266	0.665	0.349	0.411	0.220	0.969
Latent Class Probability	0.244	0.121	0.230	0.111	0.169	0.126

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A14

Analysis 2: 7-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7
CM Ep. 5							
1	0.907	0.000	0.847	0.000	0.000	0.058	0.014
2	0.065	0.003	0.102	0.101	0.108	0.151	0.036
3	0.023	0.000	0.027	0.430	0.284	0.000	0.136
4	0.005	0.048	0.025	0.188	0.296	0.207	0.464
5	0.000	0.352	0.000	0.199	0.254	0.174	0.278
6	0.000	0.335	0.000	0.074	0.059	0.148	0.037
7	0.000	0.261	0.000	0.009	0.000	0.263	0.033
CM Ep. 8							
1	0.495	0.000	0.000	0.029	0.000	0.000	0.000
2	0.330	0.000	0.091	0.108	0.016	0.102	0.000
3	0.103	0.007	0.227	0.210	0.090	0.035	0.029
4	0.012	0.000	0.249	0.215	0.232	0.178	0.242
5	0.024	0.079	0.235	0.274	0.340	0.082	0.387
6	0.019	0.245	0.149	0.146	0.214	0.140	0.195
7	0.017	0.669	0.049	0.018	0.108	0.462	0.146
PCS Ep. 5							
1	0.373	0.000	0.262	0.000	0.000	0.000	0.000
2	0.157	0.000	0.108	0.000	0.005	0.000	0.000
3	0.234	0.000	0.293	0.000	0.015	0.230	0.000
4	0.236	0.000	0.331	0.301	0.095	0.169	0.100
5	0.000	0.050	0.005	0.420	0.275	0.377	0.268
6	0.000	0.686	0.000	0.238	0.535	0.225	0.544
7	0.000	0.263	0.000	0.041	0.076	0.000	0.088
PCS Ep. 8							
1	0.303	0.000	0.000	0.009	0.000	0.000	0.000
2	0.161	0.000	0.000	0.027	0.000	0.000	0.023
3	0.326	0.000	0.014	0.121	0.009	0.174	0.001
4	0.210	0.055	0.195	0.372	0.029	0.544	0.000
5	0.000	0.109	0.326	0.335	0.234	0.258	0.322
6	0.000	0.699	0.446	0.135	0.609	0.023	0.520
7	0.000	0.136	0.019	0.000	0.118	0.000	0.134
Avoid Ep. 5							
None	0.096	0.913	0.131	0.278	0.863	0.901	0.689
Some	0.904	0.087	0.869	0.722	0.137	0.099	0.311
Avoid Ep. 8							
None	0.091	0.903	0.642	0.370	1.000	0.883	0.855
Some	0.909	0.097	0.358	0.630	0.000	0.117	0.145
Resist Ep. 5							
None	0.924	0.467	0.902	0.784	0.979	0.190	0.000
Some	0.076	0.533	0.098	0.216	0.021	0.810	1.000
Resist Ep. 8							
None	0.735	0.315	0.654	0.609	0.754	0.075	0.000
Some	0.265	0.685	0.346	0.391	0.246	0.925	1.000
Latent Class Probability	0.244	0.124	0.230	0.108	0.174	0.055	0.065

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A15

Analysis 2: 8-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8
CM Ep. 5								
1	0.908	0.000	0.846	0.000	0.000	0.065	0.015	0.862
2	0.066	0.003	0.103	0.109	0.106	0.135	0.038	0.089
3	0.026	0.000	0.051	0.409	0.276	0.000	0.134	0.000
4	0.000	0.043	0.000	0.209	0.303	0.203	0.450	0.048
5	0.000	0.354	0.000	0.195	0.255	0.176	0.281	0.000
6	0.000	0.335	0.000	0.071	0.060	0.150	0.048	0.000
7	0.000	0.265	0.000	0.008	0.000	0.272	0.035	0.000
CM Ep. 8								
1	0.558	0.000	0.000	0.026	0.000	0.000	0.000	0.000
2	0.361	0.000	0.102	0.106	0.016	0.091	0.000	0.076
3	0.057	0.007	0.161	0.206	0.091	0.038	0.025	0.391
4	0.000	0.000	0.290	0.225	0.231	0.182	0.221	0.143
5	0.010	0.078	0.231	0.274	0.337	0.082	0.390	0.210
6	0.012	0.247	0.167	0.144	0.212	0.145	0.195	0.106
7	0.002	0.667	0.049	0.018	0.113	0.462	0.168	0.074
PCS Ep. 5								
1	0.367	0.000	0.260	0.000	0.000	0.000	0.000	0.310
2	0.163	0.000	0.074	0.000	0.004	0.000	0.000	0.165
3	0.219	0.000	0.247	0.000	0.019	0.239	0.000	0.374
4	0.251	0.000	0.419	0.306	0.090	0.159	0.091	0.141
5	0.000	0.046	0.000	0.408	0.277	0.378	0.278	0.010
6	0.000	0.688	0.000	0.247	0.534	0.224	0.539	0.000
7	0.000	0.266	0.000	0.040	0.076	0.000	0.092	0.000
PCS Ep. 8								
1	0.308	0.000	0.000	0.008	0.000	0.000	0.000	0.071
2	0.164	0.000	0.000	0.040	0.000	0.000	0.000	0.036
3	0.335	0.000	0.020	0.118	0.009	0.173	0.000	0.075
4	0.193	0.056	0.168	0.358	0.032	0.563	0.000	0.276
5	0.000	0.106	0.274	0.331	0.235	0.263	0.327	0.316
6	0.000	0.703	0.513	0.144	0.608	0.002	0.531	0.220
7	0.000	0.135	0.026	0.000	0.116	0.000	0.141	0.007
Avoid Ep. 5								
None	0.093	0.912	0.182	0.273	0.865	0.912	0.718	0.046
Some	0.907	0.088	0.818	0.727	0.135	0.088	0.282	0.954
Avoid Ep. 8								
None	0.098	0.899	0.952	0.359	1.000	0.893	0.893	0.000
Some	0.902	0.101	0.048	0.641	0.000	0.107	0.107	1.000
Resist Ep. 5								
None	0.923	0.469	0.909	0.759	0.979	0.182	0.000	0.902
Some	0.077	0.531	0.091	0.241	0.021	0.818	1.000	0.098
Resist Ep. 8								
None	0.754	0.317	0.697	0.584	0.752	0.077	0.000	0.569
Some	0.246	0.683	0.303	0.416	0.248	0.923	1.000	0.431
Latent Class Probability	0.216	0.122	0.157	0.112	0.176	0.053	0.064	0.101

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A16

Analysis 2: 9-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8	LC #9
CM Ep. 5									
1	0.910	0.000	0.847	0.000	0.000	0.099	0.012	0.873	0.867
2	0.068	0.000	0.107	0.106	0.107	0.173	0.042	0.084	0.065
3	0.016	0.000	0.045	0.405	0.276	0.000	0.119	0.010	0.068
4	0.006	0.045	0.000	0.208	0.300	0.240	0.395	0.032	0.000
5	0.000	0.364	0.000	0.203	0.255	0.000	0.323	0.000	0.000
6	0.000	0.331	0.000	0.070	0.062	0.166	0.056	0.000	0.000
7	0.000	0.259	0.000	0.009	0.000	0.323	0.053	0.000	0.000
CM Ep. 8									
1	0.565	0.000	0.000	0.027	0.000	0.000	0.000	0.000	0.323
2	0.323	0.000	0.080	0.102	0.017	0.099	0.017	0.077	0.450
3	0.082	0.000	0.157	0.203	0.091	0.039	0.043	0.365	0.089
4	0.000	0.000	0.322	0.230	0.230	0.147	0.227	0.156	0.000
5	0.009	0.076	0.237	0.277	0.336	0.073	0.345	0.220	0.066
6	0.000	0.253	0.154	0.145	0.210	0.151	0.174	0.148	0.065
7	0.022	0.672	0.050	0.017	0.115	0.492	0.194	0.035	0.007
PCS Ep. 5									
1	0.369	0.000	0.256	0.000	0.000	0.000	0.000	0.279	0.397
2	0.177	0.000	0.078	0.000	0.004	0.000	0.000	0.164	0.079
3	0.214	0.000	0.232	0.000	0.018	0.343	0.000	0.380	0.271
4	0.240	0.000	0.434	0.302	0.091	0.175	0.104	0.167	0.253
5	0.000	0.050	0.000	0.409	0.280	0.352	0.293	0.010	0.000
6	0.000	0.686	0.000	0.249	0.531	0.130	0.528	0.000	0.000
7	0.000	0.264	0.000	0.040	0.076	0.000	0.075	0.000	0.000
PCS Ep. 8									
1	0.307	0.000	0.000	0.008	0.000	0.000	0.000	0.069	0.204
2	0.170	0.000	0.000	0.041	0.000	0.000	0.000	0.035	0.084
3	0.358	0.000	0.010	0.119	0.009	0.241	0.000	0.000	0.291
4	0.164	0.069	0.122	0.358	0.032	0.530	0.093	0.271	0.420
5	0.000	0.111	0.293	0.333	0.239	0.229	0.319	0.346	0.000
6	0.000	0.685	0.549	0.141	0.606	0.000	0.472	0.269	0.000
7	0.000	0.135	0.027	0.000	0.115	0.000	0.116	0.009	0.000
Avoid Ep. 5									
None	0.000	0.912	0.139	0.274	0.865	0.880	0.749	0.052	0.529
Some	1.000	0.088	0.861	0.726	0.135	0.120	0.251	0.948	0.471
Avoid Ep. 8									
None	0.000	0.895	1.000	0.353	1.000	0.854	0.908	0.000	0.587
Some	1.000	0.105	0.000	0.647	0.000	0.146	0.092	1.000	0.413
Resist Ep. 5									
None	0.904	0.474	0.904	0.763	0.977	0.218	0.000	0.904	1.000
Some	0.096	0.526	0.096	0.237	0.023	0.782	1.000	0.096	0.000
Resist Ep. 8									
None	0.704	0.315	0.676	0.590	0.749	0.091	0.000	0.587	0.937
Some	0.296	0.685	0.324	0.410	0.251	0.909	1.000	0.413	0.063
Latent Class Probability	0.183	0.122	0.138	0.111	0.177	0.041	0.077	0.097	0.053

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A17

Analysis 3: 2-class model

MEANS

	LC #1	LC #2
CM Ep. 5		
Mean	1.277	4.575
CM Ep. 8		
Mean	3.236	5.390
PCS Ep. 5		
Mean	2.631	5.582
PCS Ep. 8		
Mean	3.912	5.440

PROBABILITIES

	LC #1	LC #2
Avoid Ep. 5		
None	0.129	0.765
Some	0.871	0.235
Avoid Ep. 8		
None	0.381	0.843
Some	0.619	0.157
Resist Ep. 5		
None	0.899	0.603
Some	0.101	0.397
Resist Ep. 8		
None	0.636	0.448
Some	0.364	0.552
Latent Class Probability	0.532	0.468

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A18

Analysis 3: 3-class model

MEANS

	LC #1	LC #2	LC #3
CM Ep. 5			
Mean	1.184	4.716	1.471
CM Ep. 8			
Mean	1.835	5.454	4.404
PCS Ep. 5			
Mean	2.393	5.639	3.014
PCS Ep. 8			
Mean	2.467	5.456	5.117

PROBABILITIES

	LC #1	LC #2	LC #3
Avoid Ep. 5			
None	0.102	0.783	0.184
Some	0.898	0.217	0.816
Avoid Ep. 8			
None	0.088	0.847	0.640
Some	0.912	0.153	0.360
Resist Ep. 5			
None	0.919	0.592	0.869
Some	0.081	0.408	0.131
Resist Ep. 8			
None	0.724	0.443	0.560
Some	0.276	0.557	0.440
Latent Class Probability	0.241	0.438	0.322

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A19

Analysis 3: 4-class model

MEANS

	LC #1	LC #2	LC #3	LC #4
CM Ep. 5				
Mean	1.142	3.505	1.163	5.659
CM Ep. 8				
Mean	1.819	4.606	4.527	6.070
PCS Ep. 5				
Mean	2.374	5.215	2.693	5.814
PCS Ep. 8				
Mean	2.509	5.203	5.199	5.544

PROBABILITIES

	LC #1	LC #2	LC #3	LC #4
Avoid Ep. 5				
None	0.099	0.646	0.148	0.827
Some	0.901	0.354	0.852	0.173
Avoid Ep. 8				
None	0.094	0.756	0.664	0.868
Some	0.906	0.244	0.336	0.132
Resist Ep. 5				
None	0.922	0.722	0.881	0.497
Some	0.078	0.278	0.119	0.503
Resist Ep. 8				
None	0.725	0.537	0.556	0.364
Some	0.275	0.463	0.444	0.636
Latent Class Probability	0.242	0.271	0.258	0.229

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A20

Analysis 3: 5-class model

MEANS

	LC #1	LC #2	LC #3	LC #4	LC #5
CM Ep. 5					
Mean	1.086	2.736	1.071	6.416	4.523
CM Ep. 8					
Mean	1.832	4.303	4.528	6.306	5.255
PCS Ep. 5					
Mean	2.308	4.911	2.605	5.803	5.544
PCS Ep. 8					
Mean	2.510	5.099	5.197	5.454	5.380

PROBABILITIES

	LC #1	LC #2	LC #3	LC #4	LC #5
Avoid Ep. 5					
None	0.087	0.581	0.144	0.833	0.726
Some	0.913	0.419	0.856	0.167	0.274
Avoid Ep. 8					
None	0.087	0.732	0.662	0.858	0.806
Some	0.913	0.268	0.338	0.142	0.194
Resist Ep. 5					
None	0.923	0.788	0.893	0.418	0.619
Some	0.077	0.212	0.107	0.582	0.381
Resist Ep. 8					
None	0.721	0.545	0.556	0.329	0.480
Some	0.279	0.455	0.444	0.671	0.520
Latent Class Probability	0.234	0.163	0.238	0.114	0.251

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A21

Analysis 3: 6-class model

MEANS

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6
CM Ep. 5						
Mean	1.065	2.670	1.035	6.423	5.005	3.998
CM Ep. 8						
Mean	1.833	4.258	4.535	6.309	5.496	4.971
PCS Ep. 5						
Mean	2.286	4.832	2.562	5.801	5.727	5.322
PCS Ep. 8						
Mean	2.515	5.064	5.190	5.453	5.474	5.255

PROBABILITIES

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6
Avoid Ep. 5						
None	0.082	0.553	0.148	0.834	0.749	0.692
Some	0.918	0.447	0.852	0.166	0.251	0.308
Avoid Ep. 8						
None	0.085	0.717	0.665	0.859	0.805	0.800
Some	0.915	0.283	0.335	0.141	0.195	0.200
Resist Ep. 5						
None	0.922	0.793	0.898	0.416	0.636	0.602
Some	0.078	0.207	0.102	0.584	0.364	0.398
Resist Ep. 8						
None	0.719	0.544	0.561	0.327	0.495	0.468
Some	0.281	0.456	0.439	0.673	0.505	0.532
Latent Class Probability	0.231	0.172	0.229	0.113	0.132	0.123

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A22

Analysis 3: 7-class model

MEANS

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7
CM Ep. 5							
Mean	1.000	3.000	1.000	6.419	5.000	4.000	2.000
CM Ep. 8							
Mean	1.845	4.279	4.551	6.301	5.494	4.972	3.779
PCS Ep. 5							
Mean	2.217	4.949	2.577	5.801	5.724	5.322	4.116
PCS Ep. 8							
Mean	2.548	5.015	5.175	5.451	5.474	5.255	4.674

PROBABILITIES

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7
Avoid Ep. 5							
None	0.078	0.565	0.156	0.831	0.750	0.692	0.400
Some	0.922	0.435	0.844	0.169	0.250	0.308	0.600
Avoid Ep. 8							
None	0.082	0.691	0.676	0.857	0.805	0.800	0.621
Some	0.918	0.309	0.324	0.143	0.195	0.200	0.379
Resist Ep. 5							
None	0.933	0.826	0.902	0.419	0.635	0.603	0.737
Some	0.067	0.174	0.098	0.581	0.365	0.397	0.263
Resist Ep. 8							
None	0.734	0.529	0.564	0.331	0.494	0.469	0.547
Some	0.266	0.471	0.436	0.669	0.506	0.531	0.453
Latent Class Probability	0.217	0.116	0.220	0.114	0.131	0.123	0.080

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A23

Analysis 3: 8-class model

MEANS

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8
CM Ep. 5								
Mean	1.000	3.000	1.000	6.419	5.000	4.000	2.000	2.000
CM Ep. 8								
Mean	1.834	4.279	4.543	6.301	5.494	4.972	4.493	2.094
PCS Ep. 5								
Mean	2.218	4.949	2.573	5.801	5.724	5.322	4.360	3.539
PCS Ep. 8								
Mean	2.524	5.015	5.180	5.451	5.474	5.255	5.422	2.910

PROBABILITIES

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8
Avoid Ep. 5								
None	0.080	0.565	0.154	0.831	0.750	0.692	0.468	0.240
Some	0.920	0.435	0.846	0.169	0.250	0.308	0.532	0.760
Avoid Ep. 8								
None	0.084	0.691	0.670	0.857	0.805	0.800	0.822	0.147
Some	0.916	0.309	0.330	0.143	0.195	0.200	0.178	0.853
Resist Ep. 5								
None	0.932	0.826	0.903	0.419	0.635	0.603	0.711	0.799
Some	0.068	0.174	0.097	0.581	0.365	0.397	0.289	0.201
Resist Ep. 8								
None	0.734	0.529	0.564	0.331	0.494	0.469	0.538	0.569
Some	0.266	0.471	0.436	0.669	0.506	0.531	0.462	0.431
Latent Class Probability	0.215	0.116	0.221	0.114	0.131	0.123	0.056	0.024

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A24

Analysis 3: 9-class model

MEANS

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8	LC #9
CM Ep. 5									
Mean	1.000	3.000	1.000	6.548	5.000	6.000	2.000	4.000	4.000
CM Ep. 8									
Mean	1.844	4.279	4.552	6.357	5.494	6.125	3.779	4.779	5.143
PCS Ep. 5									
Mean	2.217	4.949	2.577	5.769	5.724	5.906	4.116	5.207	5.422
PCS Ep. 8									
Mean	2.548	5.015	5.175	5.406	5.474	5.593	4.674	5.338	5.182

PROBABILITIES

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8	LC #9
Avoid Ep. 5									
None	0.078	0.565	0.156	0.817	0.750	0.875	0.400	0.706	0.679
Some	0.922	0.435	0.844	0.183	0.250	0.125	0.600	0.294	0.321
Avoid Ep. 8									
None	0.082	0.691	0.676	0.812	0.805	1.000	0.621	0.824	0.779
Some	0.918	0.309	0.324	0.188	0.195	0.000	0.379	0.176	0.221
Resist Ep. 5									
None	0.933	0.826	0.902	0.240	0.635	1.000	0.737	0.881	0.360
Some	0.067	0.174	0.098	0.760	0.365	0.000	0.263	0.119	0.640
Resist Ep. 8									
None	0.734	0.529	0.563	0.228	0.494	0.657	0.547	1.000	0.000
Some	0.266	0.471	0.437	0.772	0.506	0.343	0.453	0.000	1.000
Latent Class Probability	0.217	0.116	0.220	0.087	0.131	0.027	0.080	0.057	0.065

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A25

Analysis 4: 2-class model

	LC #1	LC #2
CM Ep. 5		
1	0.863	0.006
2	0.079	0.080
3	0.041	0.192
4	0.013	0.233
5	0.003	0.260
6	0.001	0.133
7	0.000	0.096
CM Ep. 8		
1	0.234	0.002
2	0.213	0.030
3	0.151	0.081
4	0.122	0.175
5	0.138	0.241
6	0.089	0.207
7	0.055	0.264
PCS Ep. 5		
1	0.321	0.000
2	0.129	0.004
3	0.264	0.027
4	0.272	0.122
5	0.011	0.255
6	0.003	0.483
7	0.000	0.108
PCS Ep. 8		
1	0.145	0.000
2	0.081	0.008
3	0.174	0.039
4	0.210	0.146
5	0.171	0.235
6	0.203	0.485
7	0.015	0.088
Avoid Ep. 5		
Low	0.221	0.866
Med	0.433	0.125
High	0.346	0.010
Avoid Ep. 8		
Low	0.490	0.930
Med	0.280	0.066
High	0.230	0.004
Resist Ep. 5		
Low	0.953	0.733
Med	0.039	0.153
High	0.008	0.113
Resist Ep. 8		
Low	0.760	0.587
Med	0.176	0.246
High	0.064	0.168
LC Prob.	0.503	0.497

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A26

Analysis 4: 3-class model

	LC #1	LC #2	LC #3
CM Ep. 5			
1	0.878	0.002	0.809
2	0.069	0.069	0.106
3	0.041	0.187	0.057
4	0.013	0.234	0.025
5	0.000	0.270	0.003
6	0.000	0.138	0.000
7	0.000	0.099	0.000
CM Ep. 8			
1	0.505	0.002	0.000
2	0.337	0.032	0.100
3	0.087	0.076	0.209
4	0.012	0.172	0.219
5	0.020	0.241	0.239
6	0.021	0.207	0.150
7	0.019	0.272	0.083
PCS Ep. 5			
1	0.361	0.000	0.270
2	0.156	0.000	0.108
3	0.230	0.023	0.285
4	0.235	0.102	0.327
5	0.012	0.264	0.010
6	0.006	0.499	0.000
7	0.000	0.112	0.000
PCS Ep. 8			
1	0.310	0.000	0.003
2	0.174	0.009	0.000
3	0.319	0.040	0.047
4	0.197	0.142	0.224
5	0.000	0.234	0.317
6	0.000	0.485	0.383
7	0.000	0.090	0.027
Avoid Ep. 5			
Low	0.184	0.874	0.272
Med	0.440	0.116	0.424
High	0.376	0.010	0.304
Avoid Ep. 8			
Low	0.159	0.927	0.789
Med	0.379	0.068	0.184
High	0.462	0.005	0.027
Resist Ep. 5			
Low	0.979	0.731	0.924
Med	0.021	0.153	0.060
High	0.000	0.116	0.017
Resist Ep. 8			
Low	0.842	0.585	0.687
Med	0.127	0.246	0.220
High	0.031	0.169	0.093
LC Prob.	0.233	0.481	0.286

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A27

Analysis 4: 4-class model

	LC #1	LC #2	LC #3	LC #4
CM Ep. 5				
1	0.887	0.007	0.896	0.000
2	0.067	0.143	0.083	0.024
3	0.032	0.374	0.021	0.025
4	0.014	0.268	0.000	0.197
5	0.000	0.173	0.000	0.340
6	0.000	0.028	0.000	0.233
7	0.000	0.006	0.000	0.182
CM Ep. 8				
1	0.509	0.006	0.000	0.000
2	0.337	0.070	0.103	0.000
3	0.086	0.161	0.203	0.009
4	0.011	0.248	0.218	0.099
5	0.016	0.311	0.233	0.175
6	0.019	0.160	0.155	0.244
7	0.022	0.044	0.088	0.473
PCS Ep. 5				
1	0.364	0.000	0.301	0.000
2	0.158	0.012	0.108	0.000
3	0.233	0.042	0.297	0.019
4	0.230	0.223	0.292	0.045
5	0.010	0.344	0.002	0.161
6	0.004	0.359	0.000	0.583
7	0.000	0.020	0.000	0.191
PCS Ep. 8				
1	0.309	0.000	0.008	0.000
2	0.172	0.019	0.000	0.000
3	0.323	0.074	0.035	0.017
4	0.196	0.198	0.209	0.111
5	0.000	0.285	0.322	0.182
6	0.000	0.367	0.397	0.576
7	0.000	0.057	0.029	0.114
Avoid Ep. 5				
Low	0.176	0.771	0.254	0.931
Med	0.445	0.207	0.415	0.066
High	0.379	0.021	0.332	0.003
Avoid Ep. 8				
Low	0.154	0.872	0.790	0.962
Med	0.378	0.117	0.180	0.038
High	0.467	0.011	0.029	0.000
Resist Ep. 5				
Low	0.978	0.877	0.927	0.604
Med	0.022	0.050	0.056	0.250
High	0.000	0.073	0.017	0.147
Resist Ep. 8				
Low	0.841	0.722	0.678	0.470
Med	0.129	0.171	0.222	0.314
High	0.031	0.108	0.100	0.216
LC Prob.	0.229	0.259	0.258	0.254

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A28

Analysis 4: 5-class model

	LC #1	LC #2	LC #3	LC #4	LC #5
CM Ep. 5					
1	0.903	0.007	0.905	0.000	0.000
2	0.057	0.106	0.079	0.019	0.177
3	0.031	0.289	0.016	0.032	0.338
4	0.009	0.260	0.000	0.191	0.257
5	0.000	0.275	0.000	0.308	0.129
6	0.000	0.061	0.000	0.233	0.063
7	0.000	0.002	0.000	0.216	0.036
CM Ep. 8					
1	0.518	0.000	0.000	0.000	0.015
2	0.332	0.029	0.104	0.000	0.119
3	0.085	0.111	0.204	0.008	0.173
4	0.011	0.227	0.215	0.099	0.211
5	0.016	0.329	0.234	0.154	0.244
6	0.019	0.224	0.154	0.207	0.151
7	0.019	0.080	0.089	0.533	0.087
PCS Ep. 5					
1	0.371	0.002	0.302	0.000	0.000
2	0.161	0.003	0.107	0.000	0.023
3	0.231	0.010	0.293	0.000	0.136
4	0.228	0.111	0.296	0.049	0.312
5	0.005	0.322	0.003	0.152	0.303
6	0.004	0.485	0.000	0.600	0.217
7	0.000	0.067	0.000	0.199	0.009
PCS Ep. 8					
1	0.315	0.000	0.008	0.000	0.000
2	0.172	0.000	0.000	0.000	0.046
3	0.323	0.017	0.033	0.000	0.181
4	0.189	0.044	0.207	0.114	0.414
5	0.000	0.301	0.323	0.187	0.193
6	0.000	0.543	0.399	0.574	0.166
7	0.000	0.096	0.030	0.124	0.000
Avoid Ep. 5					
Low	0.175	0.937	0.255	0.939	0.539
Med	0.444	0.063	0.413	0.058	0.402
High	0.381	0.000	0.332	0.002	0.059
Avoid Ep. 8					
Low	0.156	1.000	0.795	0.963	0.670
Med	0.371	0.000	0.177	0.037	0.299
High	0.473	0.000	0.028	0.000	0.031
Resist Ep. 5					
Low	0.979	1.000	0.930	0.499	0.730
Med	0.021	0.000	0.053	0.319	0.109
High	0.000	0.000	0.016	0.182	0.161
Resist Ep. 8					
Low	0.843	0.880	0.684	0.348	0.540
Med	0.126	0.119	0.217	0.362	0.255
High	0.031	0.001	0.099	0.290	0.205
LC Prob.	0.225	0.195	0.257	0.199	0.124

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A29

Analysis 4: 6-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6
CM Ep. 5						
1	0.972	0.007	0.898	0.000	0.000	0.760
2	0.011	0.116	0.083	0.019	0.124	0.152
3	0.000	0.296	0.019	0.031	0.324	0.088
4	0.017	0.261	0.000	0.184	0.285	0.000
5	0.000	0.266	0.000	0.311	0.150	0.000
6	0.000	0.054	0.000	0.239	0.074	0.000
7	0.000	0.001	0.000	0.216	0.043	0.000
CM Ep. 8						
1	0.524	0.000	0.000	0.000	0.008	0.445
2	0.311	0.034	0.092	0.000	0.093	0.373
3	0.094	0.119	0.201	0.007	0.149	0.107
4	0.002	0.230	0.222	0.095	0.218	0.026
5	0.018	0.326	0.237	0.153	0.260	0.024
6	0.020	0.216	0.156	0.210	0.166	0.024
7	0.032	0.076	0.091	0.535	0.105	0.000
PCS Ep. 5						
1	0.495	0.002	0.302	0.000	0.000	0.187
2	0.203	0.004	0.109	0.000	0.024	0.090
3	0.217	0.012	0.294	0.000	0.133	0.243
4	0.076	0.125	0.292	0.047	0.256	0.468
5	0.010	0.326	0.003	0.143	0.333	0.000
6	0.000	0.473	0.000	0.604	0.245	0.013
7	0.000	0.060	0.000	0.207	0.010	0.000
PCS Ep. 8						
1	0.341	0.000	0.000	0.000	0.000	0.259
2	0.222	0.000	0.000	0.000	0.043	0.097
3	0.331	0.019	0.029	0.000	0.168	0.304
4	0.107	0.056	0.194	0.106	0.404	0.341
5	0.000	0.305	0.335	0.185	0.196	0.000
6	0.000	0.528	0.412	0.581	0.188	0.000
7	0.000	0.092	0.030	0.128	0.000	0.000
Avoid Ep. 5						
Low	0.000	0.934	0.238	0.948	0.529	0.459
Med	0.366	0.066	0.414	0.051	0.409	0.528
High	0.634	0.000	0.348	0.001	0.062	0.013
Avoid Ep. 8						
Low	0.010	1.000	0.797	0.966	0.673	0.394
Med	0.323	0.000	0.172	0.034	0.298	0.432
High	0.667	0.000	0.031	0.000	0.029	0.174
Resist Ep. 5						
Low	0.973	1.000	0.927	0.514	0.676	0.989
Med	0.027	0.000	0.056	0.316	0.125	0.011
High	0.000	0.000	0.017	0.169	0.199	0.000
Resist Ep. 8						
Low	0.802	0.881	0.677	0.366	0.478	0.895
Med	0.143	0.119	0.222	0.357	0.273	0.105
High	0.055	0.000	0.101	0.277	0.248	0.000
LC Prob.	0.131	0.197	0.250	0.198	0.115	0.110

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A30

Analysis 4: 7-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7
CM Ep. 5							
1	0.974	0.006	0.896	0.000	0.000	0.758	0.031
2	0.011	0.120	0.089	0.000	0.070	0.157	0.116
3	0.000	0.299	0.015	0.000	0.380	0.085	0.094
4	0.015	0.273	0.000	0.109	0.280	0.000	0.337
5	0.000	0.254	0.000	0.341	0.157	0.000	0.211
6	0.000	0.044	0.000	0.311	0.079	0.000	0.075
7	0.000	0.004	0.000	0.239	0.035	0.000	0.136
CM Ep. 8							
1	0.525	0.000	0.000	0.000	0.011	0.444	0.000
2	0.309	0.033	0.090	0.000	0.091	0.376	0.046
3	0.094	0.114	0.204	0.000	0.150	0.107	0.064
4	0.002	0.245	0.219	0.018	0.220	0.027	0.252
5	0.018	0.334	0.240	0.075	0.285	0.021	0.269
6	0.020	0.193	0.158	0.264	0.180	0.025	0.120
7	0.032	0.082	0.090	0.643	0.064	0.000	0.249
PCS Ep. 5							
1	0.495	0.002	0.304	0.000	0.000	0.185	0.000
2	0.203	0.002	0.110	0.000	0.034	0.090	0.000
3	0.217	0.012	0.290	0.000	0.124	0.244	0.082
4	0.077	0.127	0.293	0.041	0.243	0.467	0.138
5	0.008	0.331	0.003	0.094	0.354	0.000	0.244
6	0.000	0.460	0.000	0.633	0.233	0.014	0.462
7	0.000	0.066	0.000	0.232	0.014	0.000	0.074
PCS Ep. 8							
1	0.341	0.000	0.000	0.000	0.000	0.258	0.000
2	0.222	0.000	0.000	0.000	0.058	0.095	0.000
3	0.332	0.021	0.029	0.000	0.143	0.305	0.088
4	0.105	0.053	0.191	0.124	0.480	0.342	0.122
5	0.000	0.298	0.335	0.131	0.222	0.000	0.275
6	0.000	0.534	0.414	0.627	0.098	0.000	0.419
7	0.000	0.095	0.030	0.118	0.000	0.000	0.096
Avoid Ep. 5							
Low	0.000	0.931	0.230	0.958	0.459	0.464	0.864
Med	0.369	0.069	0.419	0.037	0.463	0.523	0.136
High	0.631	0.000	0.350	0.004	0.079	0.013	0.000
Avoid Ep. 8							
Low	0.010	1.000	0.795	0.959	0.589	0.396	0.970
Med	0.324	0.000	0.174	0.041	0.367	0.432	0.030
High	0.665	0.000	0.031	0.000	0.044	0.172	0.000
Resist Ep. 5							
Low	0.973	1.000	0.935	0.640	0.819	0.988	0.000
Med	0.027	0.000	0.050	0.273	0.128	0.012	0.412
High	0.000	0.000	0.015	0.087	0.053	0.000	0.588
Resist Ep. 8							
Low	0.802	0.830	0.682	0.483	0.622	0.894	0.000
Med	0.143	0.146	0.224	0.361	0.263	0.106	0.280
High	0.056	0.023	0.094	0.156	0.115	0.000	0.720
LC Prob.	0.131	0.211	0.248	0.145	0.088	0.109	0.067

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A31

Analysis 4: 8-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8
CM Ep. 5								
1	0.976	0.009	0.888	0.000	0.000	0.773	0.000	0.926
2	0.015	0.112	0.089	0.000	0.108	0.142	0.114	0.055
3	0.000	0.291	0.023	0.000	0.375	0.085	0.095	0.000
4	0.009	0.275	0.000	0.108	0.257	0.000	0.357	0.019
5	0.000	0.261	0.000	0.336	0.154	0.000	0.218	0.000
6	0.000	0.047	0.000	0.310	0.072	0.000	0.083	0.000
7	0.000	0.004	0.000	0.246	0.033	0.000	0.133	0.000
CM Ep. 8								
1	0.633	0.000	0.000	0.000	0.010	0.480	0.000	0.000
2	0.322	0.030	0.097	0.000	0.098	0.389	0.039	0.125
3	0.045	0.109	0.172	0.000	0.158	0.105	0.065	0.321
4	0.000	0.238	0.235	0.017	0.225	0.000	0.247	0.137
5	0.000	0.341	0.233	0.070	0.277	0.000	0.276	0.212
6	0.000	0.198	0.172	0.259	0.174	0.025	0.132	0.085
7	0.000	0.084	0.091	0.654	0.058	0.000	0.242	0.119
PCS Ep. 5								
1	0.477	0.000	0.302	0.000	0.000	0.198	0.000	0.379
2	0.230	0.001	0.092	0.000	0.033	0.082	0.000	0.163
3	0.194	0.011	0.261	0.000	0.112	0.238	0.060	0.412
4	0.091	0.113	0.345	0.043	0.278	0.468	0.126	0.045
5	0.009	0.331	0.000	0.093	0.352	0.000	0.249	0.000
6	0.000	0.475	0.000	0.632	0.212	0.013	0.489	0.000
7	0.000	0.070	0.000	0.232	0.013	0.000	0.077	0.000
PCS Ep. 8								
1	0.357	0.000	0.000	0.000	0.000	0.265	0.000	0.103
2	0.238	0.000	0.000	0.000	0.048	0.081	0.010	0.075
3	0.331	0.017	0.032	0.000	0.146	0.305	0.089	0.136
4	0.073	0.038	0.172	0.129	0.477	0.349	0.106	0.269
5	0.000	0.294	0.300	0.130	0.232	0.000	0.279	0.296
6	0.000	0.552	0.463	0.625	0.098	0.000	0.416	0.112
7	0.000	0.098	0.033	0.116	0.000	0.000	0.100	0.009
Avoid Ep. 5								
Low	0.000	0.929	0.288	0.960	0.498	0.460	0.846	0.035
Med	0.358	0.071	0.404	0.035	0.428	0.525	0.154	0.448
High	0.642	0.000	0.308	0.005	0.074	0.015	0.000	0.516
Avoid Ep. 8								
Low	0.012	1.000	0.973	0.959	0.619	0.401	0.953	0.000
Med	0.212	0.000	0.016	0.041	0.339	0.422	0.047	0.861
High	0.776	0.000	0.011	0.000	0.043	0.177	0.000	0.139
Resist Ep. 5								
Low	0.975	1.000	0.924	0.638	0.847	0.988	0.000	0.950
Med	0.025	0.000	0.060	0.276	0.116	0.012	0.393	0.039
High	0.000	0.000	0.017	0.086	0.037	0.000	0.607	0.011
Resist Ep. 8								
Low	0.839	0.831	0.689	0.480	0.643	0.911	0.000	0.621
Med	0.124	0.146	0.196	0.362	0.259	0.089	0.292	0.308
High	0.037	0.024	0.115	0.158	0.098	0.000	0.708	0.071
LC Prob.	0.107	0.205	0.207	0.143	0.097	0.104	0.067	0.072

Note. For an explanation of abbreviations, please see the Appendix introduction.

Table A32

Analysis 4: 9-class model

	LC #1	LC #2	LC #3	LC #4	LC #5	LC #6	LC #7	LC #8	LC #9
CM Ep. 5									
1	0.976	0.005	0.892	0.000	0.000	0.778	0.000	0.921	0.824
2	0.016	0.112	0.073	0.000	0.112	0.139	0.105	0.057	0.153
3	0.000	0.288	0.034	0.000	0.374	0.082	0.098	0.000	0.000
4	0.008	0.276	0.000	0.107	0.261	0.000	0.364	0.022	0.000
5	0.000	0.265	0.000	0.334	0.158	0.000	0.223	0.000	0.000
6	0.000	0.049	0.000	0.310	0.072	0.000	0.084	0.000	0.000
7	0.000	0.005	0.000	0.250	0.023	0.000	0.126	0.000	0.023
CM Ep. 8									
1	0.631	0.000	0.000	0.000	0.010	0.444	0.000	0.000	0.000
2	0.321	0.029	0.114	0.000	0.099	0.369	0.040	0.129	0.024
3	0.048	0.108	0.200	0.000	0.161	0.111	0.065	0.322	0.056
4	0.000	0.239	0.247	0.015	0.230	0.000	0.252	0.145	0.193
5	0.000	0.338	0.228	0.067	0.279	0.036	0.282	0.210	0.220
6	0.000	0.200	0.165	0.256	0.176	0.025	0.135	0.081	0.216
7	0.000	0.086	0.046	0.661	0.044	0.015	0.227	0.113	0.292
PCS Ep. 5									
1	0.469	0.000	0.295	0.000	0.000	0.221	0.000	0.381	0.277
2	0.229	0.000	0.085	0.000	0.034	0.076	0.000	0.172	0.122
3	0.195	0.011	0.258	0.000	0.102	0.230	0.049	0.435	0.301
4	0.098	0.110	0.356	0.044	0.278	0.462	0.124	0.012	0.300
5	0.009	0.327	0.006	0.095	0.356	0.000	0.252	0.000	0.000
6	0.000	0.480	0.000	0.630	0.218	0.012	0.497	0.000	0.000
7	0.000	0.072	0.000	0.231	0.013	0.000	0.078	0.000	0.000
PCS Ep. 8									
1	0.357	0.000	0.000	0.000	0.000	0.246	0.000	0.108	0.000
2	0.237	0.000	0.000	0.000	0.046	0.085	0.010	0.065	0.000
3	0.330	0.017	0.000	0.000	0.146	0.310	0.077	0.146	0.113
4	0.075	0.038	0.143	0.131	0.472	0.359	0.106	0.261	0.261
5	0.000	0.294	0.316	0.130	0.234	0.000	0.284	0.304	0.267
6	0.000	0.551	0.517	0.624	0.103	0.000	0.421	0.108	0.287
7	0.000	0.100	0.024	0.116	0.000	0.000	0.102	0.009	0.073
Avoid Ep. 5									
Low	0.001	0.937	0.274	0.958	0.504	0.471	0.846	0.024	0.288
Med	0.365	0.063	0.473	0.037	0.423	0.514	0.154	0.427	0.182
High	0.634	0.000	0.253	0.005	0.073	0.015	0.000	0.549	0.529
Avoid Ep. 8									
Low	0.012	1.000	0.955	0.959	0.620	0.420	0.951	0.000	1.000
Med	0.212	0.000	0.030	0.041	0.337	0.422	0.049	0.861	0.000
High	0.776	0.000	0.015	0.000	0.043	0.157	0.000	0.139	0.000
Resist Ep. 5									
Low	0.975	1.000	0.983	0.635	0.842	0.990	0.000	0.944	0.673
Med	0.025	0.000	0.017	0.279	0.121	0.010	0.389	0.043	0.233
High	0.000	0.000	0.000	0.087	0.037	0.000	0.611	0.013	0.093
Resist Ep. 8									
Low	0.841	0.829	0.855	0.476	0.648	0.906	0.000	0.604	0.000
Med	0.123	0.147	0.145	0.366	0.252	0.094	0.281	0.318	0.426
High	0.036	0.024	0.000	0.158	0.100	0.000	0.719	0.079	0.574
LC Prob.	0.109	0.204	0.166	0.142	0.096	0.110	0.065	0.067	0.041

Note. For an explanation of abbreviations, please see the Appendix introduction.